

# SEMI-SUPERVISED LEARNING APPROACH FOR CRACK DETECTION AND IDENTIFICATION IN ADVANCED GAS-COOLED REACTOR GRAPHITE BRICKS

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## ABSTRACT

One of the life-limiting components of an Advanced Gas cooled Reactor (AGR) is its graphite core. The bricks present in the core undergo radiolytic oxidation throughout their lifetime which causes graphite weight loss and irradiation which can result in some of the bricks developing cracks. Understanding the nature and extent of brick cracking within the core is key to ensuring continued and extended operation of the AGR fleet. A semi-supervised machine learning classification algorithm is proposed as a method for improving the detection of cracked graphite bricks, by combining the labels derived from infrequent, detailed inspections of the core, with unlabeled, more frequent monitoring measurements taken during refueling operations. Semi-supervised machine learning, which is an emerging field in nuclear power condition monitoring, is the combination of ideas from both supervised and unsupervised machine learning whereby the data that is used to train the algorithm is a combination of labeled and unlabeled data. This paper introduces the initial research that has been undertaken in creating a semi-supervised self-training algorithm to detect the presence of graphite brick cracks and then proceeds to show that there is an improvement in the classification of graphite bricks using a semi-supervised machine learning classifier compared to supervised machine learning classifiers. This improved classification performance is encouraging as it does not require time consuming and costly human analysis to obtain extra learning information from available data.

*Key Words:* Monitoring, Semi-Supervised Learning, Self-Training

## 1 INTRODUCTION

In the United Kingdom, the fleet of Advanced Gas-cooled Reactors (AGR) is entering the latter stages of their operational lives. One of the critical life limiting factors of AGRs are their graphite cores. The core of an AGR is comprised of an interlocked lattice structure of thousands of cylindrical graphite bricks stacked over multiple layers. Intersecting the graphite bricks are fuel and control rod channels. It is important to monitor the health of the graphite bricks as irradiation results in them changing shape over their lifetime. Brocklehurst and Kelly [1] have shown that as graphite is irradiated it shrinks, until a turnaround point where the graphite then starts to expand. When the graphite is formed into hollow

cylindrical bricks and irradiated from the inner bore surface (as is found in the graphite cores), this has the effect of building up internal stresses within the bricks, which can lead to cracking. When this turnaround point is reached, the internal stresses within the bricks also changes, which can introduce new cracking mechanisms. Cole-Baker and Reed [2] describe this process in further detail. Understanding these cracking mechanisms, as well as the level of cracking present in the core is key to ensuring safe continued operation of the station. Too many cracks in certain configurations, coupled with a seismic event, could lead to distortions in the core, which could lead to difficulties in fuel and control rod movement.

This paper discusses the initial work completed on detecting cracked graphite bricks from refueling data using a semi-supervised machine learning algorithm. The paper describes how utilizing more frequently available unlabeled data can improve fault detection from new, previously unseen data. The novelty of the work in this paper stems from the investigation of semi-supervised learning techniques as a method to detect the presence of cracks in graphite bricks from refueling monitoring data. The true benefit of semi-supervised learning is the cost and time savings that could occur by making use of unlabeled data. This unlabeled data is currently manually analyzed which is a time consuming process.

## **2 BACKGROUND INFORMATION**

The use of Fuel Grab Load Trace (FGLT) data to provide health information about the state of the graphite core is an ongoing research area. The earliest use of the FGLT data for condition monitoring was the generation of database to store the fuel channel and graphite brick FGLT responses to create a benchmark of normal behavior of the bricks and identifying any anomalous bricks. Simulated anomalous brick FGLT data, such as cracks, were obtained from experimental rig work to provide understanding of how certain crack configurations would manifest themselves in the FGLT response [3][4]. More recent work is ongoing to create a model that explains the relationship of the FGLT data to the bore diameter measurements of fuel channels [5]. The model isolates a component relating to stabilizing brush friction, which in turn is used to estimate the channel bore diameter.

Semi-supervised learning is an emerging concept in the field of fault detection in nuclear power stations, with only two instances being reported in the literature [6][7]. Semi-supervised learning has been shown to be useful to be able to generate a fault diagnostic classification system for a CANDU simulator and nuclear process components facility when there is limited training data available [6]. Initially limited offline data is analyzed and labels are associated to the faults. Then, during online operation, faults are detected and using a graph based semi-supervised clustering model they are provided a label. It was found that although only a limited amount of labeled data with uncertainty was used as training data all faults in the data were correctly diagnosed. Additionally the combination of both supervised and semi-supervised learning has been shown to be used to identify transients in nuclear power station data [7]. Both known and unknown transients are used to train a classifier which identifies further unknown transients. It was shown that this method of applying labels to the unknown transients resulted in an improvement in performance for transient identification compared to previously developed classifiers.

## **3 MONITORING AND INSPECTION**

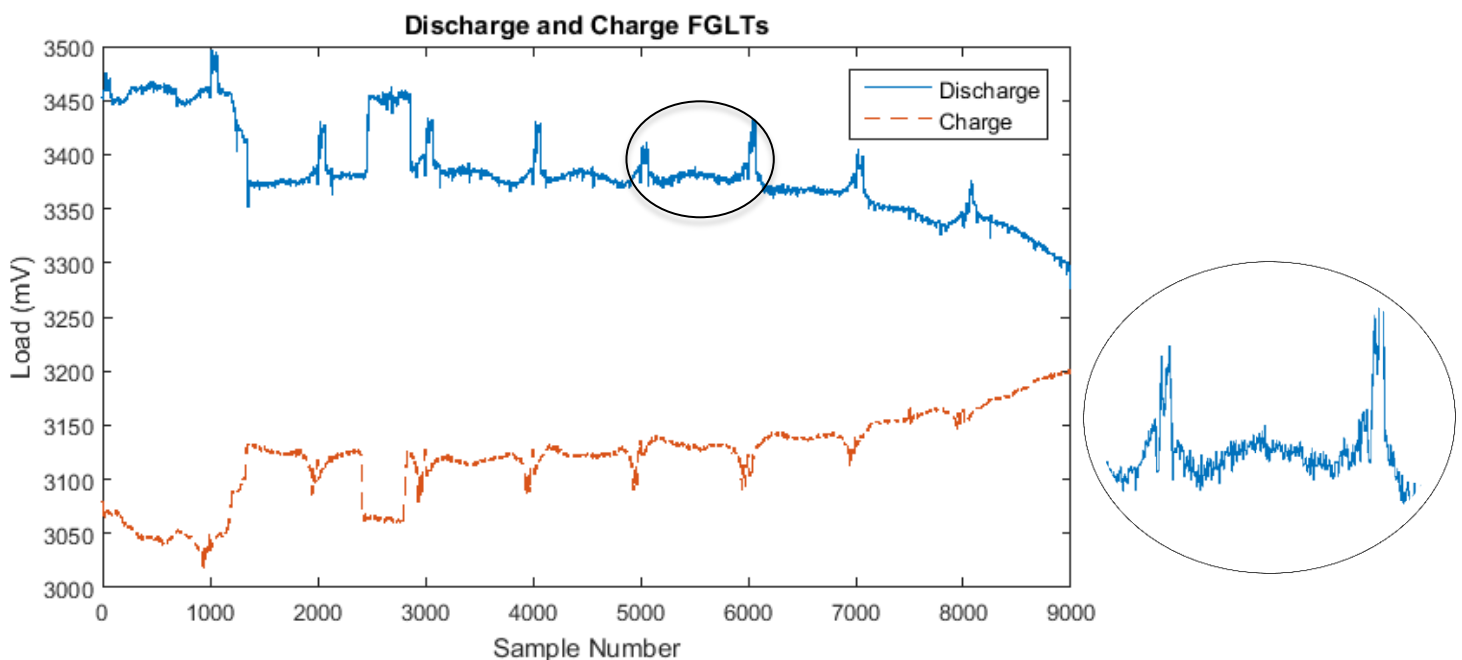
### **3.1 Fuel Grab Load Trace Data**

FGLT data is obtained during the refueling process of AGRs. Refueling events occur roughly every 6-8 weeks on a small selection of channels and can be performed when the reactor is offline or online at reduced generation capacity. During refueling the load values of the fuel stringer being removed (discharge) and inserted (charge) are recorded and stored. This data is required to be recorded and stored for safety purposes to detect faults that occur during the refueling process such as failure of the tie-bar load mechanism, ledging and false bottoming [8]. An example of a FGLT is shown in Figure 1. The two traces shown are the charge (red trace, lower load value) and discharge (blue trace, higher load value). There are four components that make up the load value of the FGLT; the deadweight of the fuel

stringer, the frictional component of the set of lower stabilizing brushes being in contact with the channel wall, the frictional component of the upper stabilizing brush being in contact with the refueling guide tube and aerodynamic contributions from the carbon dioxide coolant gas. It is important to note that the load contributions from the fuel stringer deadweight and the aerodynamic will always be a positive contribution to the load value unlike the frictional components which change depending on the direction of motion of the fuel stringer. This results in an increase in load when the fuel channel is narrow in the discharge as it is more difficult to lift the fuel stringer out and a decrease in load in the charge trace as the friction is supporting the weight of the stringer as it is inserted into the core. It can be seen in Figure 1 that there are periodic peaks (in the discharge trace) and troughs (in the charge trace) in the load value, these are the brick interface points where the channel becomes narrower resulting in increased friction. Additionally contributions from friction can be seen as step changes at sample numbers 1-1100 and 2500-2800 where there is friction introduced by the upper set of stabilizing brushes interacting with restrictions being in the refueling guide tube and the piston seal bore respectively.

### 3.2 Inspection

Inspections of the graphite bricks occur every 1-3 years during planned, periodic outages. Before



**Figure 1. Example of a discharge (blue) and charge (red) trace obtained from the same refueling event, with a magnified example of a single brick layer.**

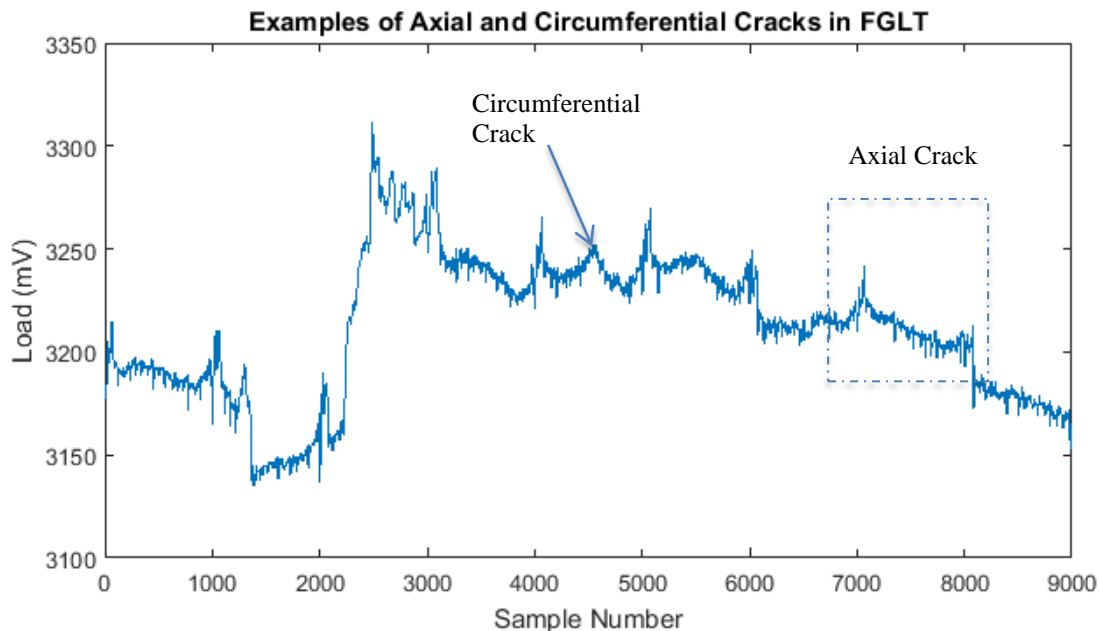
these outages core engineers select candidate channels to be inspected based on a number of factors such as those known to contain defects of interest, those which show unusual characteristics in the refueling data trace or regions of the core that are underrepresented by inspections to date. This is done to obtain greater understanding of the entire core and the CHANSELA software system has been developed to support this [9]. It is not practical to obtain inspection data for the entire core as it would be too costly to have the reactor out of operation for extended periods of time. During these inspections physical measurement and visual equipment called the Channel Bore Inspection Unit (CBIU) or New In-Core Inspection Equipment mark 2 (NICIE2) are inserted into and removed from the empty fuel channels at various orientations [10]. At multiple orientations visual footage is recorded showing the fuel channel walls, while the diameter throughout the channel is also recorded. After the inspection is complete engineers examine the inspection data and identify any abnormalities on the channel such as cracks.

These are then reported in the Television Graphite Assessment Panel (TV-GAP) reports with the type of defect found in the graphite and additional information such as description and dimensions of the features. The devices can also be reinserted and maneuvered to obtain better images of defects such as cracks. Once the inspections have been performed the fuel stringers can be reinserted into the fuel channels.

It is important to clarify that during the offload visual and physical inspections it is required to remove the fuel stringers of the respective channels being inspected. Therefore for every inspection that occurs there is a matching set of monitoring FGLT data, meaning that for offload FGLT data a label can be provided to the various layers in the trace indicating if there are cracks present.

#### 4 GRAPHITE BRICK CRACKS

Cracks in AGR graphite bricks can be caused by a number of reasons, some cracks occurred in the years following construction that are not associated with the ageing process in the core. Other cracks developed much later in the lifetime of the reactor due to the stress that is exhibited on the bricks due to weight change caused by irradiation [11]. Cracks occurring in graphite bricks can manifest in numerous ways and detailed categorization of their features are recorded in the TV-GAP reports produced at inspections. However for these cracks to be noticeable in the FGLT there has to be a change in the diameter of the fuel channel which will result in a different frictional response in load than a normal brick. This resulting change in load value in the FGLT varies with the type of crack and the magnitude of the dimensional change that has occurred. An example of a brick trace which has cracks present is shown in Figure 2 where a circumferentially cracked brick and an axially cracked brick have been indicated. The circumferential crack results in the narrowing of the fuel channel which corresponds to a prominent spike in the FGLT trace. However, the presence of the axial crack in Figure 2 is much more subtle and depends upon a number of factors, such as where the crack initiated from, whether it covers the full height of the brick and whether the crack has opened up. Domain expertise of graphite core engineers is key to determining the presence of these types of cracks and has been used to guide the selection of suitable features in the data to be used as inputs to a semi-supervised classifier.



**Figure 2. A full FGLT trace containing both an axially cracked brick and a circumferentially cracked brick which have been indicated.**

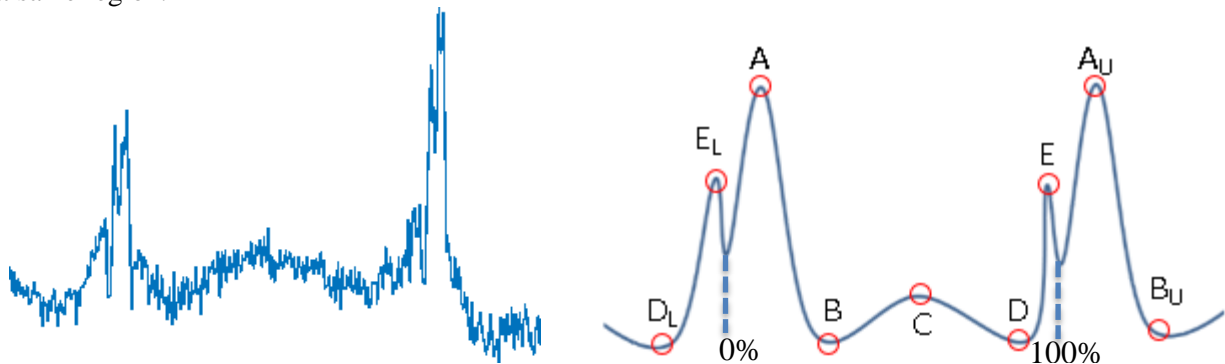
## 5 SEMI-SUPERVISED LEARNING

Semi-supervised learning is a machine learning technique which combines principles from both supervised and unsupervised machine learning methods. Typical supervised learning for classification is the default machine learning method, where a relationship between input and output data is explored through learning examples with a supply of ground truth training data. Unsupervised learning is focused on determining the underlying patterns and distributions of data with no information about the outputs [7]. Examples of unsupervised learning include clustering data into similar groupings, identifying anomalous data sample or reducing the dimensionality of data while retaining its characteristics. Semi-supervised learning combines both aspects of supervised and unsupervised learning by using both labeled data (input data with ground truth value) and unlabeled data (only input data) to improve performance than just using either labeled or unlabeled data in isolation. This can be seen as supervised learning that uses the statistical properties of all data to construct a classifier or unsupervised learning that assigns meaning to patterns or groupings based on known data [7].

Semi-supervised learning is often applied to many problems where there is a disparity between the amount of labeled data and unlabeled data. This often occurs due to the abundance of sensors recording operational data and as a result it is costly to provide labels to that data. In the case considered here detailed inspections to understand the health of the graphite can only be performed when the reactor is offline and only on a select number of fuel channels in parallel FGLT data is obtained from these channels. FGLT data is also produced at scheduled refueling events, while the reactor is operating at reduced capacity, on a more frequent basis but contains no corresponding ground truth information to apply to this data. Overall, the number of online refueling events greatly outnumbers the number of offline events which have associated labels.

### 5.1 Feature Extraction

Initially the features that have been chosen as inputs to the classifier were the base calculations which are obtained from the M/W point features [4]. The M/W point features shown on stylized discharge brick trace which can be seen in Figure 2. They are named after the general shape of a single brick in the FGLT, where a single brick can either be simplified to 5 points that look similar to the letters “M” and “W”. The points are calculated from different regions of the bricks with how their values are obtained shown in Table 1 where 0-100% indicates a relative location from the bottom of the brick to the top of the brick or left to right in the FGLT as indicated in Figure 3. These values were chosen to be able to obtain the key shape of the response of a single graphite brick in the trace. The base calculations then develop this further by performing operations on the bricks and their neighbors. These operations were originally chosen by graphite core engineers as a guideline to detect abnormal bricks and the calculations to obtain them can be seen in Table 2 where the subscripts to the M/W points are indicating if they are obtained from the neighboring bricks specifically the upper or lower bricks indicated by U and L respectively. Additional features that were included were the difference between the current bricks average load and the average load of the neighboring bricks, both upper and lower. The last feature was the difference in load of the height of the highest peak in the middle 20-80% of the brick layer and the average load over that same region.



**Figure 3. Single brick trace including interface regions with accompanying illustration of the M/W point features on stylized representation of a single brick FGLT.**

**Table 1. Calculations to obtain W point features for a single brick from a discharge trace [4]**

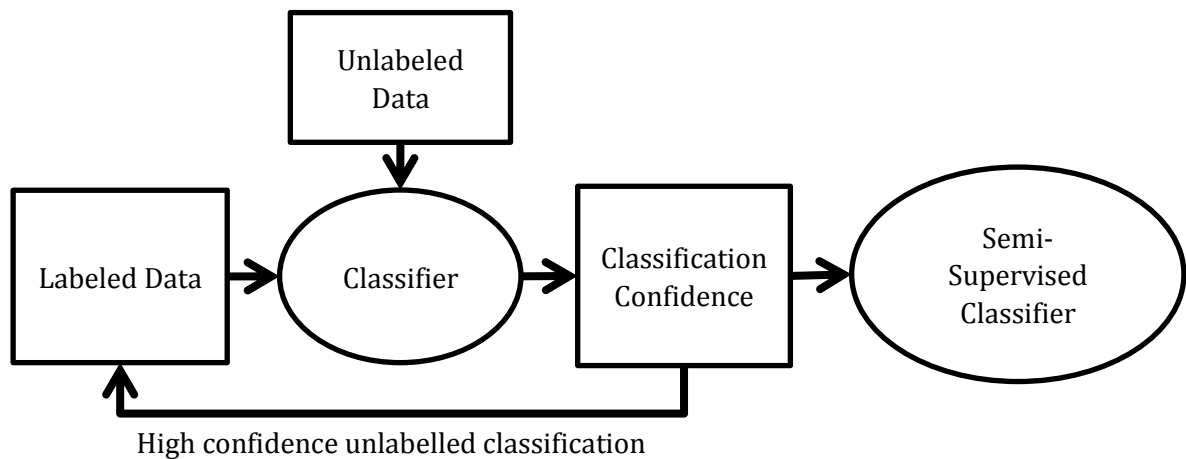
<b>A</b>	The maximum load value between 0-10% of the brick
<b>B</b>	The minimum load value between 10-25% of the brick
<b>C</b>	The maximum load value between 25-75% of the brick
<b>D</b>	The minimum load value between 75-90% of the brick
<b>E</b>	The maximum load value between 90-100% of the brick

**Table 2. Basic calculations for feature selection obtained from W point data for discharge trace [4]**

<b>BC1</b>	Height of the upper brick interface peak for the previous brick layer ( $E_L - D_L$ )
<b>BC2</b>	Difference between the upper brick interface for the previous brick layer and the lower brick interface for the current layer ( $A - E_L$ )
<b>BC3</b>	Height of the lower brick interface peak for the current layer ( $A - B$ )
<b>BC4</b>	Difference in the peak base heights between the upper brick interface for the previous brick layer and the lower brick interface for the current brick layer ( $B - D_L$ )
<b>BC5</b>	Difference in the peak base heights between the upper brick interface for the current brick layer and the lower brick interface for the next brick layer ( $D - B_U$ )
<b>BC6</b>	Difference in the upper brick interface peak for the current brick layer ( $E - D$ )
<b>BC7</b>	Difference between the upper brick interface for the current brick layer and the lower brick interface for the next brick layer ( $E - A_U$ )
<b>BC8</b>	Height of the lower brick interface peak for the next brick later ( $A_U - B_U$ )
<b>BC9</b>	The difference between the mean load value of 45-55% and mean load value of 20-80% of the brick

## 5.2 Self-Training

The self-training algorithm [12] is the simplest form of semi-supervised learning. Self-training is a wrapper algorithm which means that any base classifier can be used provided the base classifier can assign a confidence score of predicted data. The self-training algorithm can be seen in Figure 4.



**Figure 4. Flow chart of semi-supervised self-training algorithm**

Self-training initially involves splitting the available dataset into labeled and unlabeled instances of data and deciding which base classifier to implement. The labeled data is then used to train the base classifier. Once the classifier has been trained the unlabeled data is supplied to it to be classified. A subset of the highest confidence data instances is then provided with labels from the classifier. The newly labeled data instances are then removed from the unlabeled group and added to the labeled group. This process is then repeated by training new classifiers and to apply labels to more unlabeled data until defined criteria is met such as all the unlabeled data eventually being provided a label. Once the criterion is met a final classifier is trained which is then use to classify future data.

Self-training has been implemented using two base classifiers; these were an Artificial Neural Network (ANN) and a linear Support Vector Machine (SVM). The confidence scores that were used for the ANN were the output scores of the network. These indicate the likelihood of the output being correct based on their training and vary between 0-1 with 1 being strong confidence in the classification. Therefore, data that has an output that exceeds the defined threshold of 0.9 can be assumed to be classified correctly to be applied a label. Similarly the confidence score for the SVM is the distance that the unlabeled data is on either side of the separating hyperplane. The hyperplane is the boundary generated in the feature space that is used to separate the different classes. The further the sample is away from the hyperplane the more likely that it has been classified correctly. Therefore the furthest away 10% of the data from the hyperplane are chosen to be labeled.

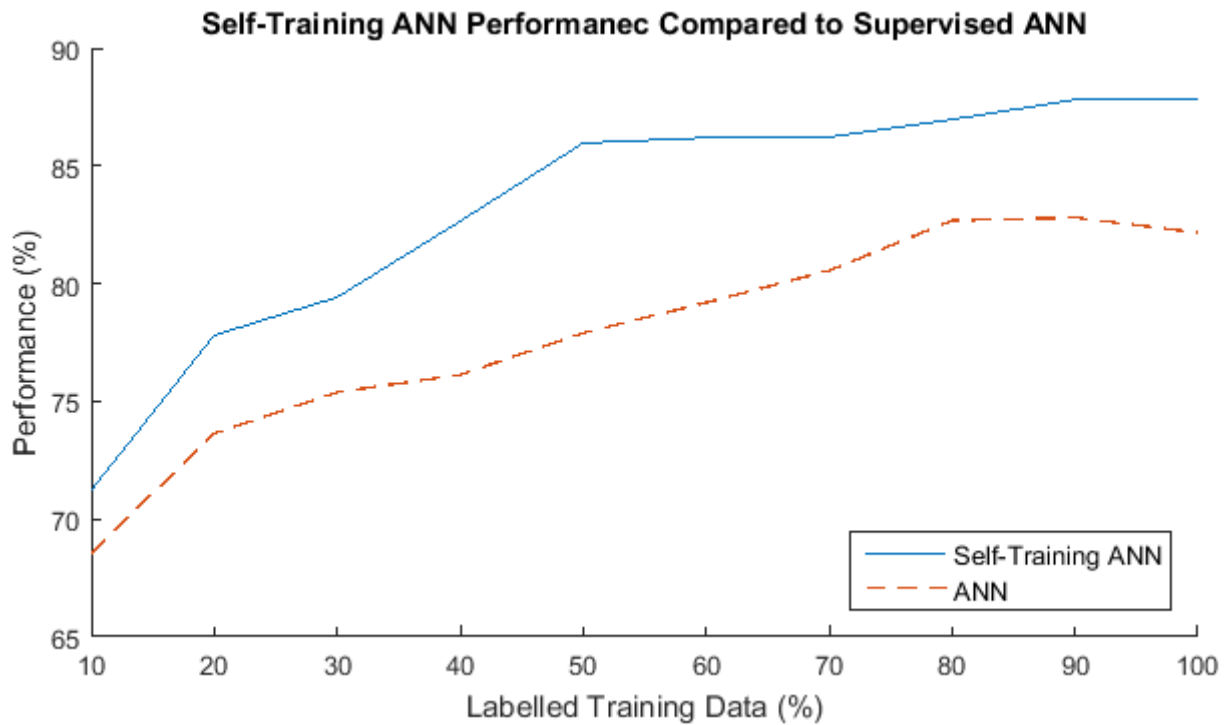
## 6 RESULTS

### 6.1 Available Data

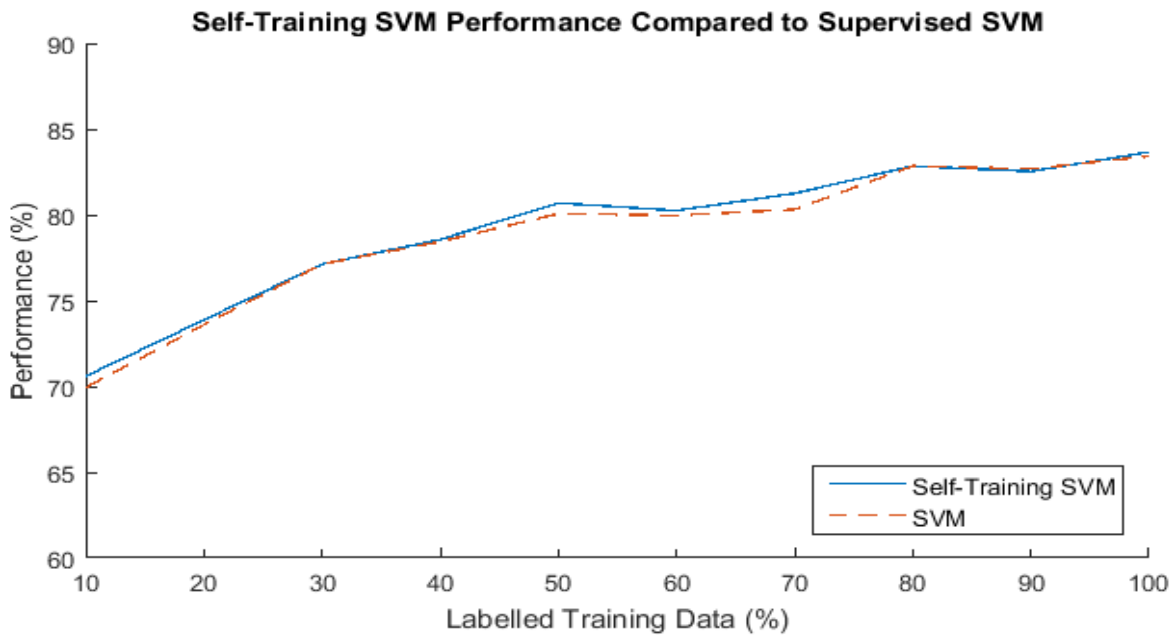
The data that is available and used to train the self-training algorithm is from roughly a decade of inspection and monitoring data from a single reactor. Of this data each brick layer is considered on an independent basis. Some layers are not able to be resolved with the M/W features such as some of which can be seen in Figure 1 particularly brick layer 4 and 5. In this example the brick layer was chosen which contained the largest amount of cracks on a single layer. The layer that was chosen contained 58 instances of inspection data which can be paired with associated FGLT data to extract the previously mentioned features. Additionally there are a further 71 instances of inspection data that can be used as training data. These are obtained from channels which have had inspections and FGLT monitoring data but not at the same time. When the monitoring data occurs prior to the inspection data only uncracked bricks can be included as training data as it is known that they were also uncracked in the past. Similarly only cracked bricks can be used when monitoring data is obtained after the inspection data as there is no guarantee that the uncracked bricks have not cracked in the time between inspection and monitoring. Lastly there are 216 unlabeled traces which do not have any associated inspection data. This large discrepancy in available labeled data was a drive to use semi-supervised learning as the labeled data on its own is not sufficient enough data to obtain a true relationship.

### 6.2 Implementation

The labeled data is split into training data and testing data, whereas the unlabeled data can only ever be used as training data as there is no true way to verify the state of the bricks without further inspection of the core. The labeled data consists of 129 instances which are composed of 33 labeled cracked bricks and 98 labeled uncracked bricks. The labeled data was randomly split into a training set and a test set with a ratio of 3:1. The training set was then split further into 10% increments of the available training data for each training session to establish how the changing amount of initial data affects the algorithm. The available unlabeled training data was available for each instance of the training and the average correct classification was calculated using the test set. This was performed 100 times at each 10% increment and the average performances calculated. This was completed for both an ANN and a SVM as the base classifiers and the results can be seen in Figure 5 and Figure 6 respectively where the blue trace is the semi-supervised self-training method and the red trace is the supervised equivalent.



**Figure 5.** Performance results for semi-supervised self-training ANN compared to supervised ANN with varying amounts of labelled training data used



**Figure 6.** Performance results for a semi-supervised self-training SVM compared to supervised SVM with varying amounts of labeled training data used



It can be seen that there is an improvement in classification performance accuracy when using unlabeled data as compared to using only labeled data for ANN however overall the performance is not yet sufficient to be fully reliant on this method of identifying the cracked bricks. Conversely the self-trained SVM does not show much of an improvement over the supervised SVM. This occurs as continually choosing the most confident data results in labeled instances which are very far from the other classification in the feature space and often they will not be used in generating the future separating hyperplane boundaries. However it is worth noting that the self-trained ANNs performed the best out of all learning methods tested and is an improvement compared to basic supervised machine learning.

It was hypothesized that when enough training data was used the performance of the supervised learning method should converge to the same performance as semi-supervised learning. This should occur as when the feature space becomes saturated with training examples no new trained data is from areas of the feature space that is unknown and therefore the current solution cannot be improved. From this choice of features for the data there appears to be valuable information that can be obtained from unlabeled data as there is still an increase in performance when all available labeled training data is used. Therefore for this particular application there is still information to be learned about the classification of cracks that cannot be obtained from the currently available data. This means that until a suitable amount of future inspections have taken place, unlabeled data is a viable solution compared to purely labeled inspection data.

## **7 FURTHER WORK**

The initial results show an increase in the performance of brick classification with the inclusion of combining unlabeled training data with labeled training data compared to training on only labeled data for ANNs. However the performance in these initial tests is not reliable enough to be fully relied on practical industrial usage. This could occur due to the features that have been chosen to train the algorithm. The features that have been chosen to characterize the shape of the brick do not allow for sufficient separation of the classes in the feature space. This means that the current features will always experience a tradeoff between false positives or undetected cracks. Possible solutions to this problem are to:

- Investigate different features in the FGLT that better represent all types of cracks in the graphite bricks
- Transform the current features to improve their separation in the feature space
- Use multiple classifiers that are used to detect individual different types of cracks

Another improvement that should be made in the future is being able to train the algorithms from more than one layer in the core or from other reactors of similar design. This has the benefit of providing both unlabeled and labeled additional data.

## **8 CONCLUSIONS**

This paper has described the initial work that has been undertaken in the initial investigation of using a semi-supervised machine learning algorithm to detect cracks in graphite bricks in AGRs. It was found that using self-trained semi-supervised machine learning algorithm produced better crack detection results than compared to a supervised classifier when the base classification algorithm was an ANN. It was shown that by utilizing the unlabeled data, which previously is unused or would require a large time commitment from a specialist to apply a speculative label, improves the ability for graphite brick health to be classified correctly. This work has also highlighted how, provided the classification performance improves, the semi-supervised learning approach could be used to augment the existing manual assessment, by leveraging more of the available unlabeled monitoring data.

## 9 ACKNOWLEDGMENTS

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