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ARTIFICIAL INTELLIGENCE FOR QUALITY CONTROL IN MANUFACTURING APPLIED TO MATERIALS DEFECTS DETECTION IN THE ITER VACUUM VESSEL WELDING OPERATIONS

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ABSTRACT

Artificial Intelligence (AI) has been applied to many different fields, such as medicine, robotics, linguistics, data mining, decision-making, videogames, and the automotive industry, whereas in others it is still to be explored. In general, this is the case of the nuclear manufacturing and, specifically, the case related to quality control in manufacturing of the large ITER Vacuum Vessel (VV). The European ITER VV manufacturing started in June 2015 and deliveries to the ITER Site, in Cadarache, are starting in 2022.

The aim of this work is to show how to enhance quality control by predicting of the weld success rate through the development and analysis of AI tools applied to the ITER Vacuum Vessel manufacturing. The selection and development of the model, related data preparation, training and testing, and the final model output and usage processes are developed herein.

The development shows that AI is an appropriate tool to predict weld success rate, resulting in a prediction accuracy of almost 100%. This allows the manufacturer and the client to focus appropriate resources, dedicated time and mechanisms in order to improve on the predicted welding rate. A successful AI application for welding quality control has a potential to save time and cost in manufacturing projects.

INTRODUCTION

Artificial Intelligence (AI) has been used in manufacturing to automate manual welds, allowing to automate our modern complicated welding processes with a large variety of parameters [1]. Nevertheless, little work has been performed on predicting welding success rate and ways to focus quality control to increase welding success rate and consequently manufacturing performance in industrial supply chains, by joining efforts of suppliers and clients.

It is important to understand what AI is and the broadness of the concept to understand the proposed solution and its development in its full depth.

Introduction to Artificial Intelligence

As described in other AI applications for manufacturing, more specifically in the field of Non-Destructive Testing [2], although many definitions of AI can be found, it is agreed to be a name coined in 1955 after the work performed by John McCarthy, Marvin L. Minsky, Nataniel Rochester and Claude Shannon. It can be broadly defined as the formalization and reproduction in a machine or processes in intelligent human behaviors, as defined on the plate commemorating their work at Dartmouth College, NH, USA. Detailed definitions range from computational thinking to computational behavior. A subset of AI called machine learning (ML) is defined as the ability to "adapt to new circumstances and to detect and extrapolate patterns" [3]. -. These relationships between AI and ML are shown in Figure 1 a).

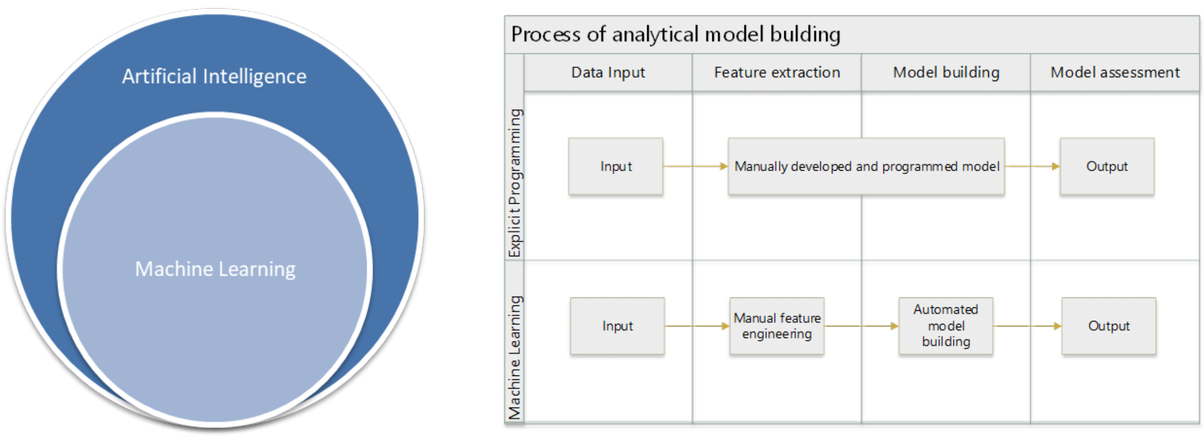

Figure 1 – a) Artificial intelligence and subfields b) Process of analytical model building

AI is often mixed with conventional programming. Conventional programming results in explicit programming of algorithms, where an algorithm is a set of rules to be followed when performing calculations or solving a specific problem, containing a sequence of steps to arrive at a solution, dependent on an input. AI, on the other hand, combines sets of algorithms to handle unforeseen circumstances. The difference between programming and ML is shown in Figure 1 b).

AI has already been applied to many different fields. It is widely in use for speech recognition in the field of linguistics and it is well developed for self-driving cars in the automotive industry, for example. Nevertheless, it is still to be explored in other fields such as manufacturing in general. A few very recent developments have been made in manufacturing regarding materials selection [4] [5].

Introduction to the ITER Vacuum Vessel Case

Within the field of manufacturing, welding is one of the core activities since it allows joining of two or more parts into an assembled entity [6]. It is a widely spread and extensively described process in literature, which does not require an introduction. Welding is a key process in nuclear manufacturing, since it is the main joining method qualified by all nuclear codes to achieve a desired component geometry. Nevertheless, welding success depends on a number of factors, such as the welder, the equipment used, the position, the type of welding, the weld form, the material, and many other factors.

This work uses the case of the European contribution to the large ITER Vacuum Vessel, which started in June 2015 and will be delivered throughout the next few years, at the time of writing. The Vacuum Vessel is made up of nine sectors, as shown in Figure 2 a), and is 12 metres high, 6.5 metres wide and 6.3 metres deep, weighing just below 500 tonnes. This doughnut-shaped double-walled torus will house the fusion reaction, reaching up to 150 million of degrees Celsius.

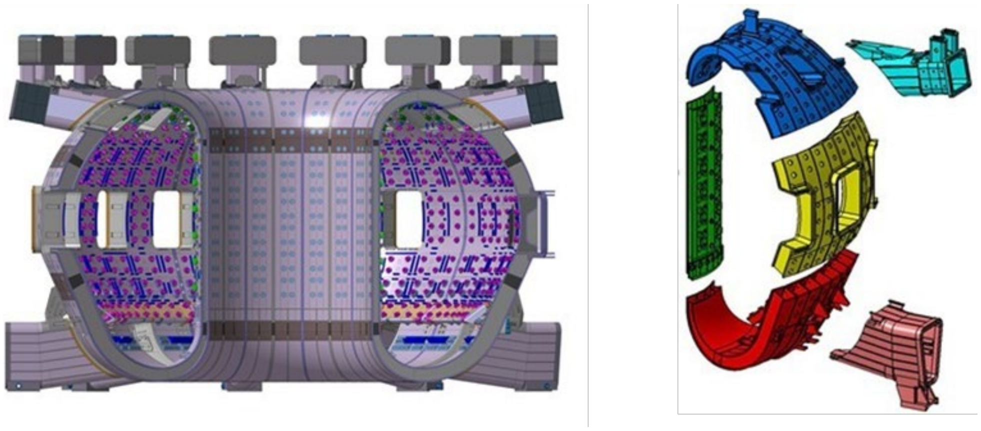

Figure 2 – a) Cross-section of the complete ITER VV b) Dissection of a single VV sector into four poloidal segments and two port stub extensions (PSE) - © Courtesy of Fusion For Energy (F4E)

Each sector is made up of four different-shaped poloidal segments as shown in Figure 2 b):

- the straightest and in-board segment in green is called poloidal segment 1 (PS1);
- the upper segment in blue, with a lifting hook and an upper port stop extension in light blue colour, is called poloidal segment 2 (PS2);
- the equatorial one, the least curved, in yellow is called poloidal segment 3 (PS3);
- the last lower one in red, with the lower port stub extension in pink, is called the poloidal segment 4 (PS4).

At the upper level, there are 18 ports of similar design. At the equatorial level, there are 14 regular equatorial ports and three ports for the neutral beam injection. There is one "blind" port. At the lower level, there are five ports for divertor cassette replacement and/or diagnostics and four ports for vacuum pumping.

Five sectors are manufactured in Europe by a single European consortium, under a contract by Fusion for Energy (F4E). F4E is the European Joint Undertaking for the ITER project. These non-identical segments are manufactured in parallel with a small gap between them, resulting nevertheless in up to twenty segments manufactured in parallel at the peak of production. After many studies and mock-ups, a top-level manufacturing plan for this manufacturing was developed.

For the PS1, a single large plate approach was taken, whereby:

- Two large plates would be curved, machined and welded together
- Over 6 metre-long T-ribs would then be procured and welded on the above plates, together with all other smaller items such as flexible housing and the divertor rail, forming the outer-wall of the PS1
- IWS blocks would then be installed
- The inner plasma-facing wall of the PS1 would be formed, similarly to the outer-facing wall in the first step, and then welded to close the PS1

For the PS2, PS3 and PS4, a subassembly approach was taken, generating in a number of subassemblies, which were then welded together, before installing the heavy borated In-Wall Shielding (IWS) blocks and the outer-shell portions of the segments:

- A number of subassemblies were identified and manufactured in a similar way to the PS1, but in smaller dimensions: plates forming, curving, machining, and installation of the smaller items
- Welding of the subassemblies together to form a single poloidal segment

- Installation of the long T-ribs.
- Installation of the IWS blocks for the poloidal segment
- Welding of the outer-shells for the segment

These four segments were then welded together, before installing and welding the PSEs.

Since the Vacuum Vessel is the first confinement barrier of the nuclear fusion installation, ensuring the quality of its welds is a serious challenge. It is manufactured following the French Nuclear Code, RCC-MR [7]. When a weld fails, this is mostly only detected after the non-destructive testing, which will show a defect. In nuclear manufacture, this defect must then be logged, through a non-conformance report (NCR), which can include a repair procedure, and which must be approved by the client and the nuclear authority delegate, such as the agreed notified body contracted by the client. Once the repair procedure is approved, repair can take place by the supplier. The repair, as the remedial action, can include grinding and rewelding through the same welding procedure or through a simpler welding procedure, depending on the original welding procedure and the repair to be performed. Since the welded component is key for nuclear safety, the root cause of the weld defect must be investigated, together with corrective actions in order to avoid defects in the future, as much as possible. This process therefore generates a great disturbance in manufacturing. Documentation resources, grinding resources and tooling, re-welding resources and tooling, rescheduling resources and their related client resources have to be shifted towards this issue in order to solve it promptly and return to conformity. This disturbance therefore has an impact on resources, time and cost. Furthermore, the time-criticality of the manufacturing of the Vacuum Vessel sectors for the ITER project renders time a scarce resource [8]. Figure 3 illustrates the process.

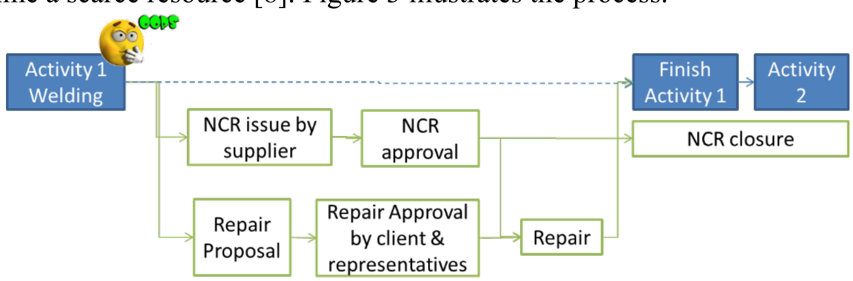

Figure 3 - NCR process disturbance representation

Due to its complexity, the manufacturing of this large equipment has generated a huge amount of data, qualifying to be called Big Data, since it is very big in size and expected to grow over time, as manufacturing of the VV sectors continues. The large number of parameters, the huge amount of data and the complexity of the process would require complex and long conventional algorithms, whereas AI is able to identify trends in huge datasets, ML allows it to learn over time and improve its accuracy and DL allows for complex relationships to be identified within the data. This case study has therefore become a perfect case to apply AI.

WELDING IN THE EUROPEAN ITER VV

Welding is one of the main manufacturing techniques used in the VV. Two techniques have been vastly used for this component, namely electron beam (EB) welding and tungsten inert-gas welding (TIG or WIG, from the letter used for tungsten, W).

EB Welding

During the various design reviews carried out for the VV, EB welding was consistently chosen as the most recommended welding technique to be used in order to achieve the tight tolerances set out on the VV [9] [10]. To weld circular joints of components to the inner shell, EB welding, as shown in Figure 4, is preferable because weld distortion is much smaller than other welding techniques, due to the tight tolerances and the high number of this type of welds required.

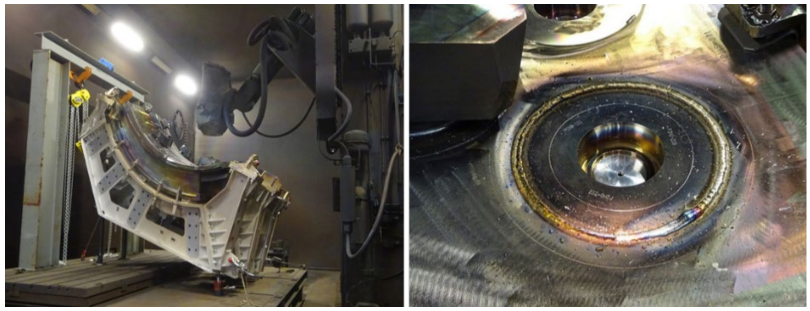

Figure 4 – a) PS2 in the vacuum chamber at the EB welding workshop. b) Close-up of the EB weld – © Courtesy of Fusion For Energy (F4E)

TIG Welding

TIG welding has been extensively and successfully used throughout the manufacturing process, along with other welding processes. TIG is also known as WIG, where W refers to the chemical symbol of Tungsten, or also GTAW (Gas and Tungsten Arc Welding). TIG can be carried out with or without a filler metal, however, in the case of the VV, a filler metal was used, which was melted through the heated arc. Tens of thousands of kilograms of filler metal have been used for TIG welding.

The benefits of TIG is that it can be applied to various different thicknesses of welds, by increasing the number of passes for thicker welds, which is necessary for the up to 60 mm plates, making up the VV double-shell. TIG is ideally used for stainless steels, as is SS 316(L)N-IG. Although TIG is a slow process than other welding processes, it enables to achieve a high-quality weld, as is required by nuclear quality manufacturing. TIG welding has not only been used to fuse two parts together, but also to repair defects generated by more advanced welding techniques.

METHODOLOGY

For the complete five sectors, a total of 10,059 welds need to be performed, of which 5,865 remain to be done at the time of the development of the AI model. In total, there is around 1 km of welding to be performed for each sector. Due to the criticality of the sectors and the large number of welds, their success rate was of utmost importance, not only in terms of nuclear safety, but also in terms of resources, time and cost. Many different welding procedures had been qualified, including 15 for electron-beam welding. Despite a very high quality of welds in terms of length, some of these procedures had shown defects when counting number of welds, for the most complex welds and in a very defined time period. Out of the 2.5 km of 60 mm-deep welds, 17 m of defects were found, representing 0.70%. Although only 0.70% of the total welded length was found to have defects, that short length was unfortunately distributed randomly on about 50% of the welds.

A series of actions were identified to improve welding quality, which concentrated on altering parameters and increasing human control over the different steps involved in an automated welding process such as electron-beam welding. The prediction of the defects was not reliable enough when using statistical methods, making their results only be used as guidance rather than input to improve quality control. Moreover, each batch of weld repairs could take anywhere from one week to one month, including the disruptions in human resources, machines and documentation. This lack of clarity and exhaustion of statistical methods to predict their success rate led F4E to investigate modern techniques such as AI to predict the success rate of remaining welds, in order to implement dedicated mitigation actions and improve quality control.

The problem faced for predicting weld success rate is considered a regression problem as the desired output is the likelihood of success of a weld. Figure 5 shows the methodology used for both developments on EB weld and TIG weld success rate prediction.

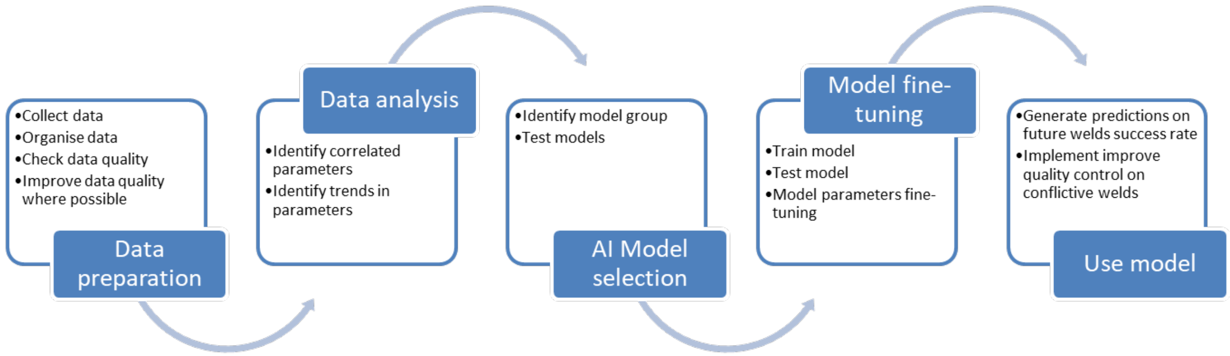

Figure 5 - Methodology used in development

Data preparation

Data was prepared in an analogous manner in both cases, for EB welding and for TIG welding. Nevertheless, TIG welding is performed by many more workshops than EB welding and, as such, data is much more diverse and of poorer quality. It was therefore difficult to improve the data quality and over 50% of the complete dataset had to be dropped in the first step of the methodology used, as shown in Figure *6*.

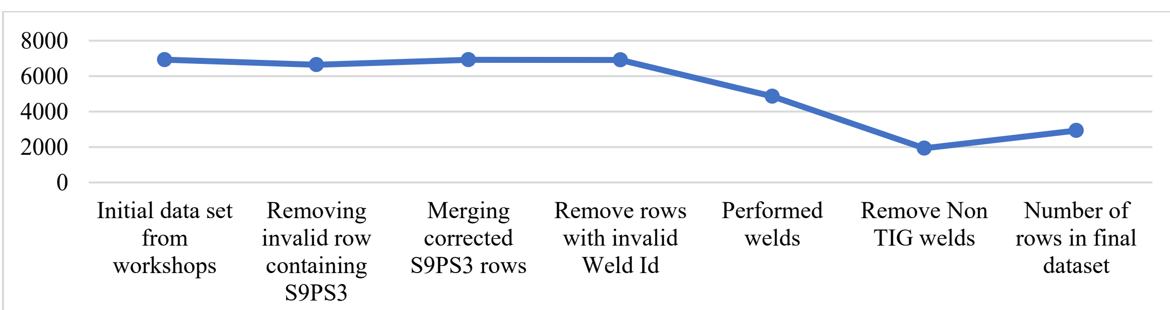

Figure 6 – TIG welds Data Cleaning

Data analysis

For the complete five sectors, a total of 1,872 EB welds need to be performed, of which 70 remained to be done at the time of the development of the AI model. At that time, 25% of the welds in number and in length had been shown to be defective, as shown in Table 1, where non-conform welds were on average a little longer than conform welds. Nevertheless, circular welds had shown more difficulties than linear welds.

Table 1 – Analysis of EB welds and their past success rate

	Performed	To be welded	Total	Note
Total				
Number of EB welds	1800	70	1872	
Length of EB welds (mm)	2,424,151	72,958	2,497,109	Average length per weld: 1,345.26 mm
Conform				
Number of EB welds	1435			
Length of EB welds (mm)	1,842,819			Average length per conform weld: 1284.19 mm
Non-conform				
Number of EB welds	367			
Length of EB welds (mm)	581,332			Average length per non-conform weld: 1584.01 mm

All available data regarding 1,802 EB welds were collected and analysed using Machine Learning. Different EB data parameters were identified to be able to classify the different welds as listed below:

- VV Sector
- VV Segment
- Type of weld
- Supplier of the part to be EB welded and performer of the tack weld
- Orientation of the EB weld
- Position of the welder for tack weld
- EB weld current
- EB focussing current
- EB Weld travel speed
- EB Weld length

On the other hand, with the clean TIG dataset, the process of identified non-conform TIG welds was repeated as performed for EB welds, resulting in 1173 non-conform welds and 1755 conform welds out of those welds which had already been performed. An analysis by length was not representative since TIG welding was used across disparate welding lengths and depths.

AI Model selection

In the third step, several different models were developed, resulting in the selection of Random Forest (RF) classification method thanks to its accuracy. The random forest model was introduced by Breiman in 2001 [11], which makes it quite a novel model. The following characteristics make random forests a good tool based on the information provided [12]:

- Naturally handle both regression and (multiclass) classification
- Are relatively fast to train and to predict
- Depend only on one or two tuning parameters
- Have a built-in estimate of generalisation error
- Can be used directly for high-dimensional problems
- Can easily be implemented in parallel
- Provide measures of variable importance
- Provide differential class weighting
- Provide missing value imputation
- Provide visualisation

- Detect outlier
- Provide unsupervised learning.

RF calculates the average from the output from various decision trees, which take different subsets of data as their input, as shown in Figure 7.

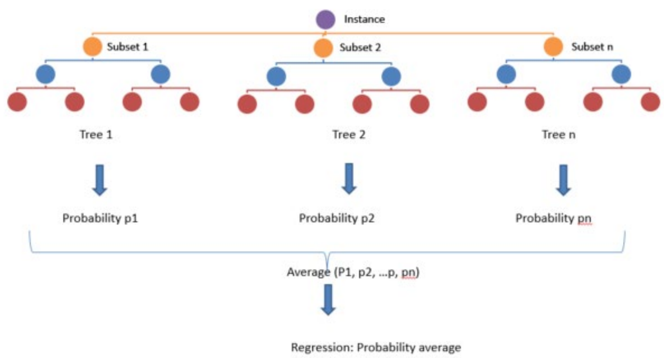

Figure 7 – Use of Random Foresting Model for weld success rate prediction

Model fine-tuning

The EB data set was split into 1,442 welds (80%) to train the model and 360 welds (20%) to test the model prediction accuracy. The same sharing (80%-20%) was done on the TIG data set.

Since TIG welding has not been completed at the time of writing, the testing output is considered to evaluate the accuracy of the model. The RF model gave 83% accuracy for TIG predictions.

Model Use

EB welding prediction output - Output was generated for the remaining 70 EB welds, adding up to the already welded 1802 welds and totalling the 1872 welds electron-beam welds. The output of the model showed that all true positives and true negatives were correct: one weld was predicted to fail at 90% probability and it was confirmed that it actually failed; another 16 welds were predicted to fail at 56%, of which 7 failed and 9 passed; and all passing predictions actually passed, as shown by the confusion matrix for this regression model in Figure *8*.

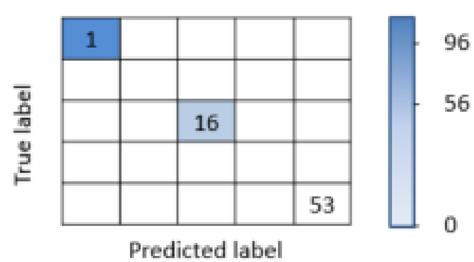

Figure 8 – Confusion matrix for EB welding model

TIG welding testing prediction output - For the remaining 2057 welds to be performed, the probability of non-conformance was identified and communicated to the client and its workshop residents. It will be communicated to the supplier next, in order to improve quality control on those welds and implement recovery plans. This information has also been linked with the schedule, to allow the development of a more confident schedule to be developed, including repair actions as needed and early allocation of resources in the workshops. The mapping of the welds into the schedule resulted in merging of some welds into a single activity, and therefore taking a conservative approach by taking the highest probability of weld NCR. This shows once again that data quality and data mapping across different data sets is important to ensure good quality control. One of the various ways to depict the output of the predictions is shown in Figure 9, which shows the number of welds predicted to fail based on the length of the joint. It is interesting to note that it's not the longer weld lengths which are more likely to have non-conformances, but instead those around a the peak of an almost-gaussian curve.

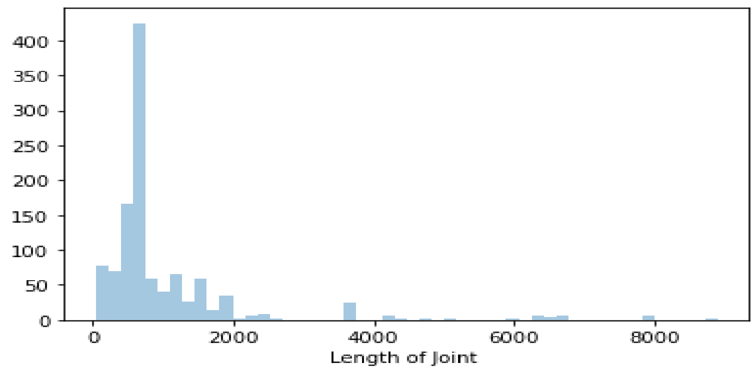

Figure 9 - Histogram of TIG weld lengths predicted to have NCR

CONCLUSIONS

Quality control is only fully in place when existing data can be fed into the system to improve it. Large datasets are generated in manufacturing industries, although they are not always used effectively. It With the developments of these models and the use of the large existing datasets to train and test the models, this final step of quality control can be considered fulfilled. Two Random Forest models have been developed, trained and tested with the EB welding and the TIG welding datasets, as described in detail. The EB welding model showed a 100% accuracy in its prediction, whereas the TIG welding model showed an 83% accuracy in its testing predictions. The actual accuracy of the TIG predictions will be tested over time. It is known that accuracy is proportional to the size of the training dataset. Nevertheless, these results show that the choice of the RF model is ideal for these situations. It is therefore recommended to use RF models for other welding predictions scenarios, complementing the work described herein.

Given the high demands of the nuclear industry for weld defects, as well as the high pressure that the manufacturing industry is facing nowadays, these results show that the application of AI in nuclear manufacturing allows clients and manufacturers to improve quality control and reduce impacts on resources, documentation and schedule. These developments have proven to bring an important gain and can therefore be considered in future nuclear and non-nuclear manufacturing programs as an effective tool to de-risk programs.

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