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A Transdisciplinary Approach to a Manufacturing Problem with a Machine Learning Solution

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Abstract. The application of machine learning to high cost, low volume (HCLV) manufacture is challenging due to prohibitive costs and low data volumes. An example HCLV application is linear friction welding (LFW) of Blisks (Bladed Disks). LFW is a solid-state joining process, typically used in high integrity aerospace applications. The successful application of machine learning (ML) has the potential to predict quality metrics and enable timely interventions to machine maintenance for avoidance of machine damage or deterioration. This paper proposes a methodology that combines expert knowledge with machine learning to minimise the quantity of weld data required to generate a robust and accurate ML model. Expert knowledge incorporation requires methods of elicitation, capture, standardisation and quantification of information (it can be qualitative, experiential and subjective) and conversion to a quantitative, data driven and digital format for input into a ML algorithm. This paper will describe the methodology developed to enable a combined data science and engineering approach to address complex manufacturing problems. If successful, this methodology will be used as a standard framework for application to HCLV manufacture.

Keywords. Machine Learning, Knowledge, Linear Friction Welding, Transdisciplinary Engineering

Introduction

This paper focuses on Machine Learning (ML) processes dealing with high cost, low-volume (HCLV) manufacture products. Linear friction welding (LFW) was selected as a candidate process for HCLV manufacture. An overview of the process and a product produced is described in Section 1.1. The successful application of ML has the potential to predict quality metrics and enable timely interventions to machine maintenance for avoidance of machine damage or deterioration. The key outcome of any data analysis is to be able to relate the findings directly to the physical process in order to realise tangible benefits from the data study (e.g. simple statistics, machine learning and neural networks).

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At the outset of the research the focus was entirely on the data produced by the process. As the research has progressed the reality has been that both data and process knowledge must be utilised to achieve the best outcome – a capable model with minimal data. In trying to resolve the LFW machine learning challenge, for the AI domain, the data has a greater significance. However if one starts from manufacturing standpoint then the voice of the process (its performance) takes priority, tempered by the constraints of the availability of expensive data. The reality is that the data scientist needs to understand what the results of any data analysis mean in the physical world and the engineer needs to appreciate data science can help make sense out of complex data. Combining expert domain knowledge adds another level of complexity to the problem. This includes capture of complexities and uncertainties of the process from the experts' experience which is personal, subjective and qualitative. This is why a transdisciplinary approach is required to combine requirements of the engineering, knowledge capture and data science problem. This area of shared knowledge is indicated in Figure 1 by the red shaded area (the intersection of the AI and manufacturing domains) which indicates minimum area of common knowledge required.

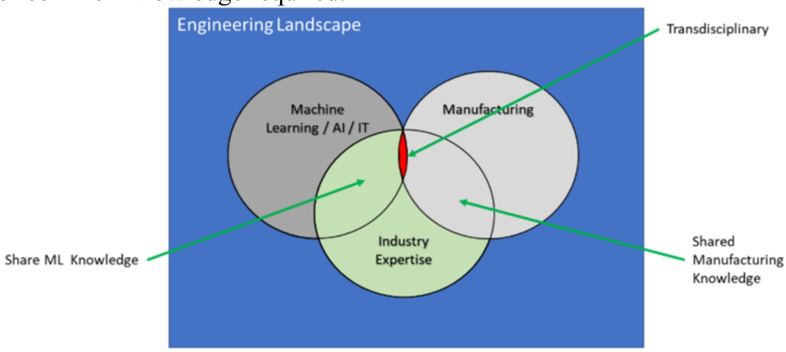
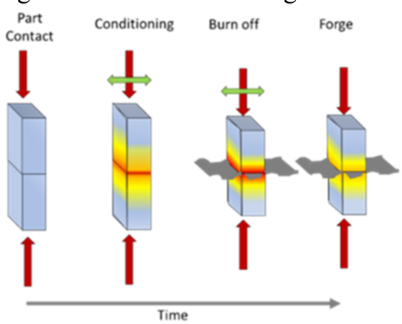


Figure 1. Knowledge interaction

1. Background and problem definition

1.1. LFW Defined

Linear friction welding is a high integrity solid state method of bonding two components together as illustrated in Figure 2:



- Heat generated by moving one workpiece against another under an axial load (normal to the direction of oscillation)
- Viscoplastic material is ejected in the direction of oscillation under the axial load.
- When the desired loss in length is achieved oscillation is stopped and the axial load is maintained as the weld cools.

Figure 2. Linear Friction Welding Process

Linear friction welding applications in the aerospace industry are typically low volume and high cost. A typical example is the bladed disc (Blisk) shown in Figure 3.

Figure 3. Rolls Royce Blisk

Because of non-destructive evaluation limitations, control of inputs and measurement of outputs are key to the validation of quality for high integrity applications of this type. There are up to 240 data channels on the most up to date machines. To validate the quality of an analysis, the signals that are a measure of KPV's (Key Process Variables), is undertaken. This analysis can be undertaken using standard numerical tools, however, these have limitations for the analysis of complex multivariate interactions that other methods, such as machine learning, can accommodate.

Due to the high cost and long lead time to manufacture LFW products, a faster and more in-depth analytical methodology was developed. Specifically, the LFW of Blisks is, globally, a niche market and there has been relatively little published research on the in-process quality validation utilising machine learning techniques.

1.2. Problem Definition

As the cost of LFW products is very high, the lead time long and the quality paramount it is imperative to have a right first time approach to product (weld) quality.

The analysis of output data from the process is one method of qualifying the integrity of the weld which necessitates accurate, capable and repeatable analysis processes. The capabilities required of the model are to assure quality as both predictive and preventative maintenance to reduce the probability of unforeseen events resulting in non-conformance.

Because of the high number of signals (between 30 to 240) machine learning, Support Vector Machines (SVM) in particular, was chosen as a candidate process because of its successful application in manufacturing [1]. One of the key requirements for a successful machine learning model is a sufficient quantity of data. In the Blisk manufacturing process production data is both expensive, due to the cost of parts, and time consuming to generate (lead time and production rate). If production standard data is required for modelling it could be expensive to obtain due to an initial increase in inventory (especially for a new product) or production standard test pieces may need to be designed and manufactured.

Experimental results have indicated that in excess of 80 welds are needed to create a capable model ($R^2 >= 0.8$). This is based upon a simple planar component on a small experimental machine (PDS – Process Development System). It is likely, because of higher complexity (240 signals), that a production machine may need more data to produce a model of similar accuracy.

The key question posed is **“how can the initial volume of data from welds that is required to produce a capable model be minimised without detriment to the model?”** This paper aims to develop a methodology for incorporating expert domain knowledge in a Machine Learning pipeline to minimise the volume of expensive data required to generate a capable model.

2. State of the Art

An Italian research team [2] has undertaken research into the application of machine learning to LFW (using Artificial Neural Networks) in conjunction with numerical modelling. However the results indicated quality as one of three states: Instability – interface liquation, Safe zone – good weld and Insufficient heat – no bond. Whilst the capability of the model, in terms of claimed accuracy of quality prediction, is very good (~95%) the three classes do not reflect the granularity of classification in an aerospace production environment. Much work has been done for friction stir welding (FSW)[3], however the process mechanism is quite different. With FSW the friction force is applied progressively by the tool’s rotational speed, traverse speed and force. In comparison, the LFW friction is applied to the whole bond surface at once. This results in a very different analytical approach and is therefore not directly relevant for application to LFW.

There are numerous papers on incorporation of domain expert knowledge into machine learning algorithms. These range from medical applications (breast cancer malignancy probability)[4] to incorporation in smart manufacturing [5]. There is no evidence of this having been applied to LFW in the literature and the challenges include the complexity of the process and its interactions, the small number of experts and their experience is personal, subjective and qualitative. The decision was taken to use simple knowledge elicitation processes that were straight forward to conduct and permit a comparison of the effectiveness of individual and combined methods. The proposed hypothesis is that the inclusion of expert domain knowledge in the ML algorithm will minimise the data volume required to generate a capable model. Chatthas’ incorporation of expert knowledge into ANN (Artificial Neural Networks) proposed a similar hypothesis [6].

3. Methodology

The initial experimental work supporting this research was undertaken on full-scale LFW machinery using 60 simple rectangular metal block welds. These were manufactured in 2 sets of 30 welds. The measure of success was an $R^2 > 0.8$. This arbitrary value is used as a comparative measure for improvements. The absolute measure is based upon the requirements of the product / process.

The results obtained using SVM (Support Vector Machines) indicated that there was not enough data (Low R^2 value <0.8). As there were no suitable extra welds available it was decided to use an experimental PDS (Process Development System) machine to produce additional data. Although the process loads and specimen sizes were much smaller than those of the full-scale machine, the process fundamentals and interactions are similar, giving validity to the choice. The PDS results were still unacceptably low ($R^2 < 0.8$) with the spread of results taken into account, but were an improvement on the full-scale welds. In considering what to try next an obvious choice was to utilise expert domain knowledge in order to create an accurate model. The hypothesis was that by incorporating expert knowledge input into the machine learning algorithm would reduce the number of expensive full-scale welds, and the data, required. The key step in tackling use of expert domain knowledge applied to machine learning was to plot the path of knowledge capture through categorisation and feature selection and ultimately to ML. This process is depicted in Figure 4.

The first task was to extract the knowledge from the experts and to try and give that knowledge a comparable weighting across a number of experts. The target was to be able to complete the knowledge network as shown in Figure 5. This each expert puts a weight on what they believe to be an influencing factor. The output signals related to the weights are categorised into machine sub-systems based on modular functions (such as control, power supply, hydrostatic oil system, process load vector systems etc.). Each of these subsystems will have a quality burden which sum to a measure of the overall quality of the weld. The knowledge is based on experts' understanding of the physics of machine and process. This conceptual framework was designed to be able to easily classify and utilise expert knowledge.

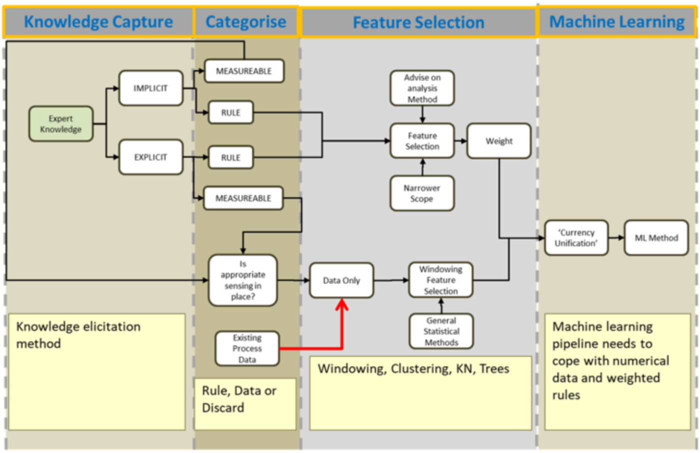


Figure 4. Knowledge Capture map

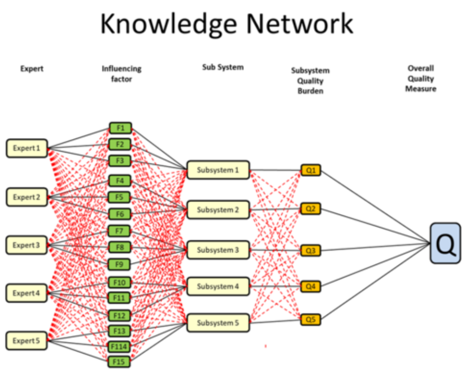


Figure 5. Knowledge Network

The categorisation of knowledge was kept as simple as possible and for each attribute there was either rule to be applied or a directly measurable output such as a force, pressure or distance. This categorisation approach also had to be applied to any available data used for the machine learning analysis. Feature selection for the existing data was based on a windowing technique that was used to filter out any large changes in the data by comparing six key measures calculated in neighbouring windows. The six measures were mean, range, standard deviation, shape function, crest function and root mean square (RMS) (see Figure 6). If the sum the results in adjacent windows were within one standard deviation window values were combined and considered as equal. If the difference was greater than one standard deviation the data in that particular window was deemed as anomalous, therefore a candidate feature.

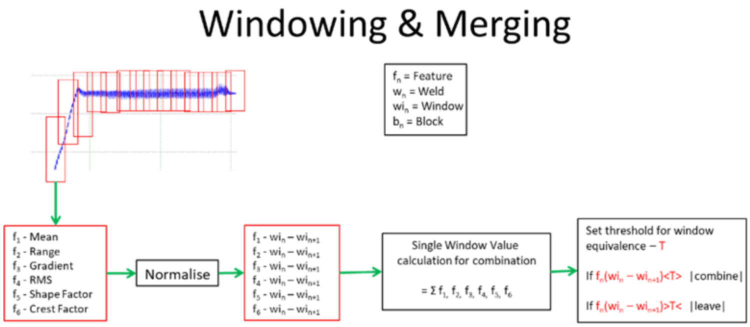


Figure 6. Windowing methodology

Different methods of knowledge elicitation were used to try to optimise the process for both individuals and groups of experts:

Standard Questionnaire – the experts were explicitly asked to comment on the impact of each signal/sub-system on the key measure of quality. The key measure is the final positional accuracy between the two welded components as this was simply and independently verified by CMM (coordinate measuring machine) measurement. On a separate questionnaire they were asked about any implicit observations that could ultimately be used to make up a rule with which to analyse data.

QFD overall signal interaction – the Quality Function Deployment methodology was modified so that comparison between all key signals recorded by the LFW was carried out by each expert and a weighting calculated to prioritise the importance of signal combinations to the positional quality measure. In this process the signals were all considered together. QFD [8] was developed as a total quality management (TQM) tool in the 1960s, used as a matrix to convert product attributes into engineering requirements. This has been modified for the knowledge elicitation application to capture the influence of process attributes on desired process outcomes and rank them in order of influence the purpose of defining features for a machine learning model. A similar approach is used in CRISP-DM (Cross Industry Standard Process for Data Mining) except expert process knowledge is not specifically included [9].

QFD pairwise interaction – this method was similar to the previous QFD except that the comparison was done pairwise meaning that only two signals were compared at once thus, theoretically, giving a closer focus on the comparison.

Graphical Highlighting – The expert opinion on what was a feature was based upon a graphical representation of each of the key signals for a weld cycle and those areas the expert believed to be of importance were given a positive weighting to amplify the impact on the windowing process. This means that features highlighted by the domain expert had an enhanced influence in the SVM algorithm. This method has some similarity to the interactive visualisation process suggested by Micallef et al [10].

For this research a combination of QFD Pairwise interaction and Graphical Highlighting was used. The former to select the most influential signals (deemed by the expert), and the latter to identify the regions on the signals that had the biggest impact on the measured output. Optimisation was carried out by adjusting the threshold values (Figure 6) based upon the expert graphical highlighting results. The data from the standard questionnaire has not been utilised as yet but will be incorporated into rules that bound the selected signals. When all of the expert data becomes available the impact of the different elicitation methods, individual and combined expert knowledge will be assessed for the greatest positive impact on the model development.

The experts comprised 3 PhD metallurgists and 2 Manufacturing Engineers. Each of the individuals had between 15 and 20 years of LFW experience. The knowledge extraction technique was focussed on those individuals with significant process knowledge and the questionnaires were designed to be able to compare knowledge between experts, and also convert that knowledge easily to a suitable machine learning format. The forms were defined by the author and discussed with the experts. The document were completed after a 2 ½ hour presentation to the experts. During the completion of the questionnaire any arising issues were resolved.

4. Illustrative Example

This methodology was used to try to optimise the machine learning modelled results for production welds in order to successfully and reliably predict the final position of the weld (to within an acceptable tolerance).

LFT80 (Production Linear Friction Welding Machine) – the first stage of the experimental process was to select a set of existing welds carried out on a production machine. The welds had to be existing due to the cost of welding. The production machine had been recently acquired, installed and passed off. As a part of this process there were two sets of 30 full-sized production standard welds available using an aerospace alloy. These welds had all been produced using the same parameters and were measured independently by CMM. The data was visualised, analysed and modelled using basic statistics, regression and machine learning (SVM – Support Vector Machines). The conclusion to this initial analysis was that there was insufficient data to accurately predict the final position of the weld.

Another untapped resource to call upon is the expert domain knowledge available for the process. At the time of writing the full knowledge elicitation feedback information was not available. However information from one expert was incorporated into the SVM algorithm and produce the range of the results shown in Figure 9. This was done with minimal tuning of the algorithm with the set of knowledge input from one expert. The work underway is extracting data in different ways from more than six experts which should have a more positive impact on the results.

The next step was to produce data using the PDS in order to increase the data volume to generate an accurate model. 80 repeat weld cycles were undertaken and analysed for positional accuracy using the SVM algorithm. The analysis was carried out using 20, 40, 60 and 80 data sets to see what influence the volume of data had on the accuracy of the model. Each of the data volumes was also analysed with the addition of expert knowledge

(AVERAGE K in Figure 7 – blue curve). Each of the data points in the graphs (Figures 8 to 11) represents the average of 400 iterations of the algorithm. This comprises of four internal iterations within the SVM algorithm and 10 repetitions of the sequence. This whole sequence was repeated 10 times with the data sets randomly selected (no duplicates) from the total data pool (80 data sets). Table 1 below shows the data for one of the 10 iterations for 1 data point. The yellow box in the table is the average R^2 (training) for that run of 10 iterations in the orange box with the average R^2 (testing) for the 10 iterations.

Table 1 – Example of modelled data

Attribute	Iteration # 1	Iteration # 2	Iteration # 3	Iteration # 4	Iteration # 5	Iteration # 6	Iteration # 7	Iteration # 8	Iteration # 9	Iteration # 10	Average	Range
Average_ytr_r2	99.945	99.932	99.933	99.949	99.958	99.955	99.946	99.957	99.938	99.936	0.999	0.026
Average_ytr_mse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Average_yts_r2	77.648	84.217	90.271	89.823	82.918	84.970	77.402	85.578	69.880	86.071	0.829	20.391
Average_yts_mse	0.006	0.006	0.004	0.005	0.005	0.005	0.006	0.004	0.006	0.005	0.005	0.002

Apart from the data set of 20 welds it can be seen from the graph (Figure 8) that as the data volume increases the testing R^2 increases. The training R^2 is very high to start off with. As the number of data samples increases the range of the repeated R^2 values decreases – this is represented by the orange (lower) and blue (upper) limits about the grey curve (testing R^2) in Figures 8 and 9.

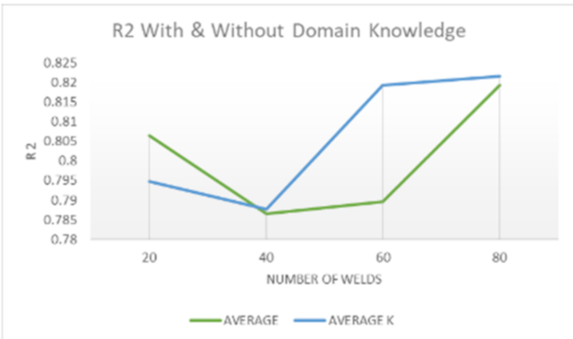


Figure 7. Test R^2 with and without Knowledge input

Figure 8. Range of testing R^2 with no Knowledge input

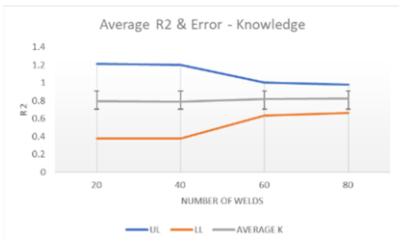


Figure 9 Range of testing including Knowledge input

The graph (Figure 9) indicates that the addition of expert knowledge on the 60 welds trials has the biggest impact increasing the R^2 from 0.79 to 0.82 this represents a 4% increase in R^2. The t-test results in Table 3 also support this finding. Table 2 below contains all the data used for plotting graphs (Figures 7, 8 and 9). The data concerns only the testing results.

Table 2. Summarised experimental results table

	80	80K	60	60K	40	40K	20	20K
MAX	0.940	0.933	0.935	0.936	0.951	0.936	0.981	0.996
MIN	0.664	0.617	0.264	0.566	0.152	0.115	0.024	0.167
RANGE	0.276	0.317	0.671	0.370	0.799	0.821	0.956	0.829
UL	0.957	0.980	1.125	1.004	1.186	1.198	1.285	1.209
LL	0.681	0.663	0.454	0.634	0.387	0.377	0.328	0.380
AVERAGE	0.819	0.822	0.790	0.819	0.787	0.788	0.806	0.795
STD	0.063	0.063	0.098	0.074	0.149	0.146	0.170	0.168

Table 3 summarises the results of a pairwise t-test for each data volume with and without expert knowledge. For example the line designated 80 WELDS has no expert knowledge input whereas the line designated 80 WELDS KN incorporates expert knowledge in machine learning analysis. For pair 2 (sample size of 60) the significance (2 tail) is under the 0.05 alpha threshold indicating a separate mean for the two data sets (60 without knowledge and 60 with knowledge).

Table 3. Paired T Test Results

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	80 WELDS - 80 WELDS KN	-.00232	.09267	.00927	-.02071	.01607	-.250	99	.803
Pair 2	60 WELDS - 60 WELDS KN	-.02975	.12159	.01216	-.05387	-.00562	-2.446	99	.016
Pair 3	40 WELDS - 40 WELDS KN	-.00118	.21161	.02116	-.04317	.04080	-.056	99	.956
Pair 4	20 WELDS - 20 WELDS KN	.01164	.23636	.02364	-.03526	.05854	.492	99	.624

Although the R^2 for testing is above 0.8 (the acceptability threshold) if the values of the testing R^2 drop to within the bounds of the lower limit – this will reduce the value below 0.8 threshold. One obvious answer is to increase the data volume above 80 sets however for production application (at which this work is aimed) this may not always be feasible. There are two actions required to resolve this issue. One is to incorporate the results of the full knowledge elicitation activity when available. The other is to determine the specific value of R^2 which correlates to the acceptable process limits.

5. Conclusion

The conclusion, so far, is that the machine learning model can be positively impacted by the inclusion of expert knowledge – albeit with initial results as yet. However this is only shown to be an improvement for a quantity of 60 welds (4% increase in R^2). One conclusion, for this expert knowledge application, is that the data from 60 welds is an optimal number for knowledge input to improve the model results. The R^2 value for 60 welds (knowledge included) of 0.819 was the same as the value for 80 welds 0.819 which implies that 60 datasets analysed using expert knowledge gives equivalent results to 80 data sets (without expert knowledge). This additional knowledge both increases the R^2 value and decreases the variability (or range) within the population of results.

Whatever the initial perspective, the tools of data science and engineering make up the broad capability of problem-solving in a transdisciplinary environment. No universal definition for Transdisciplinary has been adopted [11]. In the broadest sense a transdisciplinary approach utilises all knowledge required to solve a problem.

Knowledge could be from any discipline – (e.g. science, engineering, medicine and social sciences). A narrow range of knowledge (engineering, knowledge elicitation and data science) was used for this research. I have found that a transdisciplinary approach has helped integrate the engineering with the data science because of the greater understanding of the key nuances of each discipline. It helps eliminate the data scientists lack of knowledge of what the data is actually saying about the physical process and the engineers 'you've got the data, what's the answer' approach.

As stated the knowledge elicitation results available at the time of writing were an incomplete set from one expert. The data is to be rerun using the input from all the domain experts, both individually and collectively, and optimally tuning the algorithm.

Further work is required to understand fully the impact of the interactions between the number of datasets and the expert knowledge input and to validate different knowledge elicitation methodology, and if necessary, make further improvements.

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