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Multi-Signal Quality Monitoring of Aluminium Resistance Spot Welding using Principal Component Analysis

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Abstract: *The current migration to lighter materials in car bodies, such as aluminium, has resulted in significant challenges for joining in production. Resistance Spot Welding (RSW) is the primary sheet metal joining technique in the automotive industry due to its quick cycle time, low cost and high strength. However, aluminium RSW suffers from problems with quality consistency compared to steel, requiring more frequent interventions. This results in a higher cost in production through increased cycle times and the use of consumable electrodes.*

To address this issue, a new multi-signal quality monitoring technique is proposed to allow for complete real-time quality monitoring of aluminium spot welds in production. The proposed solution utilises multiple signals during welding and an efficient algorithm using Principal Component Analysis to determine the signal shapes of interest. It was found that an RMSE of 119N could be achieved when predicting the strength of aluminium spot welds using multiple signals, which is approximately ±5% of the mean strength of the welds and an improvement on previous attempts.

Keywords: *Resistance Spot Welding, Failure Analysis, Aluminium, Quality Monitoring, Principal Component Analysis.*

1. INTRODUCTION

Resistance Spot Welding (RSW) is a sheet metal joining technique, prevalent in a number of consumer industries where high volume joining is required such as: kitchenware products, electronics and cars. RSW is used in the automotive manufacturing industry due to its low cost and reliability in high volume production. As such, modern vehicles are constructed using thousands of spot welds [1], making the quality of each spot weld paramount to vehicle structure and safety in the event of a crash.

Reducing vehicle weight in the automotive industry is a high priority in order to lower vehicle emissions [2]. To decrease vehicle emissions, companies are looking to reduce the weight of cars by using high strength-to-weight ratio alternatives such as Advanced High Strength Steels or Aluminium for large body panels. Due to this, use of aluminium in cars is increasing causing challenges for RSW quality [3].

Aluminium is more electrically and thermally conductive than steel, which means it requires higher welding currents and shorter welding times to fuse the panels together. The higher welding currents and natural oxide layer that forms on the aluminium surface results in significant electrode wear in aluminium RSW. These harsh conditions are not conducive to consistent, high quality welds in a production environment and as such the need to monitor weld quality is higher than ever [4].

Traditionally, on-line quality monitoring in steel RSW has relied on the temperature dependence of the electrical resistivity [5]. The electrical properties such as voltage, current and subsequently resistance, are easily monitored in real-time with many modern weld timers recording them automatically. By monitoring the electrical resistance throughout the formation of a nugget, the localised temperature and therefore nugget growth can be monitored accurately throughout the welding process [6]. Unfortunately, the resistivity of aluminium does not increase as quickly with temperature as it does in steel, making it hard to derive a change in temperature from the small changes in resistivity. When coupled with the shorter welding times in aluminium RSW the weld quality becomes difficult to monitor on-line and in real-time with traditional methods.

To address the challenges associated with aluminium weld quality monitoring an efficient multi-signal weld quality monitoring model using Principal Component Analysis (PCA) is proposed. PCA is typically used to reduce the dimensionality of high dimensional data with minimal loss of information and has been used in facial recognition algorithms [7], digital data compression, and sheet metal stamping die wear monitoring [8]. The method presented in this paper uses PCA to: reduce the dimensionality of a number of available signals during welding and find the signal shapes with the highest explained variance to create a multi-signal weld quality monitoring model. The model presented provides an initial investigation into using PCA and multiple welding signals in aluminium RSW to predict weld quality.

2. LITERATURE & BACKGROUND

Real-time quality monitoring of spot welds has been a focus of RSW research for a number of years, however, the majority of the efforts have been focussed on steel and more recently, advanced high strength steels. Quality monitoring research aims to reduce the need for costly destructive and non-destructive testing methods for ensuring quality consistency in passenger vehicles. Destructive testing methods range from 'chisel tests' which allows for nugget diameter measurement, to tests such as: tensile, impact, fatigue, torsional, hardness and peel tests [9]. The major alternatives to destructive testing are the non-destructive testing methods such as: ultrasound, sonic emission [10], x-rays, and infrared thermography [11]. Non-destructive testing requires skilled technicians to interpret the results and carry out the tests [12], making them time consuming and expensive to conduct. Due to the time and costs associated with non-destructive tests, only a subset of welds can be tested in production meaning that the quality of all welds leaving the line is not known.
To reduce the need for destructive and non-destructive testing, a number of methods have been proposed that model weld quality using measurable signals during welding. In steel resistance spot welding, a number of different signals have been successfully used to monitor quality including: electrode displacement and force [13], dynamic resistance & acoustic emissions [14]. However, quality monitoring in aluminium RSW is more difficult due to the different temperature-resistivity relationship and the propensity for the material to oxidise. In Aluminium RSW, the electrode dynamics have been linked to weld nugget size, exploiting aluminium's high coefficient of thermal expansion to infer nugget growth [15]. Acoustic emission counts measured from the electrodes directly have also been correlated to nugget nucleation in a preliminary study which found relationships to nugget diameter and strength [16]. Although promising, further work is required in acoustic emissions quality monitoring to address the issues of production environment noise in RSW.

Hao et al. conducted a study to characterise the effects to weld quality of a number of varied input parameters over several datasets (current, clamping force, welding time, sheet thickness, welder type and surface conditions) [17]. Several signals were measured during welding, including: current, voltage, dynamic resistance, electrode displacement and force. The study selected a number of features from the signals such as: maximum value, minimum value, various slopes and mean values, and correlated them to weld strength. Multiple linear regression was used with a number of the features from different signals resulting in a RMSE of between 400-500N. The results showed that one feature or signal was not sufficient to provide a 'universal' quality predictor for the varied input parameters. To improve upon the methodology of Hao et al., the use of PCA is proposed allow for whole signal shapes to be represented by principal component scores for correlation. Using whole signal shapes in analysis is likely to be more robust to changes in welding conditions which can render selected values such as maximum resistance irrelevant when changing setup. One of the key findings of the work of Hao et al. was that no one signal could adequately predict the strength of an aluminium weld alone, acknowledging that further work was required in this space. Following on from the work of Hao et al., a multi-signal weld quality monitoring method is proposed using unique signal shapes extracted from: current, voltage, dynamic resistance, electrode displacement and force signals measured during welding.

3. METHOD

Five signals were collected during an aluminium RSW process with the only variation included being from electrode wear and natural variance. Time series signals for voltage, current, resistance, electrode displacement and electrode force were recorded for all 133 welds during welding. The important information from the time series signals was extracted using PCA which was used to produce the multi-signal weld quality monitoring model for aluminium RSW.

3.1. Materials and Equipment

Welds were created on AA5052-H34 of 1mm thickness using a 50kVA AC pedestal welder with pneumatic clamping (shown in Figure 1). The current used was approximately 18kA RMS and the electrode clamping force during welding was 2kN with a welding time of 0.14s (7 x 50Hz cycles). The electrodes used were made from pure copper using a domed electrode design with a 4mm flat face cut into the end (Figure 2).

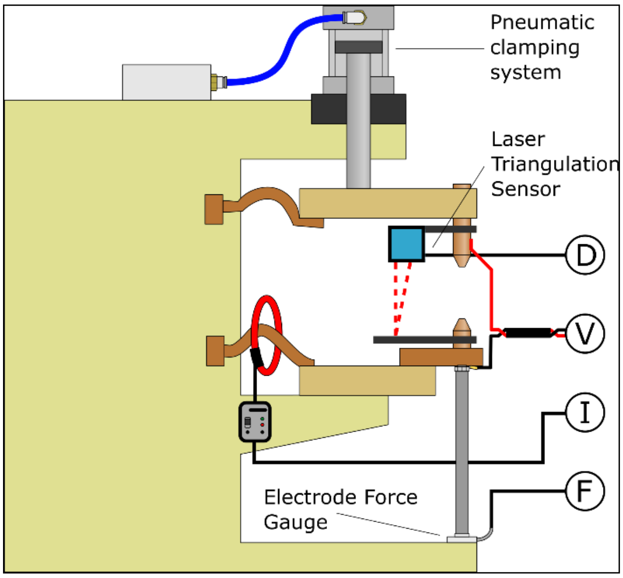

Figure 1: Pedestal Welder and data acquisition setup

Figure 2: Domed electrodes

3.2. Data Collection

For each weld a number of signals were measured at a rate of 5kHz (to ensure no aliasing occurred) including: welding current using a Rogowski coil, voltage drop across the electrodes, electrode force using a 5kN load cell and electrode displacement using a laser triangulation sensor (setup shown in Figure 1). The electrical signals were reduced to the peak values at each half cycle comprising of 14 data points for each weld. From the peak voltage and current values, dynamic resistance was calculated at each half cycle using Ohm's law (ignoring the machine inductance). The electrode displacement and electrode force signals were also reduced to a measurement at each half cycle. The tensile strength of all welds was measured in an Instron 5500R universal testing machine for use as the measure of quality in the multi-signal weld quality monitoring model.

3.3. Weld Strength Model Methodology

To build a model for weld strength from the 5 signals collected during welding each signal set was subjected to Principal Component Analysis (PCA) separately. PCA calculates a new set of orthogonal axes or eigenvectors. The principal components were sorted in order of decreasing eigenvalue, meaning that the new axes are ordered in decreasing amount of explained variance (range). All principal components from each signal set that accounted for less than 1% of the explained variance were removed from further analysis. Each remaining principal component was correlated to weld strength using its principal component scores (distance along the new axes) and a Pearson correlation coefficient, with correlations containing a p-value of < 0.05 deemed to be statistically significant. This test was used to determine which principal components were to be included in the weld quality monitoring model. Once the principal components significantly correlated to weld strength were determined, a simple linear regression model was calculated.

4. RESULTS

The five sets of processed signals for all 133 welds are shown in Figure 3, note the small variation in electrical signals and larger variation in electrode displacement and force. Electrode force and displacement are represented as changes from the initial value when welding began (represented as 0 in each figure). PCA was then conducted on each signal set producing a principal component matrix for each different signal.

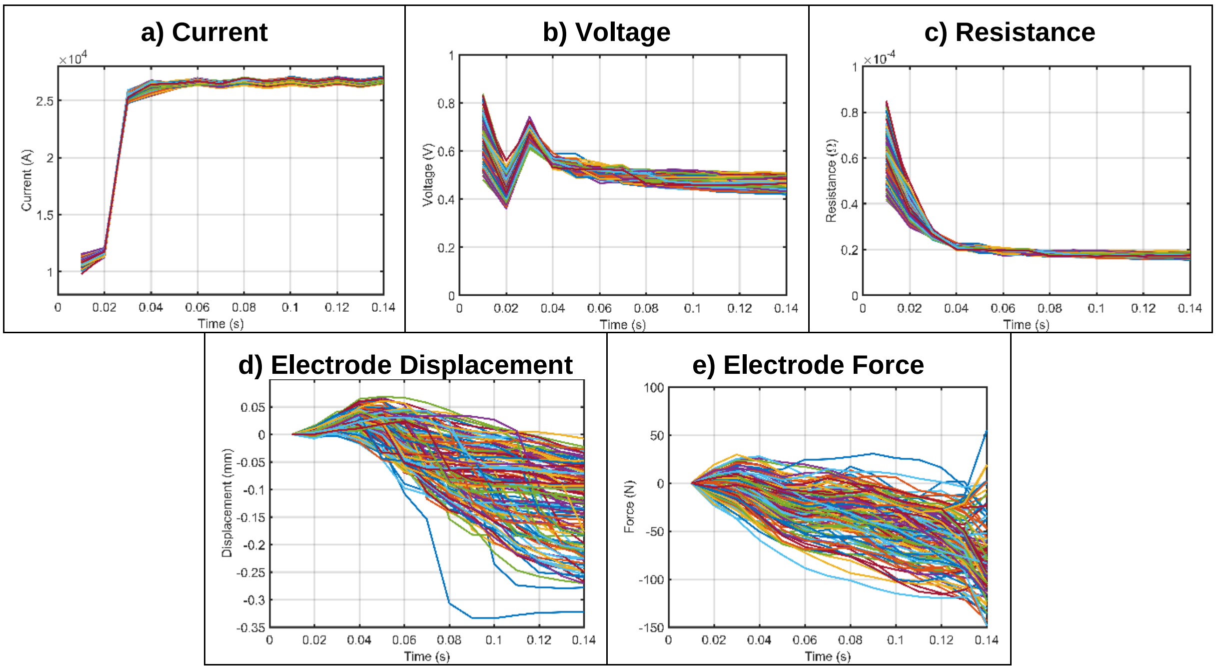

Figure 3: Processed signals measured during welding

The explained variance that each principal component describes in each signal set was calculated by dividing the principal component's eigenvalue by the sum of all eigenvalues in the data set. All principal components with an explained variance of less than 1% were removed from further analysis. After this step each signal set has been reduced in dimension from 14 data points per weld to between 3-7 depending on which signal is considered. Not only has the dimension of each signal set been reduced but the major signal shapes have been revealed by their level of explained variance in each data set which is a by-product of the new orthogonal axes calculated during PCA.
The principal components with an explained variance greater than 1% were correlated to weld strength using Pearson correlations to determine the signal shapes significantly correlated to weld quality (p-value < 0.05, consistent with statistical conventions). The significantly correlated principal components, their coefficients of determination with weld strength (R^2) and the associated explained variance of their signal set are shown in Table 1.

Table 1: Principal Components Significantly Correlated to Weld Strength (p-value < 0.05)

Signal	Principal Component Number	Name	Explained Variance (%)	R^2
Current	1	**C1**	53.3	0.04
	3	**C3**	4.8	0.29
	5	**C5**	1.5	0.05
Voltage	1	**V1**	75.1	0.12
	2	**V2**	9.9	0.48
	3	**V3**	4.4	0.04
	4	**V4**	3.8	0.06
Resistance	1*	**R1**	92.3	0.11
	3*	**R3**	1.5	0.48
Displacement	3*	**D3**	4.2	0.17
Force	1*	**F1**	70.8	0.37

*Principal component shape shown in Figure 4

The correlations to weld strength presented in Table 1 are all relatively low ($R^2 < 0.5$) showing that none of the principal components are highly correlated to weld strength when considered individually. Additionally, the major variation (1st principal component) in all signals was found to be correlated to weld strength, except in the electrode displacement signal. A selection of principal component signal shapes from Table 1 is shown in Figure 4.

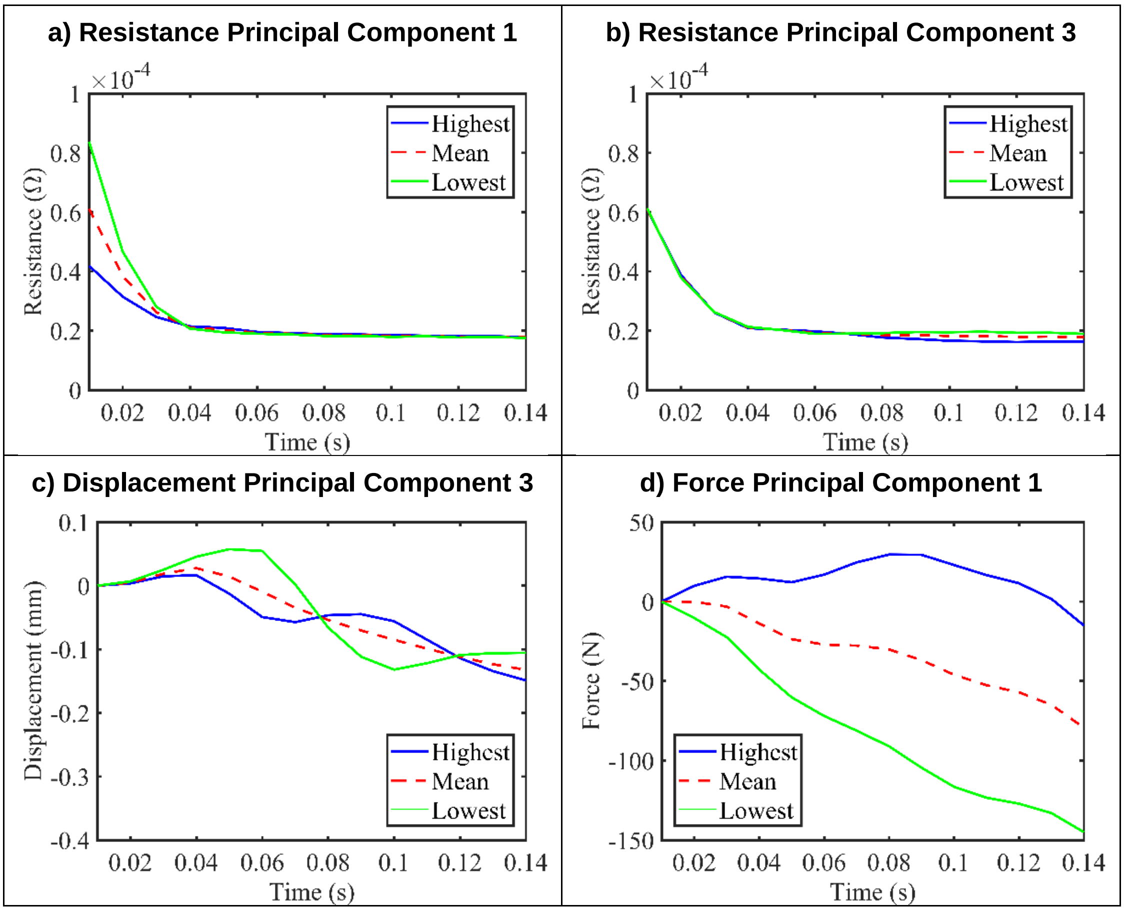

Figure 4: A sample of the principal component shapes correlated to weld strength

Once the significantly correlated principal components for each signal set had been determined, a multi-signal weld quality monitoring model could be produced. A linear regression model was calculated between the principal components in Table 1 and weld strength, shown in equation (1).

$$Y = (-0.021 \times C1 - 0.031 \times C3 - 0.25 \times C5) + (911 \times V1 - 6980 \times V2 - 3530 \times V3 + 2740 \times V4) + (-3.24 \times 10^6 \times R1 + 7.30 \times 10^7 \times R3) + (-824 \times D3) + (-363 \times F1) + 2060 \quad (1)$$

The confidence intervals and accuracy of the multi-signal weld strength model is shown in Figure 5. The model has an R^2 value of 0.769 between the predicted and measured values and a Root-Mean-Square Error (RMSE) of 119N. Welds that failed in shear and nugget pullout are denoted by crosses and circles respectively.

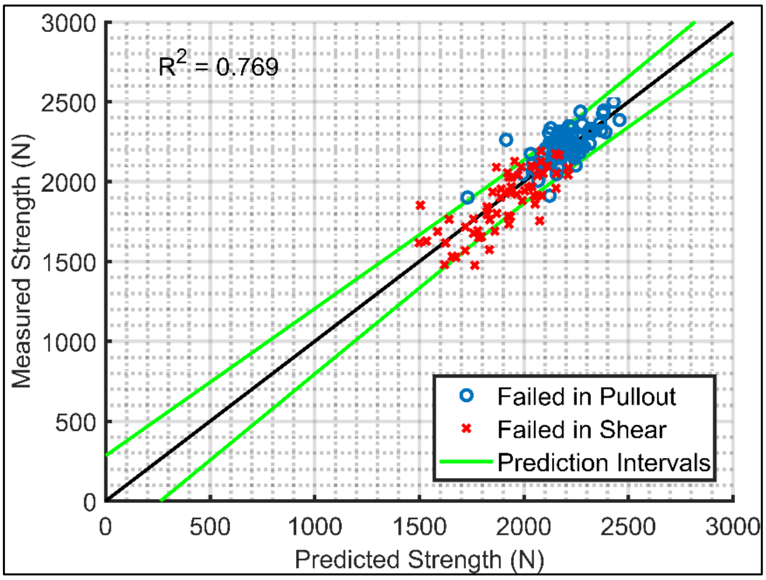

Figure 5: Multi-Signal Weld Quality Monitoring Model

5. DISCUSSION

The majority of the variation in the voltage signals was found to be correlated to weld strength, shown by principal components 1-4 of the voltage signals in Table 1. The variance between signals was more pronounced in the electrode voltage than the current signals which is due to the constant power delivery of the welder. The variation in the voltage signal propagates through to the resistance signals which are directly calculated from current and voltage. The first and third principal components of the resistance signal, R1 and R3, were found to be significantly correlated with weld strength, with variation at the start and end of the signal, shown in Figure 4 a) and b) respectively. Variance at the end of the resistance signals, described in the 3rd principal component, was more strongly correlated to weld strength (R^2 = 0.48, R3) than variance at the beginning (R^2 = 0.11, R1). A lower resistance towards the end of the signal, as seen in R3, was found to be correlated with a low weld strength. This is thought to be a consequence of expulsion at the faying surface, causing material loss from the weld nugget, explaining the reduction in overall weld strength. This is supported by the shape of the resistance signals in Figure 6 a) which are examples of signals with high and low 3rd principal component scores. Those signals with low or negative 3rd principal component scores show a distinct drop in resistance after ~0.07 seconds. The same signal variation was found to be caused by expulsion in a study focussing on expulsion detection in aluminium RSW [18]. Those signals with low 3rd principal component scores belonged to welds with low weld strengths that were more likely to fail in shear, while the opposite was found of those signals with high (positive) scores which were more likely to fail in nugget pullout.

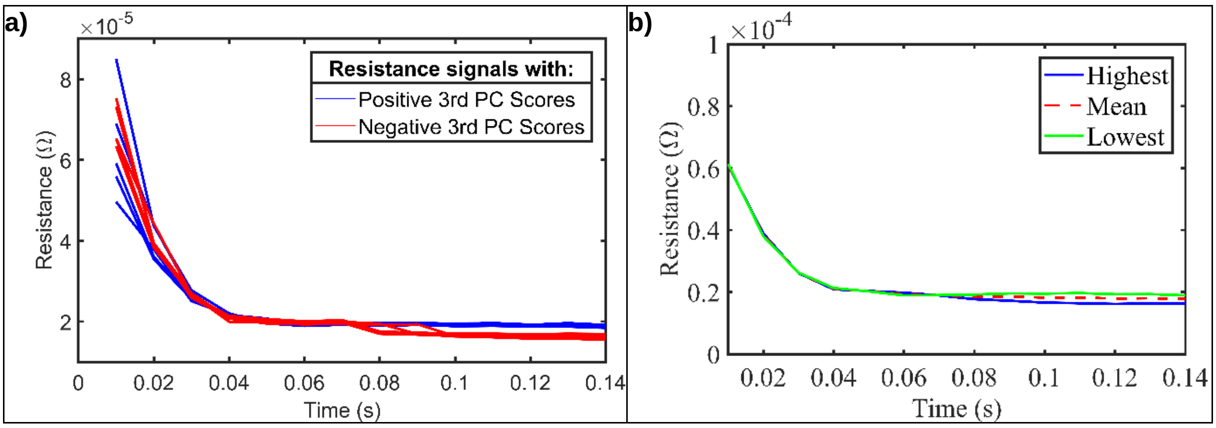

Figure 6: Evidence of expulsion in the resistance signals, a) resistance signals with high and low 3rd principal component scores, b) 3rd Principal component of the dynamic resistance signal

5.1. Multi-signal Weld Quality Model

The present weld quality model uses multiple signals measured during a RSW process to address concerns in the literature that one signal alone is not sufficient to monitor the quality of welds in aluminium RSW [17]. The model derived shows that utilising signal shapes from multiple signals to predict aluminium weld quality with simple linear regression provides an acceptable level of accuracy. The multi-signal weld quality monitoring model developed, achieved an RMSE of 119N, which is approximately ±5% of the mean strength of the welds. This result, is a significant improvement on the RMSE achieved by Hao [17], which ranged from 410-540N (~12-15% of the mean strength). Hao used similar multiple linear regression with automatically selected features from the signals such as max, min, mean and slope values. The improvement in prediction error shows the inherent value in using PCA to represent complete signal shape variation over the alternative of selected landmark points and features given that using similar linear regression with principal components yields a tighter confidence interval.

6. CONCLUSION

The multi-signal weld quality monitoring model was created for aluminium RSW using: the voltage across the electrodes, current through the workpiece, dynamic resistance, electrode displacement and electrode clamping force during welding. The major variation in these signal sets was extracted using Principal Component Analysis (PCA). Using a number of selected principal components a model was calculated resulting in an RMSE of 119N between the predicted and measured strength of the welds found through destructive testing.

Further work is required for a system that is ready to implement in a production environment. None of the principal components, when considered individually, were found to be strongly correlated with weld strength in this study (all $R^2 < 0.5$). This shows that the principal components of highest variance of the aluminium welding signals are not necessarily highly correlated to weld strength. As such, investigation into alternate methods is required to obtain better predictive results for aluminium RSW. The key limitations of the signal analysis completed in this paper are:

1. the core assumption that the directions of highest explained variance of the data should be significantly correlated to weld quality, and,
2. that the covariance between the different signals is not considered.

To address the first limitation, methods which draw out different features of the data such as different approaches to PCA and Kernel PCA can be considered. To address the second limitation, much more work is required to develop analysis techniques that account for the covariance of multiple signals in aluminium weld quality monitoring. Consideration of the interactions and covariance between the different signals is likely to improve the accuracy of the model which attempts to simplify to the complex interactions between the electrical, thermal and mechanical aspects of the process that governs the quality of aluminium resistance spot welds.

7. ACKNOWLEDGMENTS

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