# On using Machine Learning in Ultrasonic Metal Welding

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## Introduction

Ultrasonic Metal Welding (USMW) is a type of welding which is used, among other applications, in the production of lithium-ion batteries for electric cars. Presented in a short way, its mode of operation is that the «horn» compresses the workpiece (the pieces of metal to be welded) against an «anvil» with a constant downward vertical force. The horn then starts vibrating horizontally, with a main welding frequency of about 20 kHz and an amplitude of about 20 µm. This creates friction between the workpieces, which ultimately leads to the formation of a weld between the workpieces. More complete explanations can be found in [1] and [2].

One of the ways USMW can currently be improved is by improving the choice of welding parameters, such as welding pressure or welding amplitude, which also depend on the material properties of the workpieces. For different workpiece geometries and different material properties, the choice of welding parameters will influence whether a weld was correctly formed or not, as well as how strong the weld is. Currently, welding parameters are chosen based on trial and error, and on the expertise of the machine operator. For example, the machine operator might choose welding parameters that, from their experience and knowledge, would work for a specific set of workpieces with specific geometries and material properties, do a few trial welds, and take these welds to a strength test machine to test the failure strength of the welds. If the strength is deemed adequate, the welding parameters are adopted, and if not, other parameters have to be found. This is time consuming. Instead, real-time monitoring of USMW could speed this process up. An in-line quality-control system would decrease the amount of time needed to set up the welding machine by making the welding process less sensitive to the choice of welding parameters.

Another problem with USMW is that, currently, the physical phenomena which lead to the formation of a weld are not known in exact detail, although there are many experiment-backed theories [1][2]. In a simplified manner, one can describe the progress of the weld in the following way: as welding progresses, the strength of the weld increases, until a region of maximum strength is reached. At this region, the weld can be classified as a "basic weld". Before this region is reached, the weld can be classified as an "Underweld". If welding continues for even longer, then the weld strength can decrease again, and the weld is then an "Overweld" [1][2][3]. However, without exact knowledge of the mechanisms of USMW, it is difficult to know which physical process to monitor or which feature might help monitor the process.

One way to circumvent this lack of knowledge is to use machine learning algorithms, which have proven effective in similar situations [4][5].

The goal of this paper is to use machine learning to classify USMW welds into Underwelds, Basic welds and Overwelds.

## Measurement Setup

A short overview of the experimental setup is given here. It is described in more details in [3].

The vibrations of the horn and anvil were measured during welding in the direction of welding using two laser Doppler vibrometers (LDV) with a frequency range in the MHz. The airborne sound emitted during welding was measured with a GRAS ¼'' microphone placed 15 cm away from the welding site, perpendicular to the welding direction. All three sensors were synchronised with a system with a maximum measurable frequency of 125 kHz. The maximum frequency of the lasers was therefore 125 kHz, and 100 kHz for the microphone.

Copper sheets with dimensions 125 mm x 45 mm x 0.5 mm were welded. Three types of welds were welded: Underwelds (weak welds), Basic welds (strong welds), and Basic welds + (strong welds as well, but close to being overwelded). To produce these welds, all parameters were kept constant, and only the welding time was varied. The strength of the welds was measured with a tensile strength test machine, and the distribution is shown in Figure 1. In total, 42 Underwelds, 40 Basic welds and 41 Basic welds + were produced.

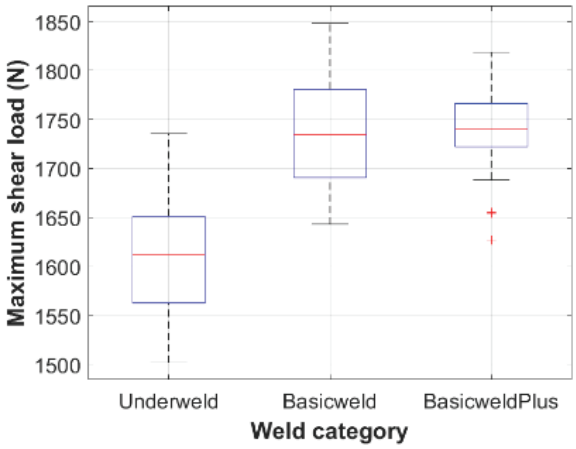



**Figure 1**: Strength distribution of all three welds categories

## Classification algorithms and implementation

Three machine learning algorithms were used in this study: Back Propagation Neural Network (BPNN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA).

The data was divided into training set and test set, with an 85%-15% allocation percentage. For each training and test set, all three algorithms were run, and the accuracy of each was calculated. For greater result stability, this was repeated

100 times with 100 different allocations of training and test sets. In each one of those hundred times, the hyperparameters of the algorithms, described below, were optimised.

**BPNN**

In machine learning, backpropagation is a widely used algorithm in training multi-layer feedforward neural networks for supervised learning. It minimises the training error in the network using gradient-based methods [6]. In this study, a BPNN with a single hidden layer was used.

Neural network performance is influenced by a large number of hyperparameters due to its high complexity. Three typical hyperparameters, the number of hidden neurons, regularisation parameter and training function, were tuned using a grid search algorithm. Additionally, 10-fold cross-validation was added to reduce the impact of overfitting.

Furthermore; in order to minimise the impact of random initialistaion on the prediction results, for a given training and test set, 10 BPNN models were created and trained based on the optimal hyperparameters, and the average classification output was taken. Using this method, the stability of the BPNN algorithm was greatly increased.

**Support vector machine**

Support vector machine (SVM) classifies data by finding the optimal hyperplane as a decision surface that separates all data points of one class from those of the other class. The best hyperplane of SVM means the one with the maximal margin between two classes. The support vectors refer to the data points that are closest to the separating hyperplane and are used as support for the optimal location of the decision surface [4]. The available optimisable hyperparameters of the SVM model are: kernel function, box constraint level, kernel scale, multi-class method and standardise data.

To find the best hyperparameters, different combinations of values within the search range were tried by using a Bayesian optimisation scheme which automatically seeks to minimise the objective function and returns a model with the optimised hyperparameters. 10-fold cross-validation technique was also used to ensure robustness.

**Linear Discriminant Analysis**

Discriminant analysis is another popular classification algorithm due to its speed, accuracy and ease of interpretation. It assumes that different classes generate data based on different Gaussian distributions. The fitting function estimates the parameters of a Gaussian distribution for each class to train the classifier [4]. In order to predict the classes of new data, the trained classifier will then find the class with the smallest misclassification cost.

The optimisation process of LDA was similar to SVM. The available optimisable hyperparameters of the LDA model are: discriminant type, linear coefficient threshold and regularisation.

## Features extraction and selection

The recorded sensor data was trimmed at the start and the end of measurement, in order to only contain measurements of the welding process. Features were then extracted from the data using the following steps.

As a first step, each measurement signal was decomposed using a level 3 wavelet packet decomposition (WPT) into 8 equal-width frequency bands. The width of the frequency bands depends on the maximum measurable frequency in the signal: for the LDV, each frequency band was 125 kHz / 8 = 15.625 kHz wide. For the microphone, each frequency band was 100 kHz / 8 = 12.5 kHz wide. The limits of the bands are shown in Table 1.

**Table 1**: Limits of frequency bands for LDV and microphone measurements (in kHz)

| Freq band | $f_{LDV\ start}$ | $f_{LDV\ end}$ | $f_{MIC\ start}$ | $f_{MIC\ end}$ |
|---|---|---|---|---|
| 1 | 0 | 15.625 | 0 | 12.5 |
| 2 | 15.625 | 31.25 | 12.5 | 25 |
| 3 | 31.25 | 46.875 | 25 | 37.5 |
| 4 | 46.875 | 62.5 | 37.5 | 50 |
| 5 | 62.5 | 78.125 | 50 | 62.5 |
| 6 | 78.125 | 93.75 | 62.5 | 75 |
| 7 | 93.75 | 109.375 | 75 | 87.5 |
| 8 | 109.375 | 125 | 87.5 | 100 |

WPT is particularly suitable for the analysis of non-stationary signals, owing to its proper frequency resolution regardless of high or low frequencies. It used an fk6 wavelet, which belongs to the wavelet family of Fejer-Korovkin filters. Both the wavelet and the level of decomposition were chosen based on the literature [5][7][8].

In the second step, the energy $E_n$ in each frequency band $n$ was calculated using the following equation:

$$E_n = \sum_{k=1}^{K} |C_n(k)|^2 \quad (1)$$

where $K$ represents the length of the WPT coefficient vector of each frequency band and C is the coefficient vector

In the last step of feature extraction, to remove any time-dependence of the energy (since longer welds contain more energy than shorter welds), the energy was normalised by dividing it by the total energy, to get the normalised energy $NE$:

$$NE_n = \frac{E_n}{\sum_{n=1}^{8} E_n} \times 100\% \quad (2)$$

In addition to being time-independent and being a standard pre-processing step in machine learning, normalising the data also reduces the impact of peaks which sometimes occur in the LDV horn measurements due to interference from particles ejected during welding.

Finally, to select the most relevant feature for the classification, a Neighbourhood component analysis (NCA) model was used for feature selection. The NCA model included an optimisation of the regularisation parameter to minimise the classification loss. Relevant features were then selected using the feature weights, shown in Figure 2, and previous knowledge of the measurements to set a relative threshold, shown as a horizontal line in Figure 2. The features kept and the knowledge basis for the decision are described in the Results section.

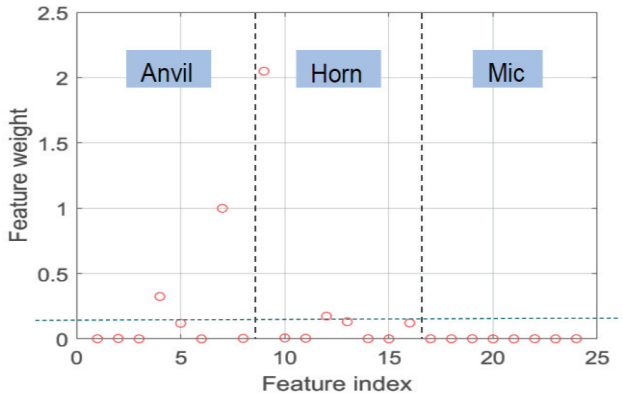



**Figure 2:** Weights of the different features after NCA

## Results and discussion

### Results of NCA

The selected features after the NCA were a total of four: anvil frequency bands (FB) 4 and 7, which contain respectively the 2nd and 4th welding harmonics, and the Horn frequency bands 1 and 4, which contain the frequency range below the welding frequency, and the 2nd harmonic of the welding frequency. No features of the microphone were kept.

The choice of these parameters was made by looking at both the NCA results and comparing them to previous findings about this data, which are detailed in [9] and [10].

First, FB 5 of both the horn and anvil were excluded. This is because they do not contain any harmonic of the welding frequency. It is possible that the peaks seen in these frequency bands are due to the piezoceramic generator of the USMW machine and modal amplification with the welding setup. Since it is not known if these frequencies occur in every welding setup, they were excluded from this analysis.

FB 4 of the anvil and horn contains the 2nd harmonic of the welding frequency, 60 kHz. This is the strongest frequency after the welding frequency, and was previously found to show significant changes when transitioning between the three welding categories [9]. These features were kept in this analysis.

FB 7 of the anvil was also kept. It is interesting to note that, with FB4, they are both the first even harmonics of the welding frequency. This is interesting to note, because the odd harmonics (40 kHz, 80 kHz, ...) of the welding frequency are actually dampened by the mechanical setup of the welding machine. This is explained in more details in [10].

FB1 of the horn, which contains neither welding frequency nor any of its harmonics, showed the highest weight in the NCA analysis, and by far. For this reason, despite the fact that it contains neither welding frequency nor harmonic, it was kept in this analysis.

### Result of classification

The results of the training and test sets are shown in Figure 3 and Figure 4 respectively.

Looking at the training results, all three algorithms showed accuracies above 93%. For all three algorithms, feature selection also led to an improvement of the results, with the highest accuracy being reached by the SVM, both with and without feature selection.

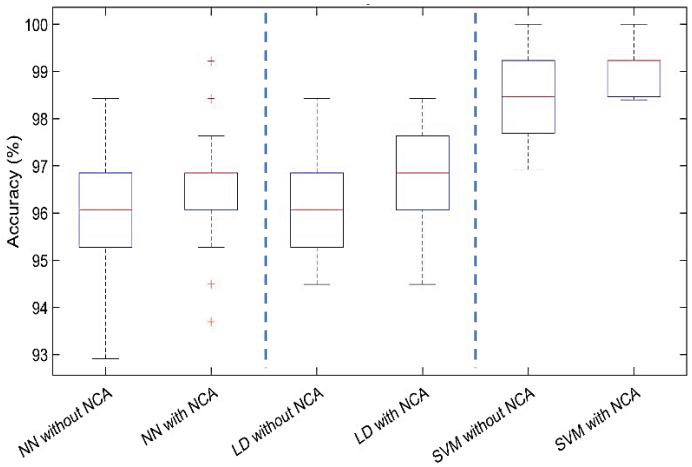



**Figure 3:** Training set results for all three algorithms, with and without feature selection

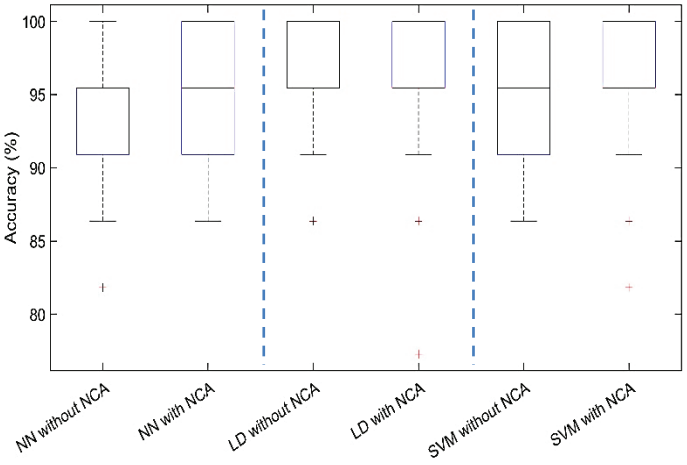



**Figure 4:** Test set results for all three algorithms, with and without feature selection

Looking at the test results, all three algorithms showed accuracies above 82%, with LDA and SVM being consistently above 86%. In the case of the NN, the test accuracy is noticeably less than the training accuracy, which could indicate some overfitting. The results also worsen with feature selection. The best results are achieved by the LDA, with and without feature selection, with SVM and feature selection having similar results, except for one more outlier in the distribution.

Overall, feature selection improved all trainings. It worsened the results of the test NN, which could indicate overfitting, had no effect on LDA, and improved the results of SVM.

## Conclusion and Outlook

The goal of this paper is to use machine learning to classify USMW welds into Underwelds, Basic welds and Overwelds. Copper welds were made using USMW, at three different stages of the weld progress: Underweld, Basic weld, and Basic weld+, which are almost Overwelds. Using the normalized energy from wavelet packet decomposition as input features, three different machine learning algorithms were able to classify these welds into their welding stages. Linear discriminant analysis and Support Vector Machine provided the highest accuracy.

A Near Component Analysis was done on the input features. From the 24 initial features, 4 were kept, based on the output of the NCA and on previous knowledge of the welding process. The accuracy of the machine learning algorithms improved slightly. The biggest improvement of feature selection would be on training speed: it is faster to train an algorithm based on 4 features rather than 24.

Further studies could try to relate the features to the welding strength rather than to the welding stage. It would also be interesting to isolate specific frequencies to find their effect on the overall algorithm, rather than take frequency bands which span over 10 kHz.

## Literature

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