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Influence of film-like contaminants on ultrasonic metal welding and their in-situ detection

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Abstract

Ultrasonic metal welding (USMW) is a solid-state welding process that is primarily used for joining electrical and electronic components. Common areas of application include series production of battery systems, power electronics and wire harnesses. The large number of disturbances in real-world applications, as well as a lack of basic knowledge about their effect on the welding result, cause difficulties to develop methods for quality prediction. In critical combinations, disturbances lead to faulty welds that can remain undetected by established monitoring strategies. Organic residues on the materials caused by production and handling have proven to be potentially critical, depending on the welding configuration. This study investigates the influence of various film-like, organic contaminants on USMW of copper sheets. For this purpose, a selection of contaminants is applied to the sheets to be joined and the welding process is monitored using a variety of sensors. In addition to evaluating their influence on tensile shear strength, suitable process signals are presented that can be used to reliably identify contamination and predict quality. For a more comprehensive analysis of the effects of contamination, differences in the thermal decomposition processes of the organic layers and their residues in the connection zone are considered. Particularly with a structure-borne sound signal at the anvil, reliable detection of film contamination is possible regardless of the welding parameters, even without complex algorithms. Maximum R^2 of 0.76 and a mean absolute error (MAE) of 150 N or ~6% in quality prediction can already be achieved using exemplary Extra Trees Regression with only 140 welds.

Keywords Ultrasonic metal welding, Process monitoring, Process modeling, Copper welding

1 Introduction

Ultrasonic metal welding (USMW) is a widely used and established industrial joining method for electrical connections [1, 2]. In most cases, the application requires the joining of unalloyed or low-alloy copper and aluminum metals with high thermal and electrical conductivity. The characteristics of a solid-state welding process offer advantages over fusion welding, particularly in terms of energy consumption and heat input in



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sensitive components [3, 4]. Furthermore, no filler material is required. Common areas of USMW application include (large-scale) series production of battery systems, power electronics and wire harnesses in the automotive industry [1, 5]. In these areas, USMW is used in both fully and partially automated applications. Alternative processes in this field include both thermally based material-locking processes such as laser welding [6] and brazing [7] but also resistance welding [8]. In some applications, friction-based connections such as screwing or (hot) crimping [9] are also competing. USMW is often the preferred choice, particularly when requirements for high production volumes, cost pressure, high electrical conductivity and mixed-material joints (e.g. aluminium-copper) coincide with temperature constraints.

The USMW process is characterized by a large number of disturbance variables [10, 11], which are usually addressed through careful, application-specific process development and strict quality control of the incoming goods [12]. Despite the considerable effort involved in monitoring parts, sporadic defects still occur, which remain undetected during the production process. These defective parts cannot always be detected by established scalar monitoring of welding time and indentation depth during USMW. The reasons for this are, in addition to the often insufficient correlation with the quality indicator, that the selection of suitable limits for these scalar values is subject to a trade-off between identifying all non-conforming parts and keeping false rejects within acceptable limits. Several approaches involving the analysis of time series data (e.g. electrical power curve) or oscillation sensors directly on the tools in combination with machine learning methods have already been investigated in the literature as an improvement [2, 3, 5, 13–16]. These methods have not yet become widely established in industry, as there is still a lack of basic knowledge about the interaction of process disturbances, that can prevent a robust implementation. There is also a lack of universally applicable, quantified process models and efficient integration methods in real production.

In addition to tool wear, component geometry, material, and oxide layers [11, 17, 18], film-like contaminants are a significant source of interference that is difficult to control in manufacturing environments, especially in manual or semi-automated processes [17, 19, 20]. Müller et al. investigated the effect of rolling oil on the USMW of copper sheets, which may remain on the surface in small quantities as a result of the preceding cold rolling process [12, 13]. Gester has investigated the effect of both stearic acid and silicone oil on USMW of aluminium wires on terminals [21, 22]. Both studies found a reduction in weld strength due to contamination, although a lack of quantification of the actual surface contamination limits the comparability of the results. Further possibilities for component contamination include the following: In addition to contamination of components by the operator (e.g. skin fats or skin protection lotions), sources of contamination include the transfer of production-related residues from involved work steps and the introduction of oils/greases through system equipment or its maintenance. Various sources describe these contaminations as undesirable, even though the process can remove these impurities from the joint zone to a limited extent at the beginning of welding [1, 19, 23]. Even a few micrograms of oil on component surfaces can lead to significant interference or even total failure. In general, consistent surfaces result in correspondingly low process variation [1, 24].

The identification and quantification of film contamination in production primarily takes place in the incoming goods section, prior to USMW. This has so far only been

done on a sample-based approach and not for each part to be welded. Proposed methods for monitoring surface cleanliness are either complex laboratory methods (e.g., FT-IR, XPS) and therefore economically inefficient, or they work with a small measuring spot (e.g., fluorescence) for in-line capability, meaning that randomly distributed contaminants cannot usually be reliably detected across the entire weld surface [24, 25].

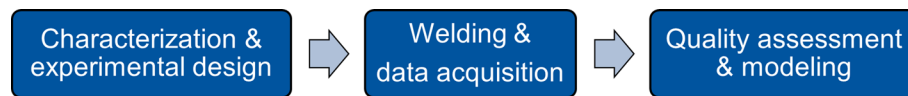
To guarantee the necessary cleanliness of components prior to welding, appropriate cleaning can be carried out following detection. In industrial applications, chemical cleaning processes are most common, but these are generally limited to use on large surfaces and are relatively harmful to the environment [26]. Alternatively, surfaces can be cleaned locally using a laser [27] or plasma [28]. What all cleaning processes have in common is that they must be adapted to the specific contamination present [24, 25, 28, 29]. In particular, cleaning copper surfaces using a laser as a preparation for USMW has so far proved challenging [29–31]. In principle, it is also possible to combine detection with subsequent component-specific cleaning using a laser or plasma, but each of these options results in further cost increase.

Research in the literature shows that data collected during the welding process can be used to detect organic contaminants [13, 17, 22, 24], which is a significantly more efficient approach. These references refer to oil or grease but usually do not provide more detailed information on the type or nature of the contamination. Studies on the amount of oil or with different dilutions are also available, but only for one type of contamination and without variation in welding parameters [10, 24]. As a result of detection during the welding process, only those parts in which critical contamination has been identified are rejected.

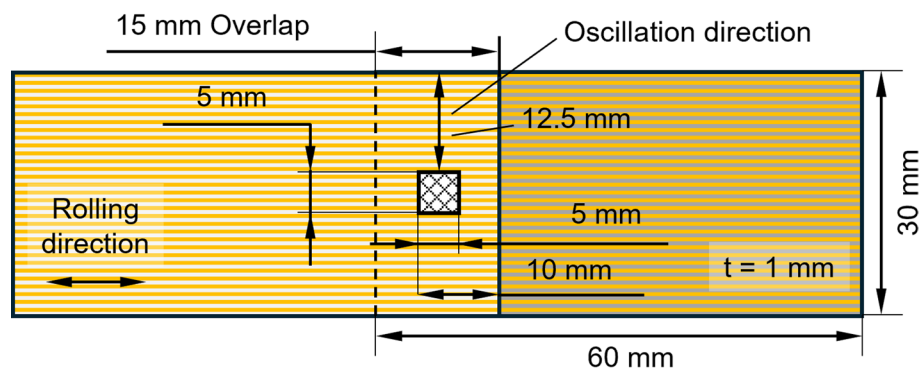
1.1 Summary and research objective

Although it is already known in the industry that film-like contaminants can have a critical impact on USMW, methods for the verification of a stable initial state are either uneconomical or not established. Furthermore, there have been many studies on the effects of organic contamination on the ultrasonic welding process [13, 17, 21, 22, 24, 32]. It has already been observed that both a reduction and an increase in weld strength can occur, depending on the boundary conditions [13, 22, 29]. However, the mechanisms responsible for this remain unknown or have not been sufficiently investigated. At the same time, it is evident that the type and amount of contamination, the materials to be welded, and the welding parameters all interact with each other.

This research gap needs to be narrowed by combining variations in the oils/greases considered with the welding parameters used. For this purpose, the oils under consideration are first characterized in terms of their thermal decomposition properties. The oils are then applied to copper samples, which are welded together and then mechanically tested to determine a characteristic quality value. In addition, contamination on the component surface is quantified. The joint quality is then correlated with the decomposition properties of the oils. Using a classification based on scalar or high-frequency recorded process data, it is then examined whether the respective types of contamination can be reliably filtered out and assigned from the high-frequency measurement data. The study also examines whether the quality of the prediction is influenced by the welding parameters used. In addition, it identifies which sensor signals are most relevant

**Fig. 1** Methodology**Table 1** Properties of considered copper material ($n=10$)

Material	Tensile strength R_m	Yield strength $R_{p0.2}$	Hardness HV0.1	Roughness S_a	Young's modulus E
Cu-ETP R240	241 ± 1 MPa	191 ± 1 MPa	79 ± 5	0.14 ± 0.04 μm	122 ± 3 GPa

**Fig. 2** Specimen geometry

for identifying contamination. The result is an in-situ methodology for quantifying contamination during the USMW process.

2 Methodology and experimental setup

The implemented methodology follows the procedure shown in Fig. 1. First, the materials involved and the methods used to characterize them are presented. Next, the test plan, the welding system including the test setup, and data acquisition are described. This is followed by the welding tests and the determination of quality data. Finally, the model is created, trained, and validated. At last quality assessment and correlation with identification and classification of signal importance is done.

2.1 Specimen configuration and contamination procedure

In this study, electrolytic tough pitch cold-rolled copper plates (Cu-ETP R240) in semi-hard rolled condition are used for the welding trials. The sheet metal is characterized in terms of several material and surface properties. Tensile strength R_m , yield strength $R_{p0.2}$, and Young's modulus E are determined perpendicular to the rolling direction [33]. The surface roughness S_a is determined using a confocal microscope [34]. A summary of these is shown in Table 1.

The sample geometry used (Fig. 2) consists of two overlapping copper sheets in accordance with the specification in Table 2, each with a material thickness of 1 mm. The sample geometry was chosen so that it could be tested as practically as possible using a tensile shear test and so that failure would occur clearly at the joint instead of a base material failure.

Table 2 Specimen configuration

Test series	Additional information	Cleaning	Contamination (dilution factor)
A1/A2	Reference (foil clean)	–	EXW
B1/B2	Reference (foil clean)	–	EXW
C1/C2	Siloxane-based grease	2-Propanol	1:100
D1/D2	Mineral-oil based grease with sodium soap	2-Propanol	1:100
E1/E2	Mineral-oil based grease with lithium soap	2-Propanol	1:100
F1/F2	Hand lotion (skin protection)	2-Propanol	1:100
G1/G2	Cold-rolling oil for copper	2-Propanol	1:100

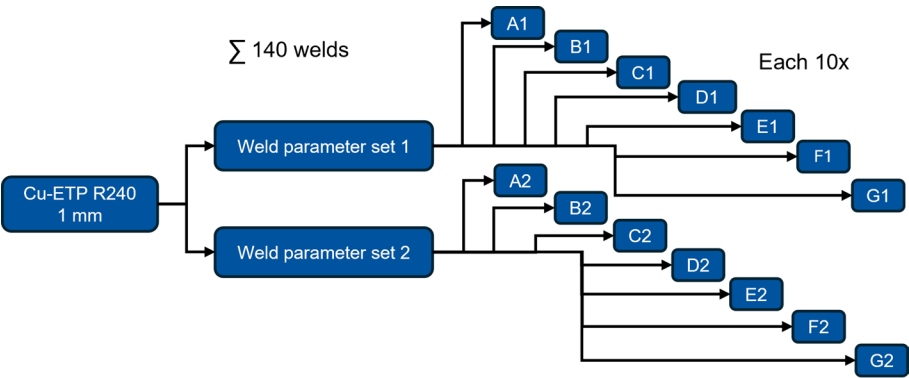


Fig. 3 Experimental layout

In addition to 10 reference samples per batch (1 & 2) and welding parameters, 10 samples per parameter combination and contamination are welded, resulting in a total of 140 samples (Fig. 3). In addition to this structured test plan, further welds are carried out on a sample basis with temperature measurements in the joint zone (Chap. 3.3) and a modified vibrometer position (Chap. 3.6) in order to describe the effects resulting from contamination. The material is stored with a protective polyethylene film, which is removed immediately before the welding process, resulting in ‘ex works’ condition (EXW). This protective film was applied manually after production and does not guarantee that the surface is completely free of particles and contamination, as these are usually unevenly distributed.

Since USMW is used in both semi-automated and fully automated applications, a selection of real-life film contaminants will be investigated. The samples are welded using two different welding parameters in order to include this influence as well. The sample groups are labeled with a letter (A-G) for the surface condition and a number (1 and 2) for the welding parameters used, depending on their condition. In addition to two reference surfaces without contamination (A1/A2 and B1/B2), which differ only in terms of the delivery batch, five different oils/greases are used. The contaminated samples are taken from batch B. A siloxane-based paste with very high temperature resistance (C1/C2) used as a release agent and lubricant in the assembly of ultrasonic welding tools. A grease with sodium complex soap based on mineral oil for sliding bearings (D1/D2), another grease based on mineral oil with lithium complex soap for rolling bearings (E1/E2), and a hand lotion to protect the skin of plant operators (F1/F2). The last variation is a rolling oil (G1/G2) used for cold rolling copper sheets, which can remain as residue on the material if it is not completely cleaned off. All lubricants are diluted with

isobutanol ($C_4H_{10}O$) in a ratio of 1:100 to create comparable boundary conditions. The dilution is applied using a micropipette in a quantity of 20 μl to each of the surfaces to be welded together. The contamination is characterized both qualitatively by means of a visual inspection of the surfaces and quantitatively by means of fluorescence measurement (Relative Fluorescence Units, RFU) using the Stokes shift [20]. For this purpose, the contactless measuring device SITA Cleanospector is used, which excites with a wavelength of 365 nm at max. 150 mW and detects the proportion of radiation which is emitted at 460 nm via fluorescence of surface contamination [24]. A higher RFU value means a correspondingly higher surface coverage with fluorescent contaminants.

2.2 Welding setup and data acquisition

The welding parameter sets investigated are determined in accordance with standard practice using parameter studies (design of experiment - DOE). An energy-controlled process is selected, meaning that the parameters (contact pressure) force, oscillation amplitude, and energy must be determined. In general, a lower amplitude should be selected for higher contact pressure in order to achieve local parameter optimization [23]. Higher contact pressure improves the coupling between the sonotrode and the upper joining part, but at the same time leads to increased component indentation, which can be partially compensated for by reducing the amplitude [35]. The parameter studies resulted in the following two locally optimized parameter sets (Table 3). One of the optimization targets was to achieve the most comparable joint quality (tensile shear force) possible in the reference state (A and B). At the same time, the settings of the parameters should differ as much as possible in order to be able to investigate the interaction between welding parameters and contamination. The vibration amplitudes of 30 μm (set 1) and 24 μm (set 2) are achieved in the middle of the sonotrode in undamped idle mode. During the process, the amplitude is dampened by the workpieces, and the welding force is kept largely constant by indirectly adjusting the cylinder pressure. The energy required for parameter set 2 is significantly lower at 750 J instead of 1600 J, making the process more energy-efficient and also significantly shorter in duration.

An industry-standard 4 kW welding system (Schunk LS-C) is used to perform the welding tests, which corresponds conceptually to the design shown in Fig. 4. An application-specific sonotrode with a square working surface of 5 mm $\times$ 5 mm and a diagonal knurl pattern in the form of a truncated pyramid (0.8 mm $\times$ 90°, flattened by 0.1 mm) is used. The application-specific anvil has a working surface of 10 mm $\times$ 10 mm with a diagonally arranged, pyramid-shaped knurl pattern (0.5 mm $\times$ 90°). The 1 mm thick copper samples are each positioned using a welding mask and then clamped pneumatically with $\sim$ 500 N force. The welding system is upgraded with additional sensors for implementing the in-situ methodology, each of them outputting analog voltage signals.

A data acquisition system from National Instruments Corporation with 500 kS/s (simultaneous) measuring rate per channel is used for voltage signal acquisition and digitization. The piezo electric shear force sensors (2x HBM CSW/8kN) are connected to a

Table 3 Welding parameters – original parameters and machine settings in brackets

Parameter	Set 1	Set 2
Force	625 N (1.25 bar)	1625 N (3.25 bar)
Amplitude	30 μm (110%)	24 μm (80%)
Energy	1600 J	750 J

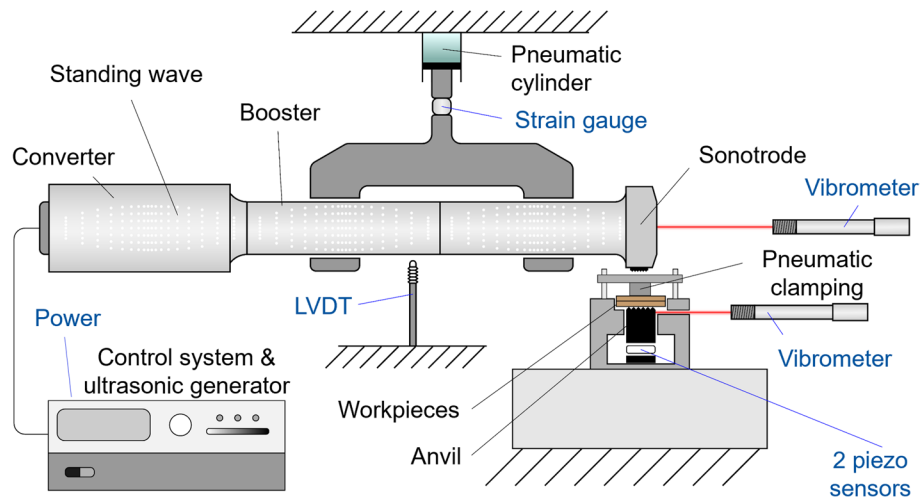


Fig. 4 Experimental setup and sensor equipment

summing box. The common signal, still a charge signal, is converted to a voltage signal, proportional to the load, by a Kistler 5015 A laboratory charge amplifier [27]. A 1D laser vibrometer from Polytec–VibroFlex QTec VFX-I-160 – is used at the anvil as a reference signal during the welding experiments to validate the data obtained from the shear force sensors, since this technology is still undergoing validation.

In addition, four further fully synchronized measurement signals are recorded for process analysis using an additional NI-9222 module. For this purpose, another vibrometer - a Polytec VibroFlex Xtra VFX-I-120 - is used on the sonotrode, and the electrical power signal of the ultrasonic generator, a linear variable differential transformer (LVDT) for the indentation depth and a normal force sensor (strain gauge) in the piston rod of the pneumatic cylinder are acquired (Fig. 4). For random measurements of the temperature in the joining zone, a thermocouple module (LEG TM1N) is added for additional samples and used with type K thermocouples ($\varnothing$ 0.21 mm).

2.3 Thermogravimetric analysis (TGA) of oils

The lubricants used are first subjected to thermogravimetric analysis (TGA) to determine their decomposition behavior with increasing temperature [36]. The measurements are performed in an oxidative atmosphere. The measuring device is a TGA2 from Mettler Toledo. The sample quantity is within the normal range at ~ 25 mg [37]. A heating rate of 10 K/min and a temperature range of 25–700 °C are selected. The sample is surrounded by 40 ml/min flow of pure oxygen. The measuring chamber is additionally surrounded by 20 ml/min of nitrogen to rule out any environmental influence.

2.4 Metallographic preparation

The procedure for sample preparation of microsections consists of the following steps: sample cutting, embedding, grinding to the target plane ‘A-A’, polishing and etching. Grinding is carried out in several stages using wet grinding wheels with gradually finer grit sizes. A polishing cloth with a diamond paste is used for polishing, followed by etching using a solution consisting of Ammonium tetrachlorocuprate(II) dihydrate, distilled water and ammonia. An example of sample cutting and target level of the microsection in the tool imprint is shown in Fig. 5.

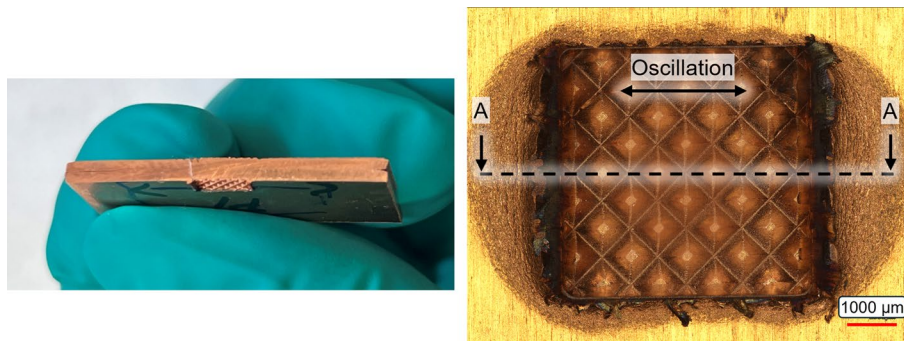


Fig. 5 Sample cutting (left) and target level of the microsection (right)

2.5 Data handling and analysis

The raw data collected must be processed in order to make it accessible to the supervised learning methods being considered here. A toolchain is built using the Python programming language and scikit-learn, which consists largely of the steps of data pre-processing, feature extraction, model training, and validation [38]. Further details of this methodology have already been explained by Müller et al. and other scientists [2, 16], which shows that this methodology has already proven itself in research on USMW. The oscillation signals (vibrometer and piezo sensor) are bandpass filtered. In addition, all signals are subjected to unit and offset correction. Envelopes are then calculated for the vibration signals (Hilbert transform). All signals are downsampled to 2000 S/s before feature extraction. Feature extraction is also performed in a similar manner to Müller et al. [16]. Extra Trees Classifier and Extra Trees Regressor are used to implement classification and regression (Chap. 3.7) [38]. The results are evaluated using an error matrix and correlation plot, as well as the parameters coefficient of determination (R^2), mean absolute error (MAE), and maximum error [16].

3 Results and discussion

First, the results of surface contamination are presented, followed by thermogravimetric analysis. These data are correlated with the additional measurements taken using thermocouples in the welding zone.

3.1 Contamination of specimen surfaces

Although identical dilution ratios (1:100) of oils, quantities (20 μ l), and the same solvent (isobutanol) are used to contaminate the surfaces, the resulting lubricating film varies significantly. This can be verified both visually or qualitatively (Fig. 6) and quantitatively by means of fluorescence measurement (Fig. 7).

3.1.1 Qualitative characterization of contamination

Due to the different wetting behavior of the oils and greases, even when diluted to the same degree, there are significant differences in surface contamination. The silicone grease (C) covers the smallest area ($\sim \varnothing$ 15 mm). Plain bearing and roller bearing grease (D & E) also cover approximately the same area in a circular pattern ($\sim \varnothing$ 25 mm), with a higher level of contamination in the central area ($\sim \varnothing$ 15 mm) than at the rim. A nearly uniform film is only achieved for F and G.

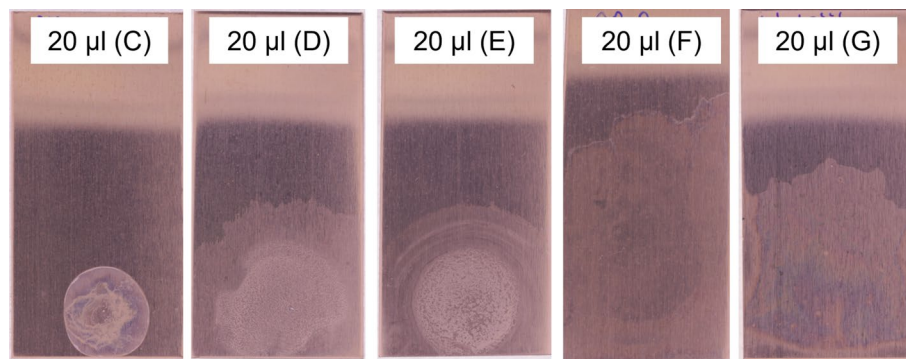


Fig. 6 Exemplary contaminated surfaces with investigated oils and greases

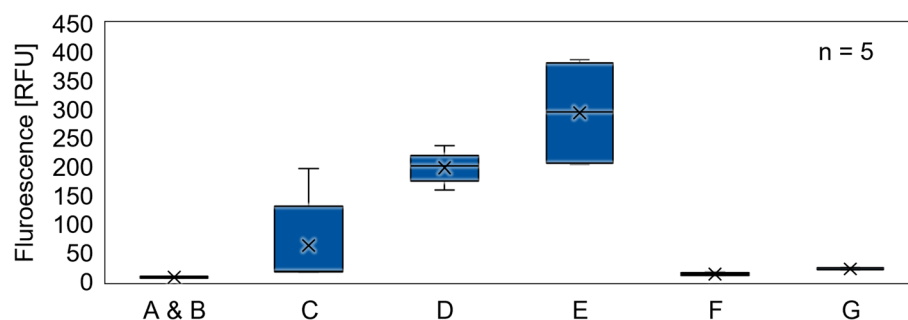


Fig. 7 Fluorescence values

3.1.2 Quantitative characterization of contamination

Whilst a purely qualitative assessment of contamination represents a first step towards risk assessment, fluorescence measurement enables its quantification and consequently objective monitoring. Analysis of the fluorescence detected shows the highest RFU values for group E. The lowest values, except from A and B, for groups F (RFU ~ 11–17) and G (RFU ~ 20–25) can be explained, amongst other things, by the fact that the solution is spread over a larger area. While the sheets ex works (A and B) with RFU values between approximately 6 and 9 are not considered free of fluorescent substances, a significant increase can nevertheless be seen in all other groups. As a result of cleaning under laboratory conditions, values of ~ 3–6 can be achieved on bare copper with the device used [24]. However, the distribution of group C over the smallest area does not result in the highest RFU values, which indicates a higher proportion of non-fluorescent components in the grease.

3.2 TGA results

The evaluation of the thermogravimetric analysis is shown graphically in Fig. 8. The hand lotion and rolling oil (F & G) can be almost completely decomposed and evaporated during USMW at typical maximum temperatures of ~ 300–550 °C. In contrast, the sliding bearing and roller bearing greases (D & E) are still largely present in the crucible in this temperature range, and a small residue remains even at 700 °C. Since, according to the data sheets, no solid lubricants are contained in either case, the residues of the lithium or sodium soap ultimately remain. In addition, significantly higher temperatures are required to break down these greases. The silicone paste (C) shows the highest

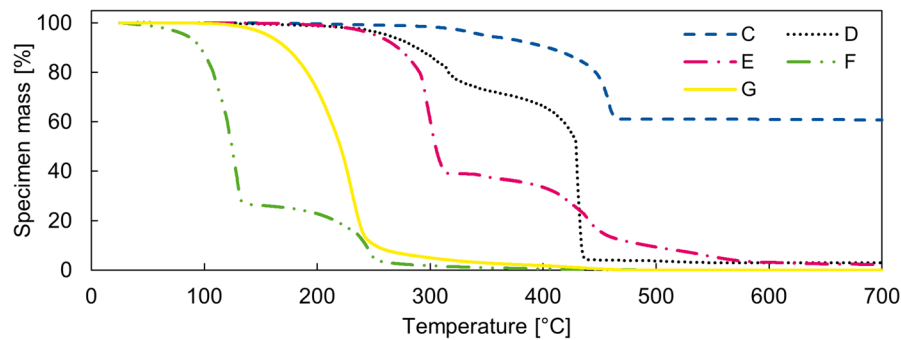


Fig. 8 Decomposition curves from thermogravimetric analysis of oils and greases

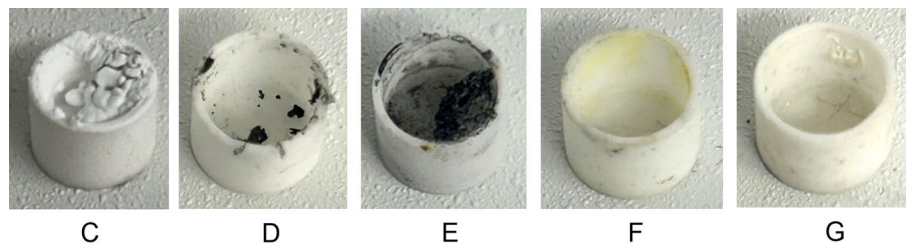


Fig. 9 Residues in sample crucibles after TGA

temperature resistance of the lubricants tested. Even at 700 °C, > 60% of the sample mass is still present.

This is also confirmed by looking at the residues in the crucibles (Fig. 9). Whilst the silicone paste (C) leaves behind a large, dry white mass, the sample of slide bearing grease (D) evaporates or decomposes almost completely when heated to 700 °C, leaving only a few black particles. Slide bearing grease (D) and roller bearing grease (E) evaporate or decompose by more than 90% when the temperature reaches 700 °C, with the roller bearing grease also leaving behind a black, brittle residue. Hand lotion (F) and rolling oil (G) are completely evaporated or decomposed at temperatures below 500 °C, so that no residue is detectable in the sample crucible. As a result of the TGA, it could be assumed that the siloxane-based grease (C) is the most critical for USMW as it decomposes only slightly at the usual process temperatures.

3.3 Thermocouple measurements

It's already known, that thermocouple measurements during USMW influence the process result [3, 35]. Nevertheless, the temperature achieved in the joining zone was determined exemplarily using thermocouples since there is no better technology available. Only samples in reference state A and the most critical contaminated state D are prepared. The temperature range achieved is stable and has been tested on several samples. No further tests were carried out on the other contaminants, as the results are expected to fall within the range of the tested variants A and D. The temperature in the joining zone is only slightly affected (overall) by contamination (Fig. 10). The differences in the process characteristic are more the result of changes in the friction and forming behavior of the microcontacts. The welding parameters, on the other hand, have a significant influence on the temperature. Temperature ranges comparable to those reported in the work of other scientists who have also investigated pure copper compounds are

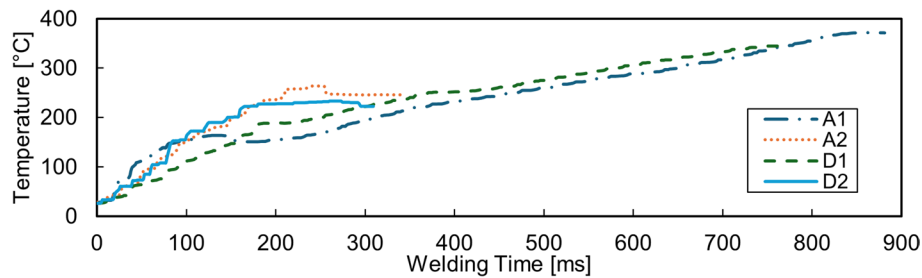


Fig. 10 Exemplary thermocouple measurements during welding

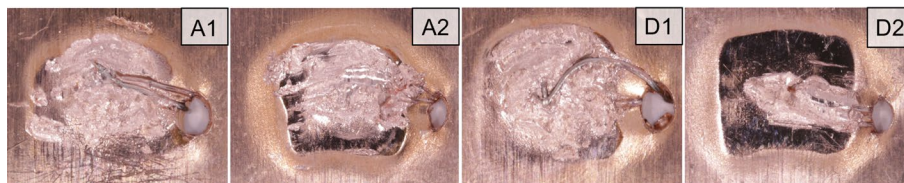


Fig. 11 Fracture pattern of exemplary welds with thermocouples

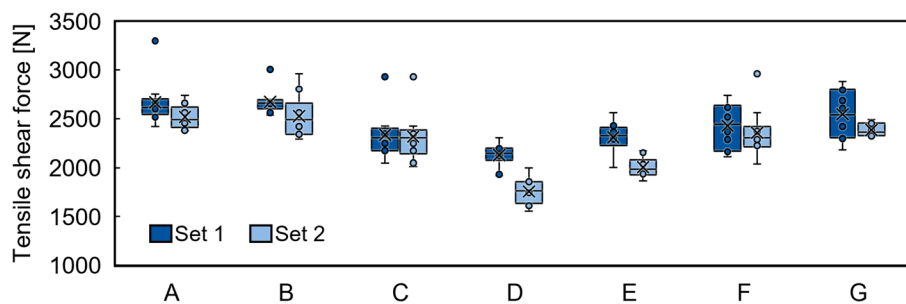


Fig. 12 Tensile shear force of weld specimen

achieved, although there are significant differences in the specific values due to the combination of tools and components as well as welding parameters [35, 39]. With parameter set 1, maximum temperatures of $\sim 340\text{--}370^\circ\text{C}$ are reached, compared to maximum values of $\sim 230\text{--}260^\circ\text{C}$ with parameter set 2. Reaching a minimum temperature is therefore not crucial for pushing the oil outside the welding area. Rather, a suitable combination of temperature, friction, and deformation is necessary to squeeze the contamination out of the joint zone. The extent to which these mechanisms are involved varies depending on the process boundary conditions and welding parameters. The higher mechanical deformation (out-plane) for parameter 2 as a result of higher normal force is also evident from the fracture patterns (Fig. 11). The results obtained with clean surfaces are consistent with those of other researchers, who have also been able to achieve successful welds using USMW across a wide temperature range below the melting point, depending on the parameters selected [3, 40].

3.4 Joint strength

The shear forces achieved for all 140 samples range from $\sim 1500\text{ N}$ to 3300 N . A correlation of the shear forces achieved (Fig. 12) with the fluorescence values determined (Fig. 7) shows that the highest amount of fluorescent residues on the surface does not necessarily result in the lowest joint quality. Rather, other non-fluorescent ingredients in

the oils (e.g., solids/soft soaps) must also be included in the risk assessment. Slide bearing grease (D) has the greatest influence on shear tensile strength. Against expectations, siloxane-based grease (C), which has the highest temperature stability, does not have the greatest influence on the welding result. Maximum temperature stability is conclusively not the only oil characteristic to influence the process. Welding parameter set 2, with shorter and more efficient process adjustment, is significantly more sensitive to interference with grease D and E.

The results of the mechanical tensile shear tests are explained in more detail below using metallographic microsections. The analysis is limited to the contaminants with the least and greatest influence on the tensile shear force (D and G). Microsections were made perpendicular to the direction of oscillation or parallel to the longer edge of the sheets. Differences in the microsections with different contaminants are visible, suitable for qualitative rather than quantitative evaluation in terms of strength. Figure 13 shows examples of microsections with parameter set 1. More distortions can be seen in the cross-section of Group D, Fig. 13a. Fewer artifacts and residues from rolling oil in the joining zone are visible (G), Fig. 13b.

Figure 14 shows examples of microsections with parameter set 2. Cracks in the upper copper sheet can be identified with the slide bearing grease (D). Less deformation is present in the joining zone with rolling oil and both welding parameters (G). To define the most relevant factors (quantity, type, and properties of the oils and greases) influencing the process through film contamination, further investigations are necessary using different dilutions of oils and greases or a different dosing method that allows reliable adjustment of a reproducible and comparable film-like layer with all contaminations.

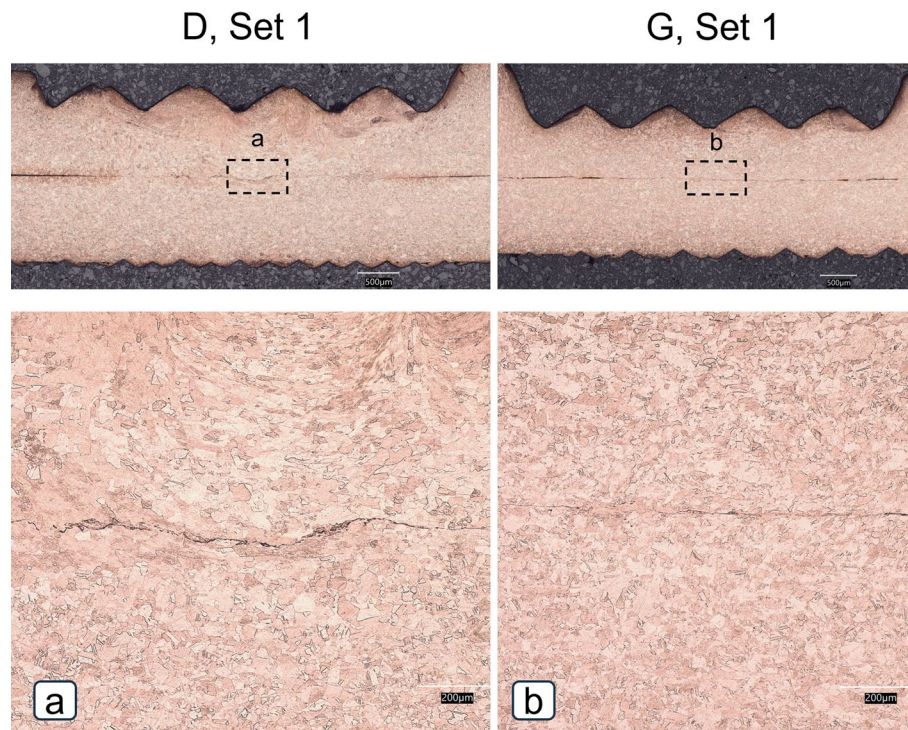


Fig. 13 Exemplary microsections of group D, set 1 (left) and group G, set 1 (right)

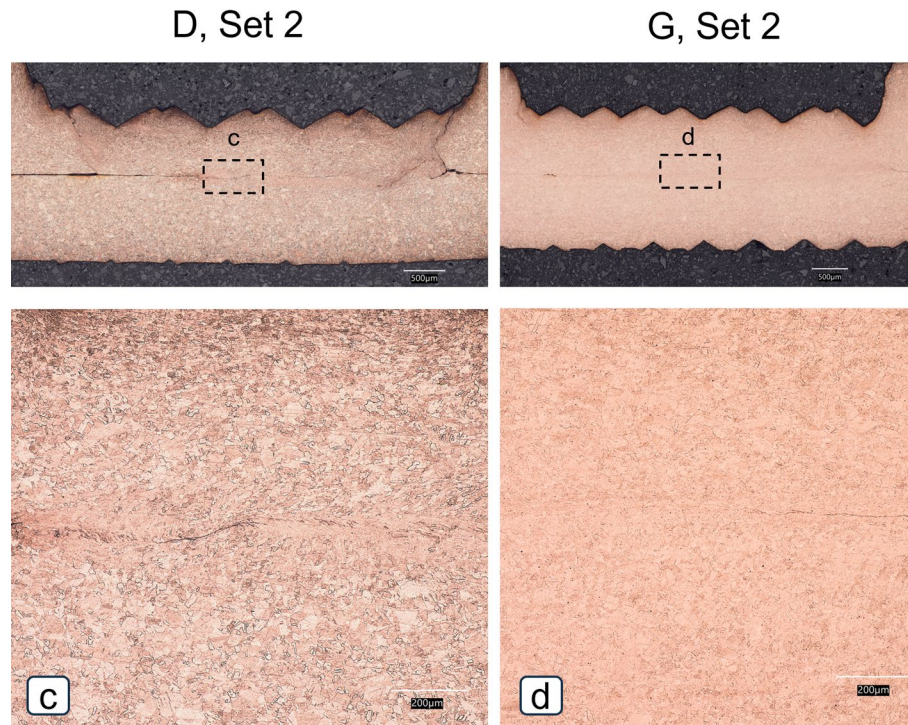


Fig. 14 Exemplary microsections of group D, set 2 (left) and group G, set 2 (right)

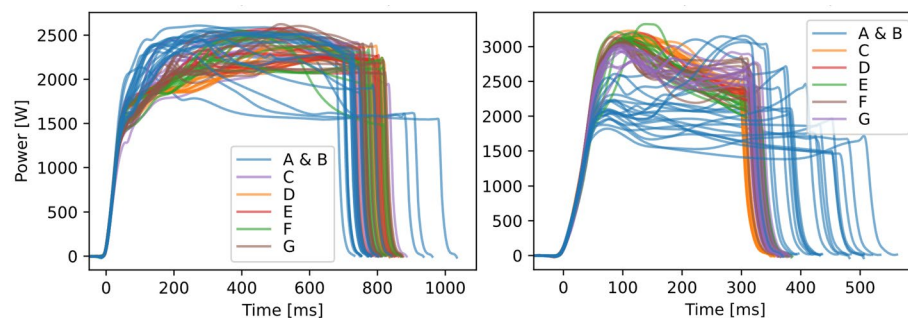


Fig. 15 Power curves for both parameter sets (left: Set 1, right: Set 2)

3.5 Measurement data and feature extraction

First, the pre-processed time series data is presented and analyzed with regard to simple correlations. It simultaneously highlights trends in a group of signals from a single sensor, superimposed by process scattering. This data then serves as the basis for classification and quality prediction. The time series data for welding power shows significantly higher values in the clean state than in the contaminated state at the start of welding for parameter set 1 (Fig. 15, left). With the second parameter set, this relation is reversed (Fig. 15, right). A similar pattern can be seen in the indentation depth data (Fig. 16). In the time range between ~ 100 ms and 300 ms, there is a higher indentation depth due to contamination under parameter set 1, which then turns into a wide spread of the end value (Fig. 16, left). In contrast, the indentation depth for all contaminated samples with parameter set 2 shows significantly higher values throughout the entire length of the process than clean samples. The reference samples are coated with protective films,

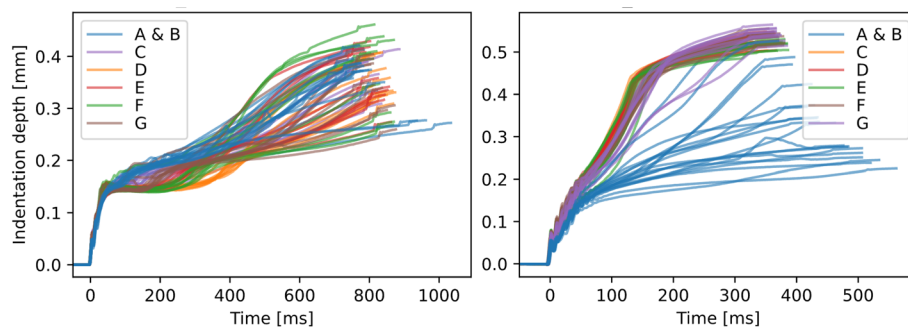


Fig. 16 Indentation curves for both parameter sets (left: Set 1, right: Set 2)

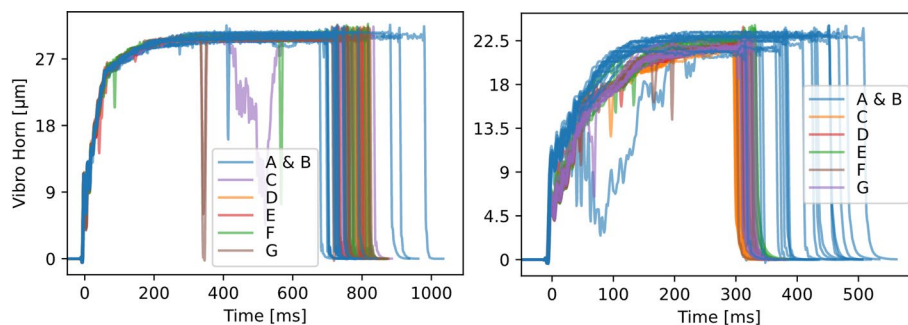


Fig. 17 Vibrometer Horn amplitude curves for both parameter sets (left: Set 1, right: Set 2)

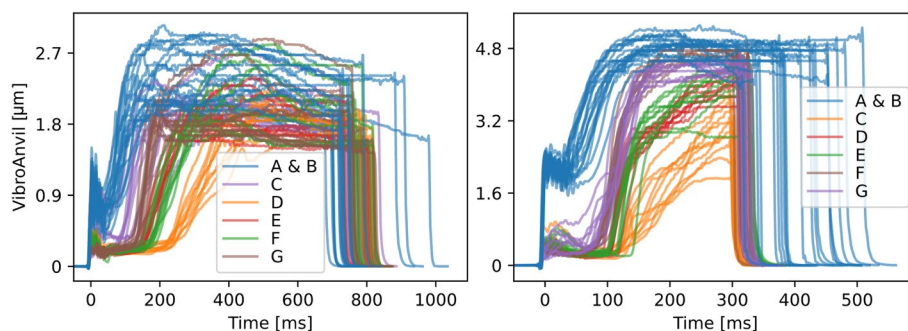


Fig. 18 Vibrometer Anvil amplitude curves for both parameter sets (left: Set 1, right: Set 2)

which are removed before welding but are, of course, not ‘perfectly’ clean. Even the slightest changes in the surface coefficient of friction affect the course of the process, which can also be seen in the horn amplitude (Fig. 17). This is also due to the significant over-excitation caused by the specimen geometry. This is only slightly recognizable in the welding result (tensile shear force). As soon as the coefficient of friction is reduced by contamination, a more consistent result is obtained for the indentation depth. Strong overlap of the influence of organic, film contamination with other disturbances like geometry and material hardness can be expected in these signals.

While the signals typically used in ultrasonic welding systems (power and indentation depth) show a reverse trend for clean and contaminated conditions depending on the welding parameters used (1 or 2), this is not the case for the shear force or vibrometer signal at the anvil (Figs. 18 and 19). Data preprocessing using bandpass filtering and envelope calculation of the signals results in the curves shown in Figs. 18 and 19 for

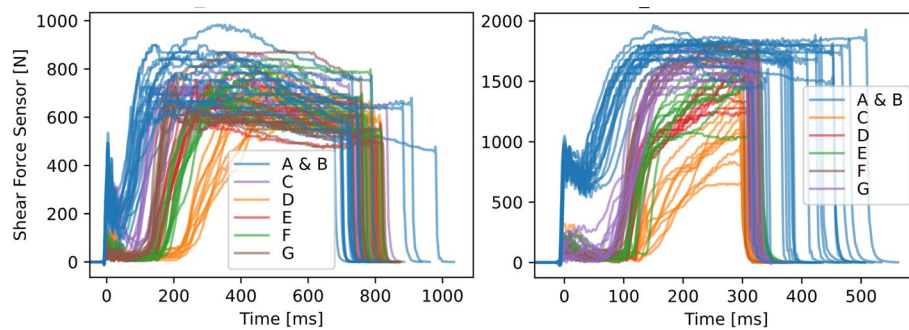


Fig. 19 Shear force sensor curves for both parameter sets (left: Set 1, right: Set 2)

the vibrometer on the anvil and the shear force sensors. The processed high frequency signals of the anvil show comparable results for different weld parameters sets. Both the vibrometer signal at the anvil and the shear force sensors have so far been investigated using only one set of welding parameters in the same application and have been identified as highly relevant signals for data-driven quality prediction [27, 32]. Here, even without algorithm-based analysis, it is possible to clearly identify which samples are contaminated and which are not. Clean samples (A & B) show higher values in the shear force sensor signal than contaminated samples (C-G) with both sets of welding parameters, especially at the beginning of the welding process, see Fig. 18.

The vibrometer signals at the sonotrode show only very slight differences due to contamination for parameter set 1 (Fig. 17, left). However, some signals show errors due to particles and fume. Due to their sensitivity to interference and high costs, the integration of vibrometers into industrial ultrasonic welding processes remains challenging, even though the process data they provide is useful for quality prediction and anomaly detection [21, 27, 35]. For parameter set 2, the contaminated samples show a significantly damped signal compared to the reference samples, particularly at the beginning but also throughout the entire welding process (Fig. 17, right). In particular, sonotrode amplitude attenuation has also been observed under certain conditions in other studies, but it depends to a large extent on the sonotrode geometry, the welding parameters used and has not been investigated further [12, 32].

3.6 Correlation of measurement data and contamination characteristics

In addition to the tests described above involving 140 welds, the measuring position of the vibrometer on the anvil was moved to the edge of the upper plate for some measurements of group A and D. This was done to analyze the influence of contamination on the excitation of the upper plate and the possible correlation with the other measurement data. The adjusted measurement position and the test setup are shown in Fig. 20.

While parameter set 1 only shows an amplitude gain on the copper sheet up to ~ 60–70 ms welding time (amplitude of upper sheet > sonotrode), parameter set 2 shows this across the entire welding time. The amplitude gain is a maximum of ~ 10 μm as a result of parameter set 1 (D1 sheet) with a maximum value of almost 26 μm . A comparable amplitude gain to parameter set 1, with an initial increase in amplitude that then falls below the level of excitation by the sonotrode within the first ~ 100 ms, can also be confirmed by other scientists [35, 41, 42]. The comparison of the resulting measurement data curves from the vibrometers is shown in Fig. 21. A maximum amplitude of ~ 37

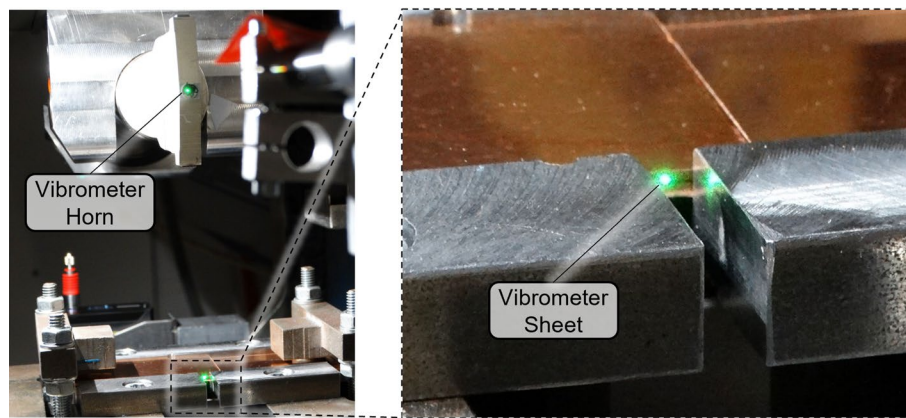


Fig. 20 Adjusted sensor position on edge of upper copper sheet

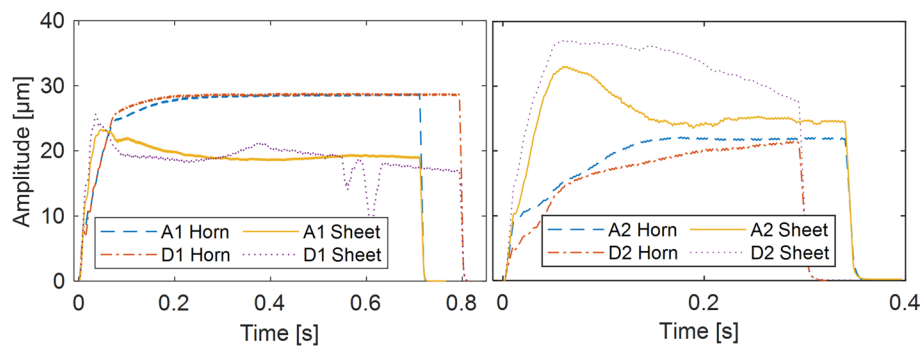


Fig. 21 Amplitude comparison on horn and upper copper sheet with parameter set 1 (left) and parameter set 2 (right)

μm is achieved on the copper sheet with parameter set 2 (D2 horn), which corresponds to a maximum amplitude gain of $\sim 22 \mu\text{m}$ compared to the sonotrode. An increase is present in both the reference state (A2) and the contaminated state, with the amplitudes approaching each other at the end of the weld. In the contaminated state (D2 Sheet), the amplitude is higher throughout the entire weld than in the reference state (A2 Sheet). The significantly higher amplitude at the upper plate in parameter set 2 is caused by the significantly better coupling resulting from the higher clamping force.

While the contaminated surfaces in parameter set 1 result in a slightly lower damping of the sonotrode amplitude (D1 horn) than in the reference state (A1 horn) up to $\sim 200 \text{ ms}$ welding time, parameter set 2 shows the opposite trend. The amplitude of the sonotrode (D2 horn) is damped more severely with parameter set 2 than in the reference state (A2 horn) due to contamination. At the same time, the amplitude of the upper plate increases significantly. This is due to the significant change in the slip between the sonotrode and the upper plate, as well as between the sheets, caused by contamination; however, without a combined analysis of the actual relative movements and control of the oscillation behaviour by the ultrasonic generator, it is not possible to determine the precise causes. The significantly greater amplitude of the upper sheet can explain the significantly shortened process duration (parameter set 2) with comparable joint qualities, as there is a higher amplitude between the sheets and contaminants can be displaced more quickly, resulting in a more efficient joint. At the same time, parameter set

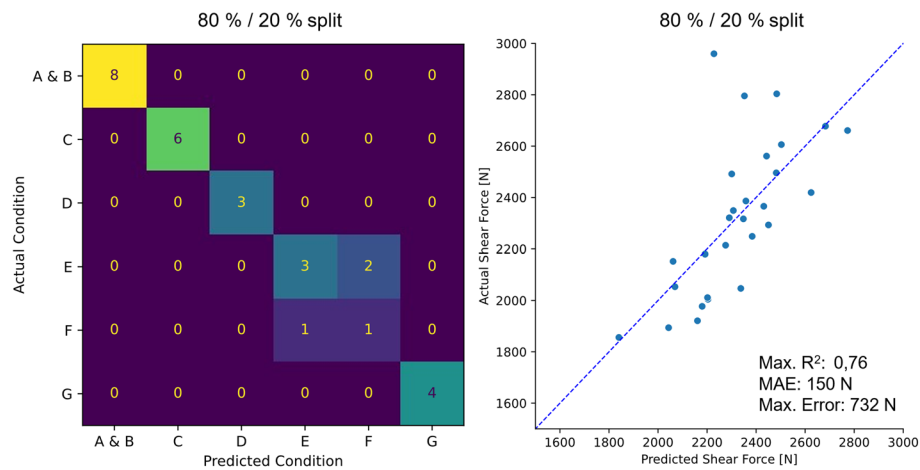


Fig. 22 Error matrix with Extra Trees Classification (left) and quality prediction with Extra Trees Regressor (right)

2 uses significantly less energy and process time, making the process less robust against disturbances.

3.7 Classification & quality prediction

The following is just a brief overview of the possibilities for predicting the type of contamination and predicting quality with supervised learning techniques. Further details will follow in subsequent publications. The classification is performed with the Extra Trees Classification. With an 80 / 20 split between training and test data, a differentiation between contaminated (C–G) and non-contaminated (A–B) samples is possible with 100% accuracy. This results in an overall accuracy of 89.3% for the condition prediction, with only a small number of samples from groups E and F being incorrectly classified (Fig. 22, left).

Quality prediction is performed with the Extra Trees Regressor [43]. The results are verified using 5-fold cross-validation, in which the dataset is divided into five groups. Each group acts as the test dataset once, while the other four groups are used to train the regressor, resulting in an 80/20 split. Regression has much higher requirements for data. Nevertheless, a maximum R^2 of 0.76 and a mean absolute error (MAE) of 150 N can already be achieved ($\sim 6\%$) in one split. The maximum error is 732 N, which is at the upper end of component quality and significantly underestimates rather than overestimates quality, making it less critical. The mean R^2 value including standard deviation of the validation is 0.55 ± 0.13 and the MAE is 150 ± 28 N. This high difference of maximum and mean values leads to the two general challenges which can be confirmed, namely that the data set under consideration with 140 welds overall is too small to build a robust prediction model and, in particular, has too few data sets at the upper and lower ends [16]. Whilst increasing the size of the dataset under consideration can improve the prediction error (e.g. MAE) and the coefficient of determination R^2 to a limited extent, a comprehensive assessment of expected process disturbances, the robustness of the quality indicator (e.g. tensile shear force) and the available measurement data are decisive for the maximum achievable prediction accuracy [16, 44]. The evaluation of impurity-based feature importance shows that the shear force sensor signal and the vibrometer signal at the anvil are most important for classification and regression [38].

4 Summary and outlook

Filmic contamination of copper sheets has a significant impact on the USMW process and the welding result. It is essential that the type and distribution of contamination on the surface is included in the assessment of its impact. With higher contact pressure (welding parameter set 2) and thus better coupling between the sonotrode and the upper metal sheet, several things can be observed. The process becomes significantly more sensitive to disturbances, with welding time and indentation depth changing much more significantly. In addition, the following findings can be summarized:

- Detectability of disturbances and faulty welds from scalar values is heavily dependent on welding parameters. Relying exclusively on initial and final values is not effective and ignores the effects that occur during the welding process.
- The sensitivity of the welding process to disturbances increases significantly with shorter, more efficient adjustment of the welding parameters.
- The influence of organic contamination on the welding result depends on the amount, the decomposition temperature and the ingredients of the oil. In general, there is a trend that contaminants with a higher decomposition temperature and solid lubricant content reduce the quality of the joint more than volatile lubricants. At the same time, it is surprising that the supposedly most critical silicone grease considered here has only a very minor effect on the welding result.
- With welding parameter 1, organic contaminants increase process scattering.
- The data sources commonly used, power and indentation depth, do not allow the detection of reliable trends caused by contaminants in USMW independently of the welding parameters.
- An amplitude or shear force signal (vibrometer/shear force sensor) applied to the anvil, on the other hand, allows such impurities to be reliably detected even without complex algorithms.

The research institutes will continue their investigations in this area with a view to producing retraceable quality forecasts, minimizing data requirements, and consistently expanding the models in application. Traceability to specific issues, including instructions for countermeasures, would be a major step forward. Since large data sets are usually required for robust quality forecasting using machine learning methods, linking the data and algorithms to knowledge-based relations could significantly reduce the effort involved.

Author contributions

All authors contributed to the study conception and design. Material characterization, material preparation, welding process development and data collection were performed by Eric Helfers. Data analysis and correlation were performed by Eric Helfers and Oliver Stockemer. The first draft of the manuscript was written by Eric Helfers and Oliver Stockemer. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding

Open Access funding enabled and organized by Projekt DEAL. Funded by the Deutsche Forschungsgemeinschaft (DFG - German Research Foundation) under Grant Number 520475171 "Hybrid Process Prediction for Ultrasonic Metal Welding - Pro²MUSS".

Data availability

Data will be made available on reasonable request by the corresponding author.

Declarations

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 30 November 2025 / Accepted: 6 June 2026

Published online: 11 June 2026

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