Development of AI-Assisted Quality Assurance for the Process of Ultrasonic Welding for High-Performance Thermoplastic Composites: A Review

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1. Abstract

Since ultrasonic welding of thermoplastic composites (TCs) gained attention from the industry in last years, the question arises, how artificial intelligence (AI) can help to establish the process in the industry and make it more reliable. This review summarizes the development of AI algorithms for the quality assurance (QA) of ultrasonically welded TCs. Focus is given to research dealing with spot welding before giving an overview about the newest developments in continuous ultrasonic welding (CUW): Many AI training approaches with different process parameters and diverse AI algorithms are described to make accurate quality predictions. One of the newer parameters for AI training is thermography. This parameter is described to be of huge potential for a reliable quality prediction in spot welding as well as in CUW and leads to AIs with high quality prediction quality. After an overview about the latest AI research, the review outlines the next steps which might be necessary in order to get a productive AI in the welding process of thermoplastic composites and describes the newest research for additional input data types.

2. Introduction

Air transport is an important factor for the global economy [1] and aircraft passenger numbers have grown exponentially in the last years [2]. To tackle this growing demand, aircraft manufacturers announce a large amount of aircraft deliveries (about 43,000) in the next two decades [3, 4]. In parallel, the need for cost efficient aircrafts is growing and the reduction of operational costs comes into focus. One potential key element to reduce operational costs is the weight reduction of each aircraft [5, 6]. A weight reduction can be realized by the use of composites as a manufacturing material [6] and by a reduction of the number of rivets, since rivets have a significant share in the weight of an aircraft [7, 8].
Ultrasonic welding (USW) is an emerging joining technology and opens the possibility to join TCs in a fast and easy way. In addition, efficient joining by ultrasonic welding could potentially reduce the number of rivets needed to build aircraft components [8]. Nevertheless, for a reliable production process with USW, quality assurance is obligatory. One method which is gaining momentum in the last years is the use of artificial intelligence for the quality prediction of joined

TCs. This review summarizes the research and development of AI approaches for the QA of ultrasonically welded thermoplastic composites. After a brief overview about the welding process, different AI methods for the QA of continuous and static ultrasonic welding are described. Further on, a new investigated data type is described which could potentially make algorithms more reliable in future AI applications.

3. Ultrasonic Welding Principles

In ultrasonic welding an electrical signal is applied to a converter transforming it to a high frequency, physical ultrasonic oscillation. [9-12]. This mechanical oscillation has an amplitude between 10 and 250 µm [9] and can be amplified by a booster which is located between the converter and the sonotrode which leads the oscillations into the parts for welding [9-12]. The oscillation causes heat generation by internal damping effects [12] and friction between the welding surfaces and molecule chains [13]. An energy director can be placed in the welding area [10-12] to build a region of heat generation [14]. If the described process is done while the sonotrode remains stationary at one position, the process is called ultrasonic spot welding. Is the sonotrode continuously moving over the welding material, a continuous seam is created and the process is called continuous ultrasonic welding (CUW). For CUW, the described welding setup is expanded by a compaction roller and a consolidation unit. The compaction roller clamps the material in front of the sonotrode while the consolidation unit applies pressure to the molten material behind the sonotrode and is responsible for the development of a strong welding connection.

4. Quality Assurance of Spot Welding

Regarding the technology of spot welding multiple attempts to predict weld quality with AI exist. A research team around Li [15] developed an artificial neural network (ANN) for the failure load prediction of ultrasonically welded carbon fiber reinforces Nylon 6 material and compared their results to calculations of a finite element model (FEM). The ANN was trained with information about welding energy, plunging speed, welding force, surface condition and annealing temperature. The AI could predict the failure load with an error of less than 5% which is a similar performance than the FEM-predicted results. Nevertheless, the team reports deviating prediction results if the welding energy is higher than 800 J. [15]
Another approach with FEM and an ANN is described in [16]. An integrated performance-process model of a FE- and an ANN model is developed to predict the failure load of welded injection-molded carbon fiber reinforced Nylon 6 composite samples. The FE model was developed to calculate the size of the welding area while the ANN was trained to predict failure loads. In addition to the information about the weld area size, trigger force, plunging speed, welding time and surface condition are fed to the network. Weld area size was at first measured manually and also used for the validation of the FE model. After a validation step, the FE model was used to calculate the welding area in order to feed the ANN the FE models calculated results. The relative prediction error of the isolated ANN is about 10 % while the FE-ANN model made predictions with a relative error of 4.3-26 % (dependent on the data set) while providing additionally information about the weld formation. [16]

From [16] it can be concluded that the welding area carries crucial information about the welding quality, since this information is reported to help an AI to predict the joint quality. This statement about the potential of the welding area for QA is backed up in the work of [17]. The welding areas of over 250 spot-welded TCs samples were measured and correlation with the lab-shear-strength (LSS) was calculated to be >0.95 (α=5 %), strengthening the hypothesis that the welding area is strongly related to the weld quality. [17]

A slightly different approach is taken in the work of Li [18] where injection molded short carbon-fiber-reinforced Polyamide 6 is used as welding material. They trained a random forest (RF) algorithms to classify the quality levels, such as under-, normal- and overwelded, while using an ANN approach for the prediction of failure loads. In their work four different welding stages are defined and the duration of each stage is measured. In addition to the duration of each welding stage, information about the net acoustic wave energy (= energy which is transduced into the welding specimens [13]) is extracted from the recorded data and fed to different AI algorithms for classification/ regression. The researchers report a relative error in prediction of the failure load around 7.1 % for the ANN algorithm and a correct classification rate of 96.7 % for the RF. Algorithms were trained with approximately 100 individual welding experiments while the failure load of the different welds was located between approx. 0 and <5 kN. [18]

Another research team used recurrent neural networks to predict quality classes about welded injection molded short carbon fiber Polyamide 6 samples. Under-, normal- and over weld are defined as possible quality classes. Sequential data of time, power, clamping force and clamp displacement are taken as input data, leading to a neural network with an accuracy in quality class prediction of 97.5 %. 129 data samples were used for the training and validation steps. [19]

A slightly smaller data set was recorded by a team of researchers which used a Bayesian Regularized Neural Network (BRNN) to predict quality classes and compared its performance to a support vector machines (SVM) and a k-nearest-neighbors (KNN) algorithm. In the described trials 116 welds with short carbon fiber reinforced Polyamide 6 were produced. Data about the power, energy, force and distance are recorded and analyzed. Weld quality depends on differences in the recorded signals so 61 features for AI training were extracted from the data. Since some features carry redundant or low-quality information, different feature selection methods are used to reduce the number of features. Depending on the selection algorithm, the BRNN reached a classification accuracy of over 0.99 (classification of three quality classes). [20]

All literature described so far deals with data sets of relatively small size (<500 samples). The team of Sun [21] did some research about tackling the challenge of small data sets by generating synthetic data on the basis of experimental data. For their investigations they used a data set of 112 recorded samples. Based on a copula multivariate Monte Carlo simulation they generated different sized data sets (560-5600 data points) of time-series process signals with similar statistical distributions as the experimental data. A BRNN for feature based- and time series data and a convolutional neural network (CNN) model for time-series data were used to predict one out of three quality classes (under-, normal- and over weld) while being compared to SVM and KNN approaches. Two different BRNNs were trained with 25 features extracted the same way as described in [20]. The time-series data was analyzed by BRNN and CNN algorithms. Therefore,

data about power, force and displacement were used as input. In almost all investigated setups the deep learning approaches outperform the SVM and KNN algorithms, achieving over 99 % classification accuracy. The synthetic data in these investigations helped to develop more accurate AI algorithms, highlighting the potential of synthetic data solutions. [21]
Up so far in literature the used AI algorithms are trained with similar data sets. To the authors knowledge the first research about an AI-assisted QA in the process of CUW of TCs is done at the German Aerospace Center (DLR) in the city of Augsburg [22-24]. The investigated parameters in their work lead in CUW to weaker AI results as in reported spot-welding experiments [23, 24]. Therefore, the authors suggest that finding additional data to the commonly used process data might be beneficial for the successful training of AIs for the QA of CUW [23, 24]. It is emphasized that for new parameters, the following characteristics are of significant importance in order to successfully integrate new methods in the process: non-destructive, inline measurable, robust, can be implemented to the system hardware/ software and low-cost solution [17]. The authors did start the search for new input factors for AI with a spot-welding experiment since the process of CUW is highly material- and time consuming. In their experiments 86 samples consisting of carbon fibers embedded in a thermoplastic matrix (Low-melt Polyaryletherketone (LM-PAEK)) were welded. Quality was defined by the LSS value of each sample. New parameters were recorded by two microphones during the welding process and a thermography camera which took an image of the upper samples surface after the welding took place (2.5s after welding signal ended). Afterwards exploratory data analysis (EDA) was performed to search for correlations between the data and the quality of a weld. The sequential sound data was firstly analyzed with a Fast Fourier Transformation (FFT) in order to get the different frequency components of a sound signal. Afterwards the frequency components are divided in 2kHz wide bins. From each of those bins the value of the maximal amplitude is selected and used to calculate correlation with the LSS value. The authors found a medium correlation (Spearman correlation coefficient) of about 0.7 between the maximal amplitudes of the 20kHz bin and the welding quality and decided to test the ability to do QA with the data. Regarding the temperature data, a region of interest (ROI) was cut from each recorded thermogram and dimensionality reduction was performed by calculating the mean temperature of each ROI. The mean temperature was then correlated visually and mathematically with the quality labels and a Spearman correlation coefficient of 0.762 was calculated. Building on this EDA, different AI approaches were used to predict welding quality with the recorded data. FFT amplitude information of the 2 kHz Bin (microphone 1) and amplitude information of the 20 kHz bin (microphone 2) in combination with the calculated mean temperature values and information about the welding time were used in this step. The welding samples were classified in good and bad welds. KNN, RF and SVM were used for the data interpretation and achieved correct classification rates of 96.15-100 %. Also, a three-dimensional scatter plot was created to perform a rule-based classification. This classification reached an accuracy of 92 % [17]. Despite the reduction of dimensionality of sound- and thermography data, it is pointed out that both investigated parameters might have potential to help an AI in the quality prediction of ultrasonically welded TCs. [25]

Summarizing this section, it is noticeable that all research is done with relatively small data sets. This can lead to overfitting [26] and networks with a lower grade of generalization. Many of the used data are welding parameters which are set up in the welding system and recorded during the welding process. First research already reports efforts to extend this set of data with some other information like thermography and sound data. Nevertheless, it is reported that the transition of knowledge from spot- to continuous welding is a challenge due to the differences between static and dynamic welding [17, 25]. Where there are different welding phases following each other in spot welding [27], in continuous welding the status of the material under the sonotrode should be always melting since a continuous line is formed [17. 25]. This difference and the fact that the data of the continuous welding process have another shape than from the spot-welding lead to open questions about how AI can be used to predict weld quality in CUW process.

5. Quality Assurance of Continuous Welding

The field of CUW is a young field [9] and to the authors knowledge the process of CUW is investigated only in a few other research institutions apart from DLR. This is why literature about AI assisted QA in CUW is relatively thin. Nevertheless, important steps are documented in the last few years:

One of the first research about the potential of AI for the QA in CUW of TCs is reported in [22]. In this work carbon fiber embedded in LM-PAEK matrix was welded and process data was fed to an AI for the prediction of weld quality (LSS value). The used AI algorithms seemed to respond to the data and show a slight learning behavior. Nevertheless, the used data set was quite small and only the general conclusion that AI could be helpful for the data interpretation was drawn. It is mentioned that more data has to be generated and different networks have to be evaluated and tested in order to get more precise statements. [22]

Building on these first results of [22] further and deeper research is done with a master thesis from Görick [23] of which a summary can be read in [24]. In this thesis carbon fiber reinforced LM-PAEK sheets are welded while the process data was recorded to be fed to an AI algorithm. Data about welding force, amplitude of welding signal, welding speed, power, pressure for consolidation, ED thickness and number and the LSS sample position in the welding plate were used to train a fully connected neural network (FCNN) and a 1DCNN (or a combination of both networks). The final accuracy for the weld quality classification was 72 % (three quality classes). Since the sample size for the described trials was <500 samples, it is discussed that a bigger set of data could optimize the accuracy further. In addition, this research provided the basis for new investigations (see [17, 25]) to find other input data which carry more information about the weld seam and allow an AI algorithm to approximate the relation between data and weld quality more accurately. [23, 24]

Based on the research in [23, 24] the search for new input data was initialized. As a first step, new input factors were defined with the help of spot-welding experiments (see chapter above). Due to difference in dimensionality between spot-welding- and CUW data, algorithms had to be developed which deal with prepossessing of the data from CUW. The use of the newly found input data of air coupled sound and thermography is investigated in the work of [17] and [28]: Carbon fibers embedded in LM-PAEK were used for CUW 45 sample plates which were cut into almost 600 individual LSS samples. For each of the welds a stack of thermogaphy images was recorded. From each image the ROI was extracted and a stack of ROIs is saved for each weld seam. With the help of information about the position an image was taken, the position of a pixel row was mapped to its real position on the welded plates. A single row of pixels is taken from each ROI and assembled to one panorama of the welding seam surface area. By concatenation all individual pixel rows, a thermographic panorama develops which shows the temperature of the upper welding plate after the welding took place. This panorama can be cut in the same way the welded plate is cut in order to get a thermogram for each LSS sample. From this point onward the thermographic data has the same shape like the thermographic data which is described in spot welding experiments [25]. The mean temperature of each image is calculated and correlation between the mean temperature and the LSS value is calculated. Depending on the calculation method, correlations between 0.6879 and 0.8186 are described. Following this EDA, the data is used to train a two-dimensional convolutional neural network (2DCNN) for regression. A mean absolute error (mae) in the LSS value prediction of <1 MPa was achieved. [17, 28] Sound data was also analyzed for its potential to train an AI for weld quality prediction [17]. Similar to spot welding, the sound data in CUW has a sequential shape but stores the data for multiple LSS samples since one weld is cut in multiple samples. Therefore, the sound files are cut in the same way the real plate is cut into its LSS samples. Afterwards EDA is performed to find correlation between data and weld quality. For EDA the mean, minimum, maximum, median and root mean square are calculated for each sound file. Beside this, a FFT is calculated and the maximum amplitudes of 2 kHz wide frequency bins (see last chapter, [25]) were detected. Correlation of the EDA values with the weld quality is investigated but no connection was found. After the EDA, the sound data were fed to a 1DCNN. In addition, the results of a wavelet transformation were used to train a 2DCNN for quality prediction. None of the attempts lead to satisfactory prediction accuracies (mae >2.9 MPa) which the authors reasoned by a comparison between spot- and continuous welding: In spot welding the material status changes in the process of the development of the bond. Since in CUW the status of melting material beneath the sonotrode should always be the same, it might be possible that no changes in the sound signal are measurable. Another point mentioned is the small difference in the prediction quality. While the spot-welding experiments report weld qualities up to 40 MPa, the CUW experiments produced qualities <15 MPa. It is reported that a bigger difference in weld quality could result in changing sound signals and further research has to be done in order to evaluate the potential of sound data. [17]

To the authors knowledge, the only research with uses a data set >1000 samples to train an AI algorithm for quality prediction is done by Görick [17]. 150 welds were created to produce 1500 single LSS samples consisting of LM-PAEK matrix with carbon fiber material. During the experiments process data (welding force, amplitude, power, pressure of consolidation unit, pressure of compaction roll, pressure of sonotrode, position of TCP, welding velocity and orthogonal displacement of sonotrode to weld specimen) is recorded while the trials were also used to validate the use of thermography- and sound data for quality prediction. After the welding took place non-destructive testing (NDT) methods were performed to get additional data about the weld quality. Namely watercoupled ultrasound (WUS) (recording the backwall echo) and laser excited acoustics (LEA) (measured in transmission) measurements were performed. In addition to the LSS value, the mean amplitude of the backwall echo from the WUS measurements was used as an alternative quality label. For a better comparison to other research this review focuses on the experiments with the LSS labels. An EDA is performed to get more knowledge about the data and possible correlations with the weld quality. Therefore, the process data is analyzed with a feature selection library (tsfresh [29, 30]) but no correlation higher than 0.6 was found. Regarding the thermography data, the mean temperature of each LSS sample is calculated (see description above) and a correlation of the mean temperature with weld quality of over 0.6 is found. Building on previous investigations ([17, 25]) sound data was analyzed by investigating the correlation of the maximal amplitude in 2 kHz wide frequency bins of the FFT of each sound signal. None of the investigated signals showed a correlation with the weld quality. For the WUS data a connection but no correlation between the mean amplitude of the backwall echo of a LSS sample and the weld quality was discovered. For the mean signal value of the LEA data a correlation value of over 0.8 was reported. The EDA is done to gain knowledge on the relationships of different data with the weld quality. Regardless of the EDAs result, each data set is used for an AI training where data sets are used isolated from each other and in different combinations to investigate their individual influence on the AI performance. Each training had a preceding hyperparamterization of 500-1000 training attempts performed by Optuna [31]. 900 data points were used for training while 300 data points were used for training or validation. After hyperparamterization the best run (lowest mae) is taken for a final training where the epoch with the lowest overfitting is selected and the network is saved. The AI prediction accuracy of the final test runs for different data sets are displayed in Table 1.

Table 1: Best training results of all AI approaches which were trained with a data set individually. Results from [17].

Data Set	Data shape	mae in MPa
Process	Time-series	3.50
Thermography	Images	1.90
Sound	Time-series	4.10
Waterultrasound	Images	2.58
Laser excited ultrasound	Images	2.39

The process- and sound data are processed by a 1DCNN algorithm. These approaches lead to networks with a mae of >3 MPa and are considered to make weak predictions. Thermography-, WUS- and LEA-data are all processed by 2DCNNs. Here, the thermography data outperforms every other approach with a mae of 1.9 MPa. Additionally, the trained AIs were connected in different combinations or connected in one conclusive AI. None of these combinations outperformed the AI which deals with isolated thermography data which leads to the hypothesis that thermography is one of the most promising data types to train an AI algorithm to predict the weld quality in CUW. Even if LEA and WUS offer also good training data for AI, the use of thermography data has the advantage, that no extra data measurement step has to be done since the thermography data is recorded during the welding process. [17]

6. Other Approaches with AI Potential

Literature reports a new sensor system which is supposed to have high potential for a new type of sensor data for the QA of welded TCs. This new sensor is called polymer-based capacitive micromachined ultrasonic transducer (polyCMUT) and can be seen as an ultrasonic sensor which is able to send and receive ultrasonic signals [32]. In literature polyCMUT sensors are described to produce data which correlate with the achieved weld quality [17, 33, 34]:
In a first research work the sensor is implemented in the CUW process and the sensor is reported to be able to perform inline ultrasound measurements of the welding zone shape without interference by the ultrasonic welding process. [33]
After a successful implementation, a series of welds were produced where inline measurements of the welding zone are performed with the polyCMUT sensors [17, 34]. When errors in the welding zone appear, the ultrasonic echoes of the polyCMUTs signal changes its echo depth. Those changes of echo depth were then visually correlated with artificially created errors in the welding zone. These results were recorded multiple times to show that repeatability in the measurement technique. The recorded data set was too small for a reliable AI training but the strong correlations of the signal with the welding zone shape imply that the polyCMUT sensors have potential to be of use for the training of AI for QA in the process of CUW. [17, 34]

7. Conclusion & Future Perspectives

USW of TCs is a new, emerging technology which can help to make the production of aircraft parts more affordable and reduce operational costs of aircrafts. While literature often describes attempts of QA in spot-welding, there is few research done for the process of CUW. Nevertheless, for both technologies first AI approaches are reported to be able to predict the welding quality accurately. One of the most promising approaches for the quality prediction is to record thermographic images of the welding areas surface for AI training. Additionally, there is a new kind of sensor (polyCMUT) which is able to record inline data which correlate with the weld quality, therefore having the potential to be beneficial for AI training. This data could gain additional information for the quality prediction and make its prediction more reliable.
The collected research results represent the first steps for a more reliable AI assisted QA in the process of spot-welding and CUW and potentially pave the way for this joining technology to find application in production. To increase trustworthiness of AI applications, more research has to be done to sharpen the hypothesis about the different potentials of process data for AI training and to generate more understanding of how the decision process of those algorithms works. For the establishment of AI in the industry a clear set of rules and guidelines has to be defined, especially if the application case is the QA of primary structural parts with a high degree of safety needed.

8. References

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