Process data driven advancement of robot-based continuous ultrasonic welding for the dust-free assembly of future fuselage structures

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Abstract:
High volume aerospace programs require efficient, flexible and robust welding technologies. Since continuous ultrasonic welding is a highly transient process that depends on a number of processing parameters, such as weld energy, amplitude, travel speed and consolidation pressure, process monitoring is crucial for the welding result. Furthermore, it is not possible to look into the welding zone during the welding process.
In order to mature this technology an in-line process monitoring has been setup that collects all relevant parameters and uses a Neural Network to predict the welding quality directly after the welding process.

Keywords: continuous ultrasonic welding, thermoplastic composites, LM-PAEK, artificial intelligence, automated aerospace assembly, Fuselage of Tomorrow

Introduction

At the moment a lot of effort is done in the development of reliable welding technologies for Carbon fiber-reinforced thermoplastics (CFR-TP's). The use of these materials in aircraft engineering opens up completely new possibilities, as manufacturing processes can be changed. One example is the system integration, which in the case of today's metal-made A320 is carried out after the Major Component Assembly (MCA) in the Final Assembly Line (FAL). The main reason for this is that chips produced during drilling could damage the coating of the systems over the life cycle of the aircraft and thus lead to a short circuit.

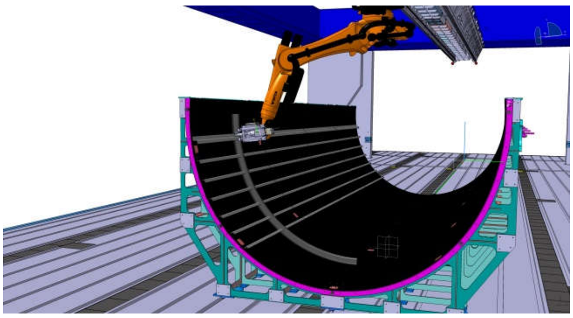

***Fig. 1:** Multifunctional Fuselage Demonstrator (MFFD)*

Currently the Center for Lightweight Production Technology (ZLP) Augsburg and its project partners AIRBUS, Premium AEROTEC and Aernnova are involved in the European Clean Sky 2 Large Passenger Aircraft (LPA) project which faces the challenge to build an 8m thermoplastic upper shell fuselage demonstrator with around four meters in diameter. This demonstrator called Multifunctional Fuselage Demonstrator (MFFD) will be manufactured out of carbon fiber-reinforced low melt polyaryletherketone (CF/LM-PAEK) CETEX® TC1225 provided by Toray Advanced Composites. The skin will be manufactured with In-Situ tape laying process. In the next step the stringers will be integrated by continuous Ultrasonic Welding (cUW). Fig. 1 shows a CAD image of the test setup. A ceiling-mounted KUKA Quantec KR270 robot welds the stringers onto the thermoplastic skin using a welding effector.
Fig. 2 shows a close-up of the welding process. An Omega stringer (for MFFD Z-stringers are used) is shown being welded onto the skin. In the middle of the picture, marked with a yellow sticker, the so-called sonotrode or horn can be seen.

***Fig. 2:** Welding of omega-stringer with continuous Ultrasonic Welding(cUW)*

By the horn, the mechanical vibration generated by transducer and booster is transferred to the substrate. This oscillation is converted into heat by inter molecular friction in the energy director and inter surface friction of all joining partners [1].
The direction of travel of the end effector in this picture goes from left to right. After the heat has

been generated, the welding zone is consolidated by a consolidation following the horn. The remaining stiffening elements like frames, frame couplings and cleats will be integrated into the demonstrator by electrical resistance welding.

The presented work focusses on the possibility of the prediction of weld strength using continuous Ultrasonic Welding (cUW) directly after the process, using data which is collected during the welding.

State of the art Artificial Intelligence (AI) for welding prediction

To the authors knowledge there are currently not many models for the quality prediction of ultrasonic welded thermoplastic composites available. One research group generated a deeper understanding of the general mechanisms in ultrasonic welding and observed power- and displacement curves of the sonotrode in order to explain changes in the weld interface [2]. These changes can then be connected to the final quality of a weld. The research team developed a method to explain the welding process and thereby have information to evaluate the quality of a weld by using signals of the welding process. In addition, the used procedure can be used to define optimal welding parameters for other welding setups. Another attempt was done by developing a wave transmission model for the weld process of carbon fibre composites in order to predict the weld quality [3]. In this attempt the quality of a weld was defined by three different levels which the model should predict. Dependent on the setup for the welding, error rates for prediction range from 42% to 2%. It is pointed out that better prediction results could be achieved by generating a deeper understanding of the physical principles of the welding technique because more knowledge could lead to a better mathematical description of the process.
From these two studies it can be seen that previous attempts for the weld quality prediction are dominated by analysing the process of ultrasonic welding and understanding it. In our work we try to evaluate the potential of Artificial Intelligence (AI) for quality prediction of ultrasonic welding which should not depend as strong on the understanding on the principles than the methods described above.

Setup of continuous Ultrasonic Welding (cUW) system

The core components of the welding end-effector are a Branson 20 kHz round sonotrode driven by a Branson 4.00 DCXs 20VRT generator with a peak output power of 4 kW. In order to introduce the process force through the sonotrode into the joining zone, it is pressed with a pneumatic cylinder with a maximal force of up to 3 kN. For process control, a force sensor was integrated between sonotrode and cylinder which measures the current process force with a resolution of 10 kHz. The air pressure in the cylinder is controlled by a Festo proportional valve (type VPPM) with a sampling rate of 1 kHz [4] [5]. To support the joining process, additional a compaction roller in front and a compaction unit behind the horn were integrated. Both are controlled by a cylinder with 1.7kN force and a proportional valve (type VPPM). In addition, displacement sensors are located on the cylinders, which record the setting path (i.e. weld collapse) of the joint by measuring the height difference and displacement during the weld process.

The control and the recording of process data during the welding was realized by EtherCAT components from Beckhoff with a sampling rate of 1 kHz.

For process monitoring and prediction of joining strength data like welding amplitude, power and force and robot velocity are logged. In further data processing steps the weld- force, power, amplitude, and velocity are used as sequential data and the information about the thickness of the used energy directors and their number are considered as single values and saved together in data files. During the process the accumulated data is stored in a textual file with TwinCat Scope.

Data collection and preparation

The basis for the prediction tool was to collect the data for training. The training data consists of the process data recorded during welding and the corresponding LSS (lap shear strength) values achieved at the corresponding points.
For welding single lap samples according test standard ASTM 1002 with an overlap of 12.7 mm (½") were designed.

Samples were prepared welding two organo sheets with the size of 265x102mm to one another. After cutting, the organo sheets were cleaned with ethanol to degrease and remove other contaminations. Conditioning in a climatic chamber for a minimum of 24h at 60°C and 0% humidity was done.
As material carbon fibre reinforced Toray TC1225 low-melt polyaryletherketone (LM-PAEK) laminate was used with a thickness of 1.8 mm and a stacking sequence of $[(0/90)_3]_s$. Two to four layers of neat

Tab 1: Parameter-Set used for welding data generation

Parameter	Weld Force (N)	Amplitude (%)	Velocity (mm/s)	Consolidation Pressure (bar)	Energy Director (µm)
Low	400	95	21.5	5	120 (2x60µm)
High	600	100	23.5	8	240 (4x60µm)

matrix film with 60µm thickness were applied as energy director (ED).

To get different process data and LSS values a test plan was designed by the use of DesignExpert8 software for statistical design of experiments (DoE). A screening with 5 factors (weld force, amplitude, pressure, travel speed and ED configuration) was performed. The parameters are listed in *Tab 1*. The force of the compaction roller in front of the horn was kept constant. After the welding process the labelled plates were cut into nine single specimens for mechanical testing. An overall 13 welds were performed with parameter variation according to the DoE screening. In total 117 pairs of process data and the corresponding lap shear strength value were available to train the AI system.

Artificial Intelligence (AI) – Process analysis

After the welding data had been collected, the next step was to prepare them for the AI prediction application. The implementation was done with Python 3 programming language using different Toolboxes including Matplotlib, Pandas, Numpy and Keras with TensorFlow as backend engine. The following pre-processing steps are necessary before training a neuronal network: (1) pre-processing the raw data from the weld process, (2) cut the data in single samples according to the samples which were cut from a welded plate and label this data, (3) train and validate the neuronal network which structures are inspired by the instructions of F. Chollet [6]. Step one is based on the condition that the recorded parameters of a weld are stored in textual data files. Here, every weld has its own data file. In the pre-processing steps all important values are normalized to assure values are all within the same range. The signals can be noisy or edgy because of the limited sampling rate of the measurement. Because of this, a moving average is run over the data in order to smooth the signals and eliminate noise (see Fig. 3). After this pre-processing step is done the data are saved in textual data files again. One weld of a plate produces several samples for further investigation of the weld quality. As shown in Fig. 4 the plates are each cut in nine samples for quality evaluation (weld strength) and one polishing sample. The data files with the parameters of a weld have to be cut similar to the real cutting process to be able to sort the values of a weld to the corresponding sample. This whole cutting process in done in step two. In addition, the labelling process in which each cut sample data is linked to its corresponding weld strength is carried out. After the data are pre-processed and cut in their single samples the data are

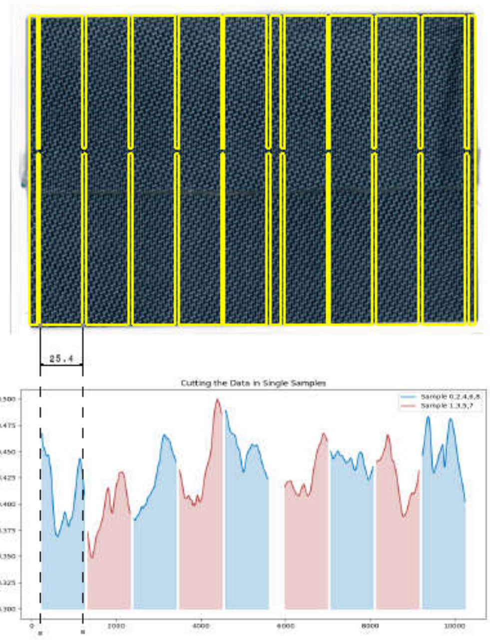

Fig. 4: *Welded sample (top) and corresponding process data (bottom)*

fed to a neuronal network (NN). The network is designed to process sequential data on the one hand and single data input on the other hand. Altogether 117 samples of 13 different welds are processed. From the raw data four sequential and two single values are used as input data. Fig. 5 shows the training and validation process of the developed network.

The loss functions of the training data and the validation data decline which means that there is an actual learning process. In addition, the mean absolute error (mae) decline as well. This behaviour

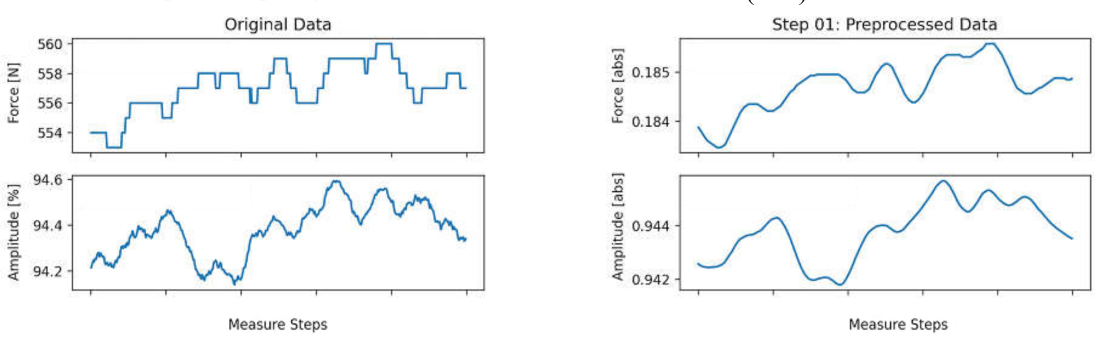

Fig. 3: Normalization and Moving average on Welding Force and Branson Amplitude data

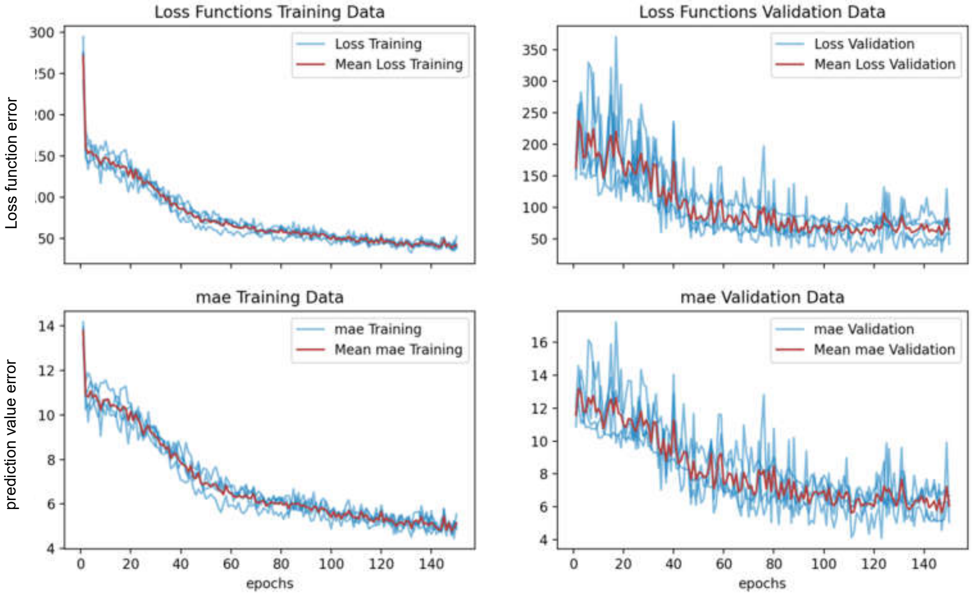

***Fig. 5:** Loss Function and prediction value error*

displays that the network learns the characteristics of the weld parameters which belong to different weld strength. Because of the small amount of data samples there is no testing phase implemented so far.

Summary and outlook

Process data driven models to predict the weld quality of cUW for thermoplastic composites is a very new field and there are only a few attempts reported in other research projects. The dropping loss function during the training process of our Neural Network (NN) shows characteristics of loss functions described in [6] for other NN. This leads to the hypothesis that the attempt to predict weld quality with process data and the use of AI could lead to outstanding results. Nevertheless, further research with more data of welding processes and different network architectures have to be done to confirm this hypothesis. In addition, more training data will make it possible to make a statement about the accuracy of the developed network.

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