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Expert system-supported optimization of laser welding of additively manufactured thermoplastic components

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Abstract

Laser transmission welding (LTW) is a known technique to join conventionally produced thermoplastic parts, e.g. injected molded parts. When using LTW for additively manufactured parts (usually prototypes, small series), this technique has to be evolved to overcome the difficulties in the part composition resulted in the additive manufacturing process itself.
In this paper, a method is presented to enhance the weld seam quality of laser welded additively manufactured parts assisted by a neural network-based expert system. To validate the expert system, specimens are additively manufactured from polylactide. The parameters of the additive manufacturing process, the transmissivity, and the LTW process parameters are used to predict the shear tensile force with the neural network. The transparent samples are welded to black absorbent samples in overlap configuration and shear tensile tests are performed. In this work, the prediction of the shear tensile force with an accuracy of 88.1% of the neuronal network based expert system is demonstrated.

Keywords: Laser transmission welding; additive manufacturing; fused deposition modeling; transmissivity; neuronal network; shear tensile force

1. Introduction

The fused deposition modeling (FDM) is a popular manufacturing process for rapid prototyping, small batches, and customized mass production with thermoplastics. To prepare a 3D-CAD part for the deposition process, the part has to be converted in a format that describes the outer surface, such as the STL format. At the next process step a software cuts the surface model in defined layers with a description of each layer infill and generate a machine-readable code such as G-code. Within this process, the deposition parameters such as layer thickness, layer infill pattern, print velocity or line width are defined. Finally, the FDM-printer uses the G-Code to form the 3D object. A thermoplastic material, provided as a filament, is melted up by the print head, extruded through a fine nozzle and laid up line by line to form a layer in the X-Y plane. After solidification, the Z-axes moves the value of the layer thickness and the next layer will be deposited. After additional layers are deposited on each other, the 3D object is formed [1].

LTW is based on the optical transmittance of thermoplastic material for near-infrared radiation. For joining two parts, the radiation has to pass through the transparent part to reach the surface of the second part, which absorbs the radiation. After absorbing, the optical energy is transformed into thermal energy. Heat conduction transfers the heat to the transparent part, so both parts melt at their interface. After cooling and solidification, the two parts form a bond. For the heat conduction a good surface contact is necessary, which requires a constant joining pressure along the weld seam and a smooth surface at the parts' interface [2]. Kuklik et al., 2019,

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demonstrated a fundamental study of LTW for additively manufactured parts. They investigated the influence of additive manufacturing process parameters on the transmissivity as well as the weldability of natural and black polylactide parts. For the highest weld seam strength, an energy per unit length of 4.0 J/mm at a weld velocity of 2.5 mm/s was recommended applying contour welding. Cavities were observed in cross sections of the weld seams. The authors suggested that voids from the additively manufacturing process and the surface roughness resulted in small gaps between the parts causing these cavities [3]. Vazques-Martinez et al., 2020, investigated a laser welding process with a pulsed fiber laser system and a large welding area of 5 x 5 mm². The authors also observed the formation of gaps and cavities between the additively manufactured components and described that a high energy of the laser pulses resulted in shrinking marks on the upper surface of the transparent part. They assumed that the high energy density of the focused beam leads to a melting of the transparent part at the point of entry and thus to the collapse of the upper surface [4]. Kuklik et al. demonstrated in 2020, that the cavities inside the weld seam of laser welded FDM components could be avoided by using a bar of extra material on top of the absorbent part. During the welding process, the bar melts down and provides an extra amount of material in order to fill the voids. This resulted in weld seams without cavities [5]. In 2021, Kuklik et al., changed the additive manufacturing parameters in a fractional screening for design of experiments in order to investigate the influence of these parameters on the transmissivity. The authors assumed that the change of the additive manufacturing parameters influences the transmissivity and scattering behavior and this leads to a change of the weld seam width [6].

Developing an LTW process for thermoplastics is often combined with high cost and high number of experiments to optimize the welding parameters laser power and feed rate. Therefore, in recent years, mathematic models, finite element method, and artificial neuronal networks were investigated in order to reduce the numbers of experiments. In 2011, Acherjee et al. used different neuronal network architectures to predict the weld seam strength and weld seam width for LTW of acrylic polymers and compared the results to linear and polynomial models. For the data set used, the neuronal network shows a better prediction than the mathematic models. The mean prediction error for the best neuronal network was 4.4% [7]. Acherjee also compared in 2019 the prediction of a neuronal network to the simulation using the finite element method for the weld pool dimensions in the LTW process. The author assumed that the sequential integration of both the simulation with the finite element method and the prediction with a neuronal network could minimize experimental effort to save time and cost [8]. In 2022, Kuklik et al. used a neuronal network to predict the transmissivity of additively manufactured components based on the manufacturing parameters. The accuracy of the used neuronal network was 87.8% [9].

2. Experimental Setup

For the investigation of LTW of additive manufactured components, samples were manufactured with an Ultimaker FDM desktop printer of the 3rd generation. This printer has a heated build plate and a resolution of 12.5 µm in the X-Y plane and 2.5 µm in Z direction. The used nozzle has a diameter of 0.4 mm.

Table 1. Manufacturing parameters for FDM parts to investigate the transmissivity of additively manufactured components.

Manufacturing parameter	Levels of the experimental design			Reference "fast" profile
	-	O	+	
Sample thickness	1.5 mm	2.25 mm	2.5 mm	-
Layer height	0.125 mm	0.15 mm	0.225 mm	0.2 mm
Line width	0.325 mm	0.35 mm	0.4 mm	0.35 mm

The material of the transparent part and the absorbent part is polylactide in transparent and black, respectively. The software Cura from Ultimaker was used for slicing of the CAD models. This software provides default profiles for the process parameters. The "fast" profile can be used for faster manufacturing by reducing the resolution of the parts. With the default profiles "fine" and "extra fine" the layer height and the printing velocity are reduced to achieve better printing results in complex structures. To minimize the production time the laser absorbent samples were sliced with the "fast" profile of Cura. In order to reduce cavities inside the weld seam, a bar of extra material was added on top of the absorbent part [5]. The manufacturing parameters sample thickness, layer height and line width for the transparent parts were changed on three levels ("+", "O" and "-") as shown in table 1 in order to vary the transmissivity. Twenty sets of parameters were formed from the manufacturing parameters in table 1 and 16 specimens were produced of each set for the laser welding experiments, (cf. [9]). The samples had a dimension of 50 mm length and 25 mm width. A diode laser with a maximum power of 300 W and an emission wavelength of 940 nm was used to weld the samples. The laser beam was guided with an optical fiber to a scanner optic. This generated a focal diameter of 2 mm and maximum scanning speeds up to 5 m/s. To fix the alignment and generate a clamping pressure for the welding, the parts were pressed together between a glass plate and by a pneumatic cylinder. Fig. 1 shows the experimental setup. The samples had an overlap of 12.5 mm and were welded together with a scanning speed of 4 mm/s and laser powers from 8 W to 15 W. An artificial neuronal network (ANN) was used to predict the shear tensile force of the welded and tested parts. The ANN has eight input variables: material, layer infill, sample thickness, layer height, line width, transmissivity, welding speed, and welding power. Furthermore, it contains two hidden layers with in total eight neurons and the shear tensile force as the output variable. The ANN was trained in a supervised learning strategy. For the activation of a neuron, a hyperbolic tangent function was used. The weights of the neurons were optimized with the stochastic gradient decent solver. The development of the ANN was done in a preparatory work.

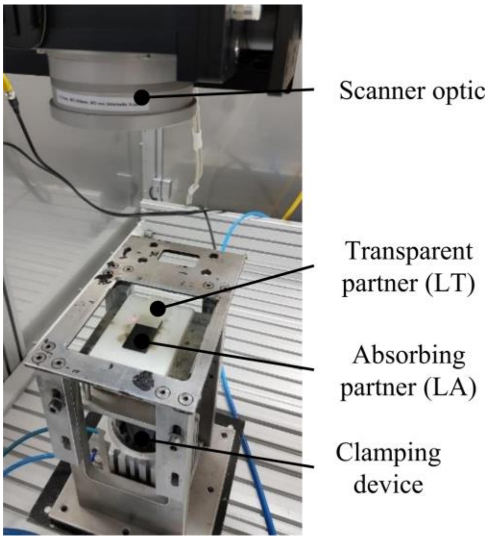

Fig. 1. Experimental set up for the laser welding experiments.

3. Results and discussion

The transparency of the samples was analyzed with a spectrometer Lambda 1050 from Perkin Elmer. The spectrometer measures in range of 200 nm to 3000 nm with a resolution up to 0.1 nm. To collect all the transmitted light an integrating sphere was used for the detection. The transmissivity of the samples were between 45% – 75% with a standard deviation for the additive manufacturing parameter set between of 2% – 4.3%. The transparent parts were welded in overlap configuration to the black samples for lap shear tests in order to study the influence of welding parameters on the resulting weld seam strength. The welding was performed with laser powers taking into account the transmissivity.

The samples with a high transmissivity were welded with less power in the range of 8 W – 11 W to avoid decomposition. Samples with low transmissivity were welded with higher power between 11 W – 15 W, because a lower power was not sufficient to generate a continuous weld seam. For statistical validation, each experiment was performed four times. Overall, 320 samples were welded with 80 different setups for the additively manufacturing and welding parameters. Fig. 2 shows the maximum shear tensile force of the lap shear tests with respect to the transmissivity of the transparent samples. The applied laser power during the welding is marked with the different colors. The shear tensile forces of the lap shear tests varied between 390 N – 1144 N. The standard deviation of the 80 different welding and manufacturing setups varies between 10 N – 144 N.

The dataset of the 320 experiments was randomized three times and divided into two groups, one for training and testing as well as one for validating the ANN. To validate the ANN in dealing with missing or limited data, 16 parameter sets were included in the training and test group with one of four experiments and eight parameter sets were omitted. As a result, the ANN must predict the results of four experiments from eight parameter sets and three experiments from 16 parameter sets in the validating group without having a broad database in the training group. The ANN was trained for 100.000 epochs and the same data set was used to test the accuracy of the ANN. Fig. 3 shows the relationship between the measured and with the ANN predicted shear tensile force for the training and test data set. For 93% of the results the difference between the predicted and the actual measured value were less than 10%. A better prediction of the test data set was not possible with the ANN because of inconsistent in the data set itself. As shown in Table 2 as an example for this parameter of the test data set the transmissivity varies inconsistent to the shear tensile force, while all other parameters kept constant.

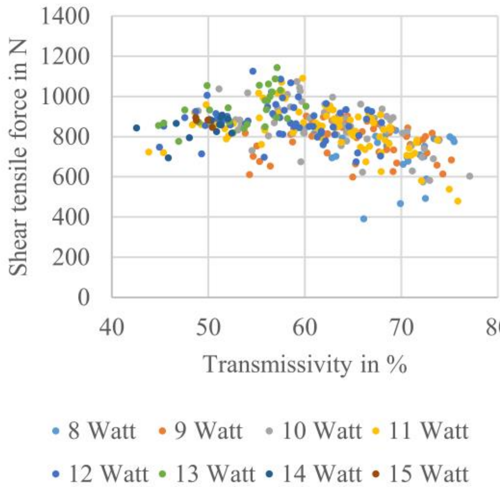

Fig. 2. The maximum shear tensile force of the weld seams sorted by the applied laser power in relation to the transmissivity of the transparent sample.

Table 2. Results of a series of experiments with the same additive manufacturing and laser welding settings

Experiment No.	1	2	3	4
Transmissivity in %	67.96	64.77	68.48	69.11
Shear tensile force in N	936.88	832.692	826.869	895.72

To analyze the performance of the ANN, it was evaluated if the predicted and the measured shear tensile force of an experiment was inside the range of +/- the single or double standard deviation of the mean value of the parameter set. The possible outcomes for the test are true positive (TP), the prediction and the measured value are in the specified range, true negative (TN), the prediction and the measured value are not in the specified range, false positive (FP) and false negative (FN), the prediction or the measured value is in the specified range and the other is not. With these the performance parameters precision, recall, accuracy and F-Score can be calculated with the equations below:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$F - Score = 2\ \frac{Precision * Recall}{Precision + Recall} \qquad (4)$$

In summary the difference between the predicted value and the mean of the experimental value, the precision, was 77.6% for the single standard deviation and 91.9% for the double standard deviation. The accuracy of the ANN was 60.6% tested on one standard deviation and 91.9% for the double standard deviation. The F-Score was 0.725 tested on one standard deviation and 0.958 for the double standard deviation.

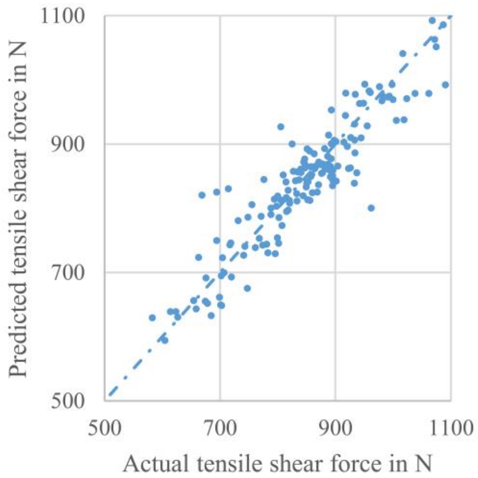

Fig. 3. Comparison of the teaching data set to the prediction.

In Fig. 4. the relationship between the measured and predicted values of the validating data set is shown. The difference between the predicted and the actual measured value were less than 10% for 84.4% of the experiments. Tested on the single and double standard deviation, the difference between the predicted value and the mean were in 64.8% of the cases truly smaller than the single standard deviation and in 88.1% of the cases truly smaller than the double standard deviation. The prediction accuracy of the ANN was therefore reduced to 55.6% for the single standard deviation and 88.1% for the double standard deviation. The F-Score was 0.664 for the single standard deviation and 0.937 for the double standard deviation.

Fig. 5. shows the F-Score in dependence of the tested standard deviation. The blue curve shows the F-Score of the ANN performance for the test data group. The orange curve shows the F-Score for the validation data group. It can be observed that the performance of the ANN for a standard deviation greater than 0.7 σ gets less for the validation data set. The grey and the yellow curves show the F-Score of parameter sets, which were represented with three (data 1) and four experiments (data 2) in the validation data group. Therefore, these parameter sets were represented by one or zero experiments in the test and training data group and did not have a broad database for training the ANN. While the F-Score of the ANN for data set 2 is lower, the grey curve follows the F-Score for the train data set. Therefor it can be concluded, that the ANN is very stable as long as one experiment with the same additive manufacturing and welding parameter settings is represented in the training data set.

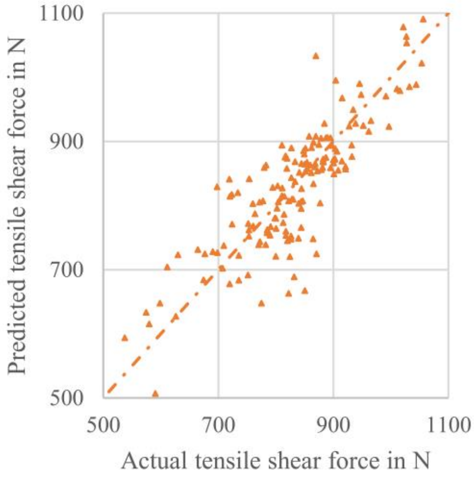

Fig. 4. Comparison of the validating data set to the prediction.

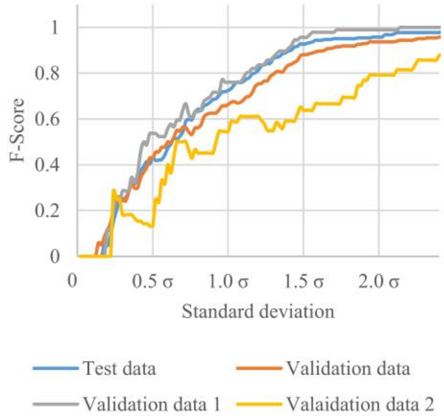

Fig. 5. F-Score in dependence of the tested standard deviation.

4. Conclusion

This work examines an ANN based approach to predict the shear tensile force of laser transmission welded additively manufactured components made in a fused deposition modelling process. For the investigations the results of 320 experiments with differences in additive manufacturing and welding parameters were used to train and validate an ANN. Therefore, the database was split in a train and a validation group. The results show, that the performance and accuracy of the ANN based on the used data decreased for the validation data group. The accuracy of the ANN that the predicted shear tensile force of an experiment is truly in the range of the double standard deviation around the mean was 88.1%. Furthermore it was observed, that the F-Score for the ANN tested with a dataset, which included only parameter sets, which were represented one time in the training data group, were similar to the F-Score tested with the training data set.

With the presented ANN, the shear tensile force of additively manufactured and laser welded samples could be predicted with a high accuracy. To increase the accuracy and F-Score of the ANN and reduce the standard deviation of the experiments, more welding experiments have to be done.

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