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Quality monitoring of projection welding using machine learning with small data sets

Johannes Koal[a]* and Tim Hertzschuch[a**] and Martin Baumgarten[a] and Jörg Zschetzsche[a] and Uwe Füssel[a]

[a] *Technische Universität Dresden, Institute of Manufacturing Science and Engineering, Chair of Joining Technology and Assembly, Dresden, Germany*

** Johannes Koal, johannes.koal@tu-dresden.de, ORCID: 0000-0003-0763-552X*

*** Tim Hertzschuch, tim.hertzschuch@tu-dresden.de, ORCID: 0000-0001-5030-0819*

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Quality monitoring of projection welding using machine learning with small amounts of data

Capacitor discharge welding is an efficient, cost-effective and stable process. It is mostly used for projection welding. Real-time monitoring is desired to ensure quality. Until this point, measured process quantities were evaluated through expert systems. This method takes much time for developing, is strongly restricted to specific welding tasks and needs deep understanding of the process. Another possibility is quality prediction based on process data with machine learning. This method can overcome the downsides of expert systems. But it requires classified welding experiments to achieve a high prediction probability. In industrial manufacturing, it is rarely possible to generate big sets of this type of data. Therefore, semi-supervised learning will be investigated to enable model development on small data sets. Supervised learning is used to develop machine learning models on large amounts of data. These models are used as a comparison to the semi-supervised models. The time signals of the process parameters are evaluated in these investigations. A total of 389 classified weld tests were performed. With semi-supervised learning methods, the amount of training data necessary was reduced to 31 classified data sets

Keywords: resistance welding; capacitor discharge welding; projection welding; machine learning; supervised learning; semi-supervised learning, process monitoring

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Introduction

Capacitor discharge welding (CD welding) is mostly used for welding rotationally symmetrical components. Finished components with diameters of up to 200 mm can be joined within a few milliseconds [1]. The capacitor discharge is an uncontrolled process. There are no standardized test methods for evaluating the joint [2, 3]. Destructive press-out tests are usually performed or metallographic cross-sections are prepared. Monitoring of the process parameters is also usual in addition to the evaluation [4-8]. The evaluation of these process parameters is empirical and based on years of experience. Peak current, current integral, maximum force, force collapse, sinking distance, and fatigue distance are continuously monitored. The essential process parameters and curve characteristics that are supposed to indicate the quality must be determined separately for each application. Another possibility is machine learning (ML) for recognition of specific characteristics. Several studies for resistance spot welding using mid-frequency direct current (MFDC) considered the time signals of electrode travel and force, welding current and electrode voltages [15, 18, 19]. These investigations showed good results and proves, that ML algorithms for evaluating the process curves and classifying the welding result can be trained. The advantage is the process-integrated evaluation within the welding control system without the downsides of expert systems discussed above. Furthermore, machine learning algorithms can detect previously unknown specific characteristics, ensuring reliable quality monitoring [19]. So far, no investigations have been made for capacitor discharge welding regarding this topic. Therefore, the motivation of this study is to obtain such results for projection welding by capacitor discharges. ML models of MFDC welding cannot be applied to CD welding, as the process characteristics are different. No welding nugget is generated, the process is not controlled and the quality criteria are different and not standardized.

Semi-supervised learning significantly reduces the amount of classified data required. Great effort is required to generate extensive classified weld tests. As the number of classified data increases, the quality of the models increases [9]. A weld test is considered classified when destructive or non-destructive testing is used to evaluate the welding joint. This is time, resource, and cost intensive. Hence, the second aim of the study is to reduce the amount of classified data needed for development of the ML models. This applies to the amount of data sets as well as the quantities measured per

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data set (industrial scale, laboratory scale).

The use of machine learning is a novelty for the uncontrolled capacitor discharge welding process. Furthermore, semi-supervised learning used to reduce the effort of developing ML models in resistance welding for the first time. Based on the state of the art, the following main research objectives were carried out:

- Comparison of the classification accuracy of different ML models with respect to joint quality.
- Investigation of the classification accuracy of ML models when reducing the amount of training data
- Investigations on semi-supervised learning

Experimental methods

Experimental Setup for the Collection of the Dataset

The basic experimental setup is shown in Figure 1 as a section view. Both joining partners have a hole, where the device for centering is placed. This guarantees the centric positioning of the welding partners relatively to each other. The ring projections diameter is 20 mm, the outer diameter 25 mm, and the projection height 2 mm. The sheet dimensions are 40 mm x 40 mm with a sheet thickness of 3 mm. The samples are drilled to determine the transition voltages between each contact area. The tests were performed on a multi-pulse portal-type system from the company KAPKON GmbH in Germany. The welding system reaches a peak current of 210 kA in 2.1 ms with a transformer ratio of 1:20, a maximum charging voltage of 1300 V and a maximum capacity of 19.78 mF.

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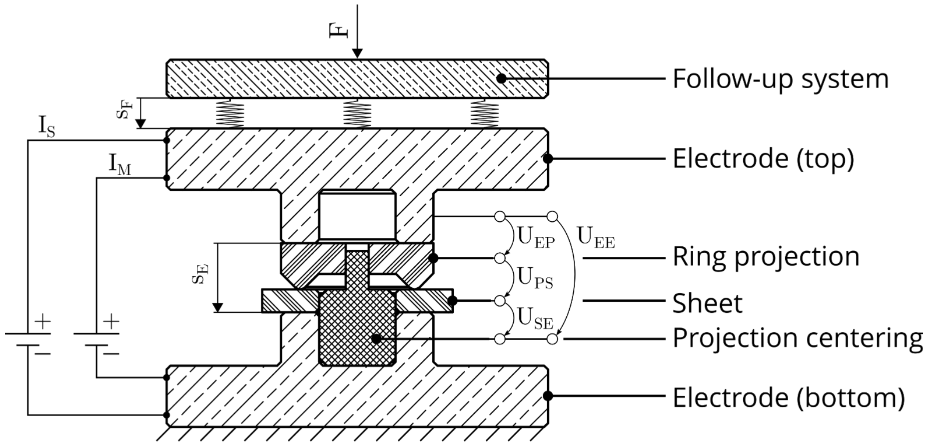

Figure 1. Section view of the experimental and measurement setup. Measurement of U_{CA} and U_{CB} is not shown because they were measured at the machine.

Figure 1 shows all measured variables (excluding the Capacitor Voltages) that are recorded and evaluated:

- Current I_S during welding
- Current I_M during contact resistance measurement
- Voltage U_{EE} from electrode to electrode
- Voltage U_{EP} from electrode to projection
- Voltage U_{PS} from projection to sheet
- voltage U_{SE} from sheet to electrode
- Electrode force F
- Electrode distance s_E
- Spring distance s_F

Design of the welding experiments

Four different material combinations were investigated. Table 1 lists the material combinations for the projection and sheet components. The minimum yield strength $R_{p0.2}$ is used to calculate the minimum press-out force for the lower limit of the weld areas following [11, 12]. The calculation depends on a non-breaking space $w_{min} = 0.5$ mm and the ring projection diameter $w_B = 20$ mm and results as follows:

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$$F_{min} = R_{p0,2} \cdot \left(\frac{\pi}{4} \cdot \left((w_B + w_{min})^2 - (w_B - w_{min})^2 \right) \right) \quad (1)$$

Table 1. Investigated material combinations

Material combination	**A**	**B**	**C**	**D**
projection	16MnCr5	16MnCr5	18CrNiMo6	18CrNiMo6*
sheet	16MnCr5	S355MC	DC01+ZE	DC01+ZE
$R_{p0,2}$ in MPa	425	355	280	280
$\boldsymbol{F}_{\mathbf{min}}$ in kN	13.35	11.15	8.80	8.80

Based on the welding ranges, a total of five tests were carried out and evaluated for each parameter constellation in Table 2. The charging voltage was increased in 100 V steps until severe weld spatter occurred. This corresponds to weld spatter classes 2 and 3 according to [13-14]. Preliminary tests with 500 V charging energy did not lead to any bonding between the joining partners. Therefore, a minimum charging voltage of 600 V was selected for the capacitors.

Table 2 Experimental Design

Nr.	**Material combination**	**Electrode force in kN**	**Charging voltage in V**
1	A	10	600 - 1000
2	A	15	600 - 1100
3	A	20	600 - 1200
4	A	25	600 - 1300
5	B	10	600 - 900
6	B	15	600 - 900
7	B	20	600 - 1000
8	B	25	600 - 1000
9	C	10	600 - 900
10	C	15	600 - 900
11	C	20	600 - 1000
12	C	25	600 - 1100
13	D	10	600 - 900
14	D	15	600 - 900
15	D	20	600 - 900
16	D	25	600 - 900

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Determination of the connection strength

To test connection strength of the joints, quasi-static strength tests were carried out on a universal testing machine "inspect 250" from the company Hegewald & Peschke in Germany. The testing speed was set to 5 mm / min.

Machine learning methods

Feature extraction

Features are the input data of a ML algorithm. In this study individual statistical characteristics of the measured signals as well as the measured signals them self during welding were used. Additionally, the measurement of the transition voltages of all contacts during CD projection welding was performed for the first time. Following [10], the data are classified into three different categories of feature sets: *series production*, *laboratory low scale* (total transition voltage), and *laboratory high scale* (all transition voltages). Table 3 lists the measurement signals included in each category. The pre-welding and post-welding categories correspond to a transition resistance measurement before and after welding. The *series production* category represents a measurement setup that is usually found in the delivery condition of the machines. *Laboratory low scale* adds a measurement of the electrode voltage to the *series production*. This can be realized with little effort. *Laboratory high scale* considers the measurement of all transition voltages at each contact. This cannot be realized in a production environment.

Table 3. Classification of the measured variables in different feature categories

Prewelding	Postwelding	Series production	Laboratory low scale	Laboratory high scale
I_M	I_M	I_W	I_W	I_W
U_{EB}	U_{EB}	F_E	F_E	F_E
U_{BB}	U_{BB}	s_E	s_E	s_E
U_{BE}	U_{BE}	s_F	s_F	s_F
		U_{CA}	U_{CA}	U_{CA}
		U_{CB}	U_{CB}	U_{CB}
			U_{EE}	U_{EP}
				U_{PS}
				U_{SE}

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Additionally, Figure S1 shows a schematic overview of the measured time periods and signals. The sampling rate is 200 kHz with a resolution of 16 bit. Including the integrated transition resistance measurement, around 840000 data points can be derived from the measurement during welding test. The data used in the development of the models are smoothed with a moving average over five measurement data points. The data are then reduced by averaging all ten data points. The data is divided into times before (pre), during and after (post) the welding process. The use of pre and post welding features did not lead to a significant improvement of the results. Therefore, only data measured during the welding are used in the models discussed in this paper. Statistical values are determined from the time-dependent data. These are median, standard deviation, mean value, maximum value, minimum value, and the values at the time of the current maximum t_p, the current drop to 50 % t_h and the current flow time t_I. Both, the prepared signals and the statistical values, were used in this investigation. All data are normalized by a min-max standardizer. The splitting into training and test data is discussed in the corresponding chapters.

Classification of the welding results

The classification of the data regarding the connection strength was performed by comparing the press-out force determined with the quasi-static strength test and the minimum press-out force required according to Table 1 (see equation 1). This classifies the press-out force into classes one (sufficient press-out force) and zero (insufficient press-out force). The classification of the spatter class was also reduced to a binary problem. The weld spatter classes zero and one corresponded to the classification one "spatter class okay" and the weld spatter classes two and three were assigned to the class zero "spatter class too high". Figure S2 shows the statistical evaluation of the welding results.

Algorithms for machine learning

The results of a ML model are the correct and incorrect predictions of the classification, which are often summarized in a confusion matrix. The predictions can be divided into four categories: True Positive (TP), True Negative (TF), False Positive (FP) and False Negative (FN). Based on [15, 16] the classification accuracy (ACC), the F-score and the integral of the Receiver Operating Characteristic (ROC) can be derived from this. The

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classification accuracy (ACC) indicates the proportion of correctly classified objects to the total of all objects to be classified [17] (see equation 2). The F-score combines the classification accuracy and sensitivity (see equation 3). The ROC curve represents the sensitivity as a function of 1-specificity [17].

$$ACC = \frac{TP}{TP + FP} \tag{2}$$

$$F_{Score} = \frac{TP}{TP + \frac{1}{2}(FN + FP)} \tag{3}$$

The following ML algorithms were investigated in this study:

(1) XGB: XGBoost (Extreme Gradient Boosting)
(2) RFC: Random Forest Classifier
(3) DTC: Decision Tree Classifier
(4) ADC: AdaBoost Classifier
(5) kNN: k-nearest neighbours Classifier
(6) SVM: Support Vector Machines Classifier
(7) MLP_1: Neural network with one hidden layer
(8) MLP_3: Neural network with three hidden layers

The hyperparameters of models (1) to (6) were optimized by using a stratified nested cross fold (n-fold) validation (n=5). The neural networks were optimized using the one factor at a time (OFAT) principle in combination with a grid search. In this method, all s hyperparameter are tested. The setting which achieves the highest classification accuracy is adopted. The number of neurons, activation function, optimizer, weight initialization and number of epochs were optimized in this way. This increases the evaluation metrics of the models (accuracy, F-score and ROC integral).
. With these evaluation metrics, the top five trained models of each ML algorithm type (determined through the n-fold-cross validation and OFAT) were evaluated over 1000 trials at random train-test splits.

The investigation of the achievable accuracy with small amounts of data was carried out for a neural network with one hidden layer and the XGBoost algorithm.

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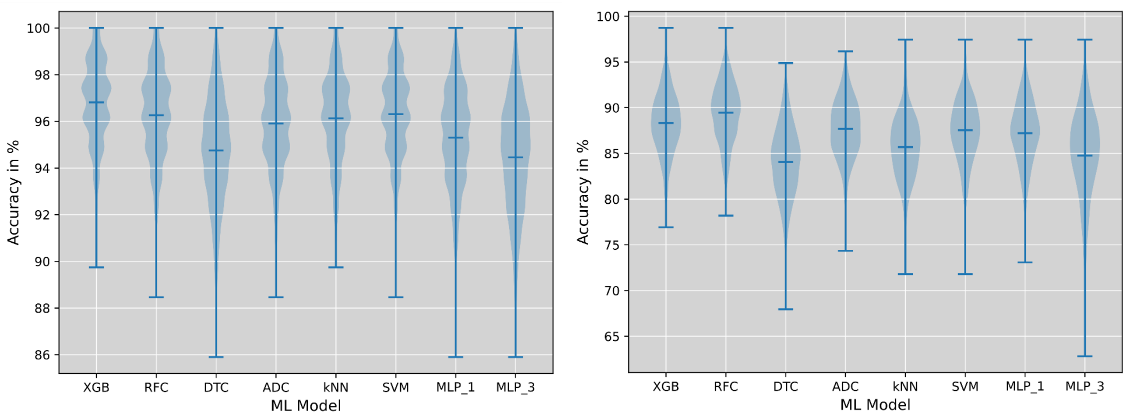
Therefore, the training data was successfully reduced and the test data was increased by the same amount. The reduction of data is described as ration of test to training data. The reference is a total of 389 data sets. Table S8 additionally shows the transfer of investigated ratios into number of data sets. Supervised learning was used.

The XGBoost algorithm was trained subsequently using the learning strategy of semi-supervised learning. The goal is to use pseudo-labels to increase classification accuracy when learning with small amounts of data. Pseudo-labels are labels of unclassified data predicted by the algorithm itself. For this purpose, the available measurement data were randomly divided into 311 training data and 78 test data. The training data were then divided into a data set with classified and a data set with unclassified training data. Initially, the ML model is trained on the data set for which the labels are known. Then, the ML model predicts the classes of the unclassified training data. The data for which the algorithm classifies a class with high probability (>0.95) in the process are then assigned to the training set of classified data. This process was repeated 1000 times for the ratios 0,1 to 0,95 in 0,1 increments. Additional information about the size of data sets is shown in Table S9.

Results regarding machine learning

Results of the ML models trained with Supervised Learning

The training and test procedure was repeated 1000 times in order to statistically validate the results [15].



(a) press-out force (b) weld spatter formation

Figure 2. Distribution of classification accuracies of each ML algorithm over 1000 trials regarding: a.) press-out force, b) spatter class classification.

Figure 2 shows the achieved accuracies of the optimized investigated ML algorithm over 1000 repetitions regarding press-out force and spatter class classification.

Evaluation of press-out force classification

The results in terms of press-out force show that all the investigated models achieve very good accuracies of over 94 %. The dataset was split into 311 training data and 78 test data. This corresponds to a commonly used ratio of 80 % to 20 %. The best results were obtained with XGBoost of 96.8 %. An analysis of variance (ANOVA) was performed to test whether the ML algorithms had statistically significant different accuracies, F-score and ROC. Therefore, the following hypotheses were made:

- H_0: there is no difference between the mean values of the achieved classification accuracies between the studied ML algorithms.
- H_1: there is a difference between the mean values of the studied ML algorithms.

1000 repetitions of training and test for each ML algorithm were done. The statistical results of these repetitions were considered in the ANOVA. The p-values of all metrics are less than 0.001. Hence, the null hypothesis of equal means was falsified. Additional results of the ANOVA are summarized in Table S1, S2 and S3. To determine the ranking of ML algorithms regarding their accuracy, F-score and ROC, the Games-Howell test was performed. The results are shown for the 95% confidence interval in Table 4.

Table 4. Results of the Games Howell test for the 95% confidence interval regarding significant differences between the means of the trained ML algorithms for press-out force classification Two ML algorithms are statistically significant different if they do not share the same letters (a = best value, f=worst value).

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ML algorithm	ACC in %			F-Score in %			ROC in %		
	Mean	STD	Group	Mean	STD	Group	Mean	STD	Group
XGB	96.8154	1.8103	a	96.1366	2.2155	a	0.9589	0.0256	a
SVM	96.3077	1.8462	b	95.4263	2.3379	b	0.9446	0.0287	d
RFC	96.2641	1.9547	b	95.4777	2.3872	b	0.9531	0.0271	b
kNN	96.1244	2.0020	bc	95.2919	2.4483	bc	0.9498	0.0279	c
ADC	95.9090	2.0086	c	95.0517	2.4452	c	0.9492	0.0279	c
MLP_1	95.2999	2.1230	d	95.3	2.1230	bc	0.9386	0.0297	e
DTC	94.7487	2.3454	e	93.6718	2.8279	d	0.9366	0.0309	ef
MLP_3	94.4564	2.4704	e	93.3043	2.984	d	0.9324	0.0335	f

The results confirm the observation that the XGBoost algorithm achieves the best classification accuracies under the given boundary conditions. The second-best results are provided by the RFC. The SVM is better than the RFC in terms of classification accuracy but has significantly worse ROC values.

Evaluation of spatter class classification

The same procedure as in the evaluation of press-out force classification was conducted. The results of the ANOVA are show, that the null hypothesis of equal means was falsified. This is due to p-values less than 0.001 for accuracy, F-distribution and ROC. Hence, it can be assumed that there are significant differences between the mean values of the individual ML models. Additional results of the ANOVA are shown in Table S4, S5 and S6. The results of the Games-Howell show, RFC provides the best results for all evaluation metrics. Also, the XGBoost algorithm performs second best and the MLP with one hidden layer performs fourth place. Additionally, the whole ranking is summarized in table S7.

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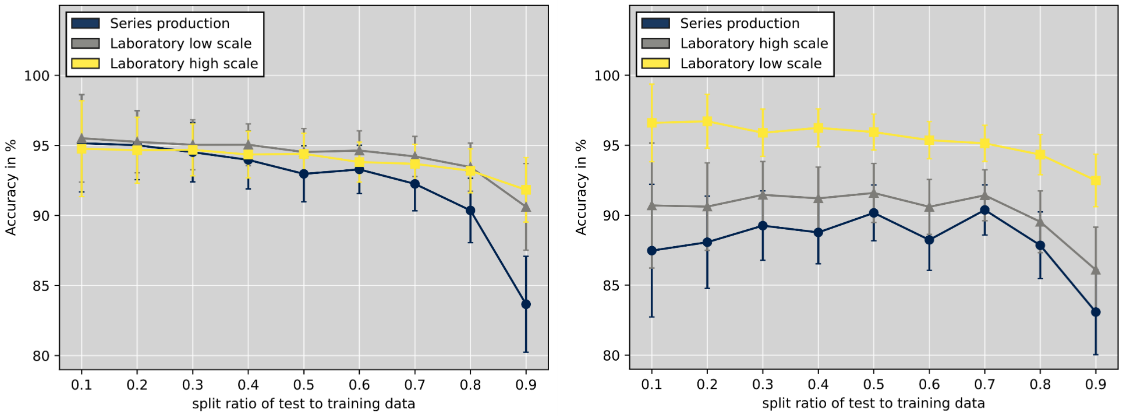
Results of ML models for learning with small amounts of data to classify the press-out force.



(a) Neural Network (b) XGBoost

Figure 3. Classification accuracy of the press-out force as a function of the training data amount and the number of provided features (1000 trials per graph point).

Figure 3 shows the classification accuracies achieved by the neural network and the XGBoost algorithm as a function of the quantity of training data for the three different feature categories. With the neural network, the classification accuracy decreases as the number of training data decreases. It is interesting to note, that up to a ratio of 0.4 of test to training data, no differences are detectable between the investigated feature sets. From a ratio of 0.6 (= 156 training data), the classification accuracy drops significantly with the serial production feature set. There are only minor differences between *laboratory low scale* (total voltage) and *laboratory high scale* (partial voltages). For a set of 39 training data, classification accuracies of over 90% are achieved with both feature sets. The feature set *laboratory high scale* performs best for this ratio. For the XGBoost algorithm, regardless of the amount of training data, the best results are achieved with the laboratory scale (partial voltages). XGBoost achieves better results when the partial voltages can be measured separately. Otherwise, neural networks achieve better results when measuring the voltage between the two electrodes.

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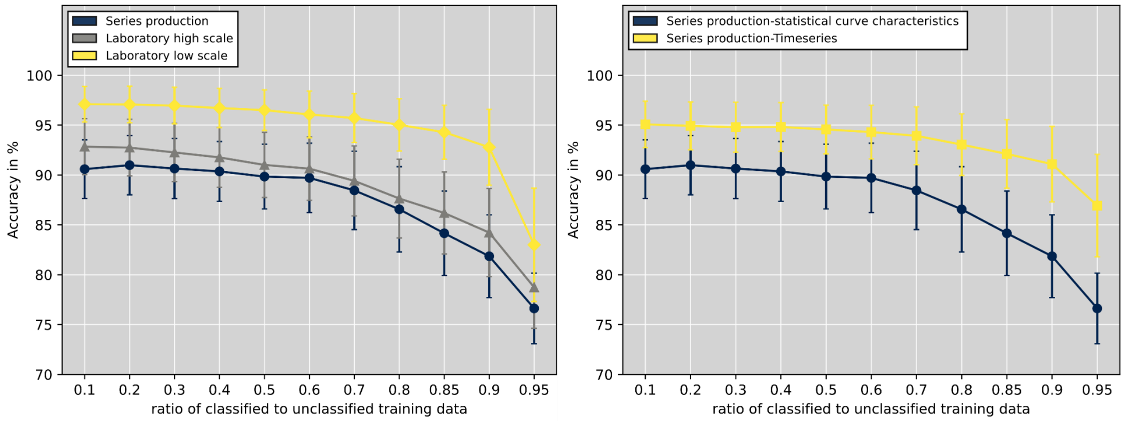
Results with XGBoost for classifying the press-out force using semi-supervised learning



a) Comparison of the three feature categories

b) Individual statistical curve characteristics vs. the entire measured signal

Figure 4. Results of semi-supervised learning to classify the press-out force.

Figure 4 presents the achieved classification accuracies for the press-out force of XGBoost as a function of the amount of training data for two different types of measured data with semi-supervised learning. Figure 4a presents the comparison between achieved accuracies for the extracted individual statistical curve characteristics such as median, mean, max, standard deviation and minimal value (individual statistical characteristics). The feature dataset *laboratory high scale* (all transition voltages) achieves the best results. The classification accuracy is still about 93 % for 31 labelled data. This is about 1 % higher than the classification accuracy of 92 % observed for fully supervised learning on 39 labelled training data. This leads to the conclusion that the classification accuracy can be slightly increased by using pseudo-labels. Comparing the *serial production* and *laboratory low scale* feature sets show that for semi-supervised learning, a big improvement in classification accuracy is achieved by measuring the voltage between the welding electrodes. If a Measurement of the three separate partial voltages between the electrodes and joining parts as well as the two joining partners is possible, the classification accuracy can be further increased (comparison of the curves *laboratory low scale* with *laboratory high scale*. It was investigated whether extracting individual statistical values, such as maximum or mean value (statistical curve characteristics) or using the entire measurement signal

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(Timeseries) achieves better results. Figure 4b shows the results of this investigation in dependence of the labelled training data. The use of the whole measurement signal achieves significantly better results. The differences in terms of classification accuracy increases as the amount of training data decreases. This means that trained ML models based only on individually extracted statistical values leads to significantly worse results. The increased computing time during training as well as the increased amount of data provided are disadvantages.

Summary and Outlook

Summarizing the results the following statements can be made:

- Quality monitoring for resistance projection welding was performed for the first time using machine learning. A classification accuracy of over 95% was achieved.
- Reducing the amount of training data leads to decreasing classification accuracies. Addressing this issue semi-supervised learning was used and lead to an increased accuracy while simultaneously decreasing the amount of training samples compared to the trained ML-models using supervised learning
- Using the entire measured signal for Machine learning increases the accuracy of the XGBoost algorithm compared to extracted curve characteristics

The results of the classification accuracy of the press-out force show that all investigated ML algorithms achieve an accuracy over 94 %. The significantly best results were achieved by XGBoost (96.8 %). This could be demonstrated by means of ANOVA and Games-Howell test for the 95% confidence interval. The values of the other evaluation metrics, such as F-score and ROC value, were one percentage point lower. The results for classification accuracy are comparable to those presented in [18] for resistance spot welding. Similarly, to this study in [18], the best results were also obtained with boosting algorithms. The results show that quality control of quasi-static connection strength for CD projection welding based on ML models is possible with very good accuracy. For the spatter class, the significant best results were obtained with the Random Forest Classifier (89.5 % classification accuracy). The values of all evaluation metrics, such as F-score, ROC value and classification accuracy were significantly lower compared to the press-out force. Despite the high accuracy, the

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models do not yet reach the 6σ target that allows 34 misclassifications per 1,000,000 parts. Further investigations to improve the classification accuracy are necessary.

Regarding learning with small amounts of data, it was shown that with a small amount of 39 labelled training data, classification accuracies for press-out force of 93 % are achieved with XGBoost. This requires measurement of all transition voltages between components (U_{EB}, U_{BB}, U_{BE}). If only a simple or no voltage tap at the electrodes is possible, neural networks are recommended for process control. Here, significantly better results (91 %) were obtained compared to XG-Boost (86 %) for a set of 39 labelled training data. This can also be seen in the results for larger data sets. The neural network achieves classification accuracies of 95 % with the *serial production* and *laboratory low scale* feature sets. In comparison, the XG-Boost algorithm only achieved classification accuracies of a maximum of 90 % with the *serial production* feature set and 92 % with the *laboratory low scale* feature set. From the results, it can be concluded that the choice of ML algorithm for process control of CD projection welding depends on the application scenario. Higher classification accuracies were observed with a larger number of measured signals acquired during the welding process, regardless of the algorithm. Semi supervised learning with pseudo-labels showed good results. The classification accuracy of XGBoost could be increased with a simultaneous reduction in the number of labelled training examples for the feature set *laboratory high scale*. With 31 labelled training samples an accuracy of 93% percent can be achieved. Additionally, some more accuracies for the two different learning strategies at different amounts of labelled data are shown in Table S10. In addition, the use of the entire measurement signal resulted in a significant improvement of the classification accuracy compared to the extracted statistical single values.

In further investigations, a comparison with a test set of constant size will be performed and the pseudo-labels will be generated using General Adversarial Networks (GANS). Furthermore, it will be investigated whether two training cycles are sufficient for semi-supervised learning or whether a higher number of training step/80s is necessary.

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