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Data-Based and Analytical Models for Strength Prediction of Mechanical Joints

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Abstract. The effort for the demand-oriented design of mechanical joints is very high at the current state of the art. Despite constantly changing design conditions, suitable process parameters must be determined and the corresponding joining results, such as the joining contour and strength, must be elaborately determined by experiments. This paper describes alternative ways of using data-based and analytical models for strength prediction when using the clinching joining process. For this purpose, extensive process data were determined via experiments and by means of numerical simulation, and the predictive capability of the models built with these data was compared.

Introduction

Clinch forming allows assembling thin metal parts by solely relying on the local plastic deformation of the base materials. A die, a punch and a blank holder are used to establish the joint. The geometrical parameters typically measured during a cross section analysis are shown in Fig. 1. With f is the interlock, t_n the neck thickness and t_b the bottom thickness. These parameters are typically considered when assessing the joint quality since they correlate with the mechanical strength of the joint. In this regard, the geometrical parameters are used to validate clinch forming simulations. Additionally, the experimentally acquired process graph (i.e. the punch force versus the punch stroke) is often used to validate the simulated stress state within the joint after joining. Further validation of the computed stress state within the joint can be pursued by conducting mechanical strength tests. In this paper, we confine the mechanical strength tests to the top tensile test and the single lap shear test.

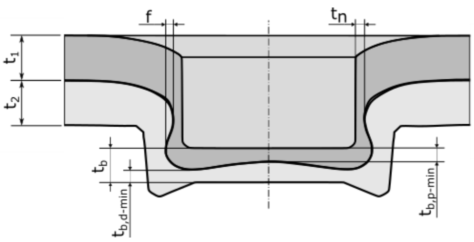


Fig. 1: Schematic view of clinch cross section with: f=interlock; t_n=neck thickness; tb=bottom thickness; $t_{b,d\text{-}min}$=minimum bottom thickness die sheet; $t_{b,p\text{-}min}$=minimum bottom thickness punch sheet

The use of data-based models for mechanical joining has already been explored in projects with different approaches. For example, simulative [1] or experimental data such as micrographs around force-displacement curves were used to train neural networks [2]. In [3] an attempt was made to classify on the basis of the sheet thickness ratios whether one can be joined or not. In [4] very recent results are shown for the data-based prognosis of the mechanical joining technology self-pierce riveting. Thereby both the joint contour as well as the joint strength can be predicted via Machine Learning models.

The paper is organized as follows. In the next section, the experimental test campaign is described. Then we embark on the strategy to generate the synthetic data base. In addition, we use the experimental and analytical data base to assess the predictive accuracy of various analytical strength prediction models for clinching. In the last section, we draw the most important conclusions and discuss future work.

Experimental Reference Data

For the clinching process a combination of steel and aluminum sheets is investigated. Thereby, the materials and thicknesses listed in Table 1 are considered.

Table 1: Considered specimen with mechanical properties

Material	R_m / $R_{p0,2}$ in MPa	Thickness in mm			
EN AW-5182	≈ 285 / 145	1,15	1,25	1,5	2,0
DX56D	≈ 300 / 150	0,7	1,0	1,2	1,7
CR330Y590T-DP	≈ 650 / 380	0,8	1,2	1,6	
CR440Y780T-DP	≈ 840 / 500	0,9	1,2	1,5	1,75

Based on the materials from Table 1, a statistical test plan with 73 material combinations was created for the experimental tests. These were joined using clinching based on experience-based tool selection and analyzed via micrographs and tested via quasi-static shear and top tensile tests. These results serve on the one hand as experimental data set for the later training of the data-based models and furthermore as reference data for the validation of the following simulation models.

Numerical Data Generation

For all 73 material combinations joined by clinching, simulation models for the joining process as well as the quasi-static shear and head tension test were built and calculated in Simufact Forming. The flow curves were obtained from the upsetting test [5]. Due to the main objective of numerical data acquisition, compromises had to be made in terms of accuracies and in favor of computational efficiency. Therefore, the joining process as well as the top tensile test were modeled in 2D and the shear tensile test in 3D (Fig. 2). In order to implement the desired amount of simulations, the joining simulation was integrated into the testing simulation with little effort [4].

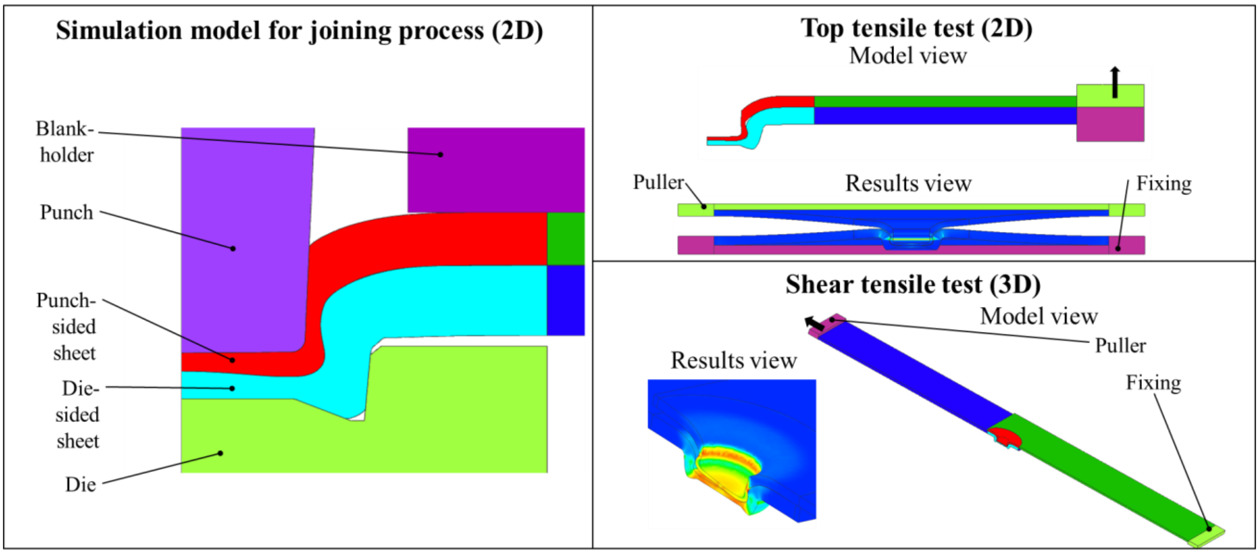


Fig. 2: Structure of the simulation models for the joining and the strength simulation of the clinching process

Validation of the simulation models

For the 73 considered material combinations, it was observed that the frictional condition has a strong influence on the geometrical parameters, the overall contour and the process curve. In the joining simulation, three contact pairs are used to tune the frictional condition between the punch and the upper sheet, the upper and the lower sheet, and, the lower sheet and the die, respectively. The frictional conditions were identified by minimizing the difference between the computed and experimentally acquired contour. The combined friction law was used to model the frictional conditions. To limit the number of unknown frictional parameters, the Coulomb parameter was kept constant to a value reported in [5]. The shear parameter of each contact pair was inversely identified based on the cross-sectional contour. The average shear friction parameters per material combination can be found in Table 2 for all 73 cases.

Table 2: Reference values of the shear friction parameter for each contact pair per material combination. The Coulomb parameter is 0.1 except for the Alu-Alu material combination it is 0.2.

Material [Punch-Die]	Punch side	Sheet side	Die side
Steel-Steel	0,27	0,16	0,39
Steel-Alu	0,31	0,14	0,27
Alu-Steel	0,22	0,11	0,61
Alu-Alu*	0,41	0,07	0,37

* Coulomb parameters = 0,2 (by default 0,1)

After the forming simulation, the solution variables are transferred to the strength simulations. To validate the forming and subsequent strength simulations, the most important parameters are compared by considering the absolute deviation. For the joining simulation, this means that the geometrical parameters and the joining force are compared. In the case of the mechanical tests, only the maximum forces are considered. These deviations are shown in Figure 6. The reported overall deviation (i.e. the average of the deviations found for the joining and strength simulations) considers the 50 best results. It can inferred that the overall simulation accuracy is 16% , 20% and 22% for the forming, top tensile and lap shear simulation, respectively. These 50 simulation models were used for the numerical variation simulations.

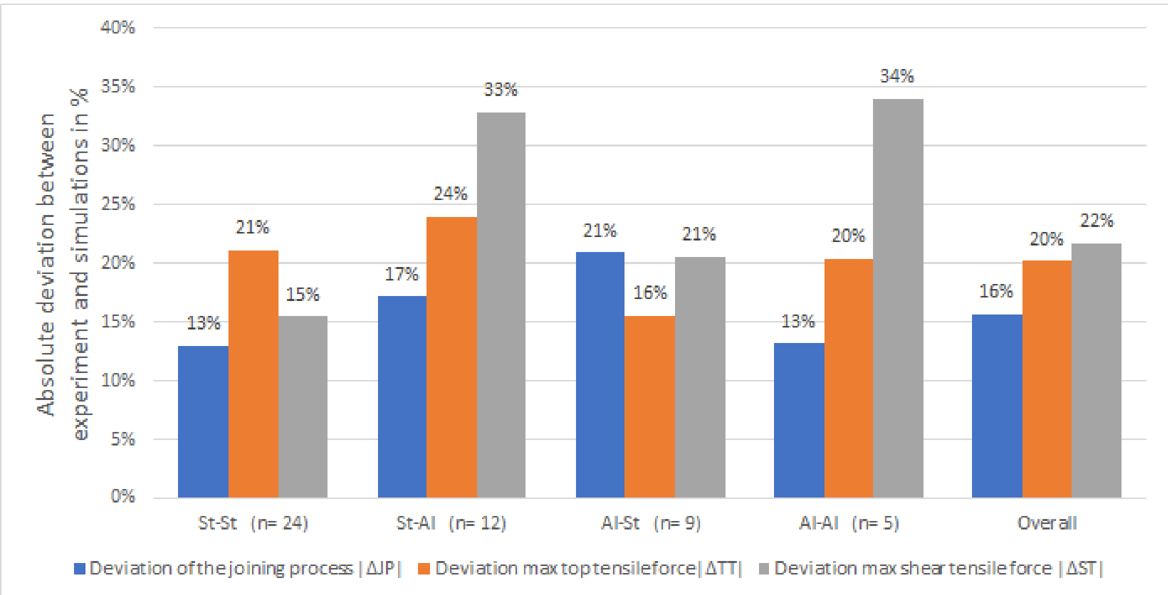


Fig. 3: For each material combination and for the 50 cases (overall), the absolute deviation was calculated between experimental data and the geometrical parameters and the joining force (blue), the maximum top tensile strength (orange) and the maximum shear tensile strength (grey) based on FEA data.

For each of the 50 simulation models, 20further variations were calculated in which the material strength, bottom thickness and punch and die geometry were varied on the basis of a statistical test plan. From these 1000 built and calculated joining process and test simulations, 712 could be evaluated in a technologically meaningful way for clinching. [6]

Algorithm-Based Strength Prediction

Table 3 lists the investigated models for the prognosis of the joint strength. In this regard, the experimental data with the results of 73 joints and the numerical data with 712 joints is used to train and validate the regression algorithms.

Table 3: Considered algorithms and the number of hyper parameter variations [6]

Algorithm	Hyper parameter variations
Linear regression (LR)	1
Huber regression (HR)	36
Support Vector Regressor (SVR)	40
k-nearest-neighbor (kNN)	40
Gradient Boosted Decision Tree (GBDT)	9
Multilayer perceptron – artificial neural network (MLP)	27

The algorithms are evaluated on basis of the coefficient of determination R^2 (Eq. 1). For this purpose, the available data are divided into training (80%) and test (20%) data and the prediction results are compared with the test data. [7]

$$R^2 == 1 - \frac{\sum(y_i - \hat{y_i})^2}{\sum(y_i - \bar{y})^2} \tag{1}$$

Input and output data are divided as follows:

Table 4: Input and output data for the training of the algorithms [4]

Category	Characteristic value	In-/ Output
Material properties (Table 1)	Ultimate tensile strength	Input
	Sheet thickness	
	Type of material (steel, aluminum)	
Process parameters	Die geometry	
	Punch geometry	
Geometrical joint characteristics	Interlock f	
	Neck thickness t_n	
	Min. thickness die & punch-sided part $t_{b,d\text{-}min}$ & $t_{b,p\text{-}min}$	
	Bottom thickness t_b	
Joint strength	Max. top tensile force F_{maxTT}	Output
	Max. shear tensile force F_{maxST}	

The results show that for the simpler algorithms, such as Linear Regression, the influence of the amount of data is rather small and no sufficient forecast quality (R^2 approx. 0.6) can be achieved. With more complex algorithms like the Gradient Boosting Decision Tree or the MultiLayer Perceptron, very good forecast qualities (R^2 approx. 0.9) can be generated with the larger numerical data set. This confirms that a higher effort in data acquisition and as well as in training is necessary for usable data-based prediction models.

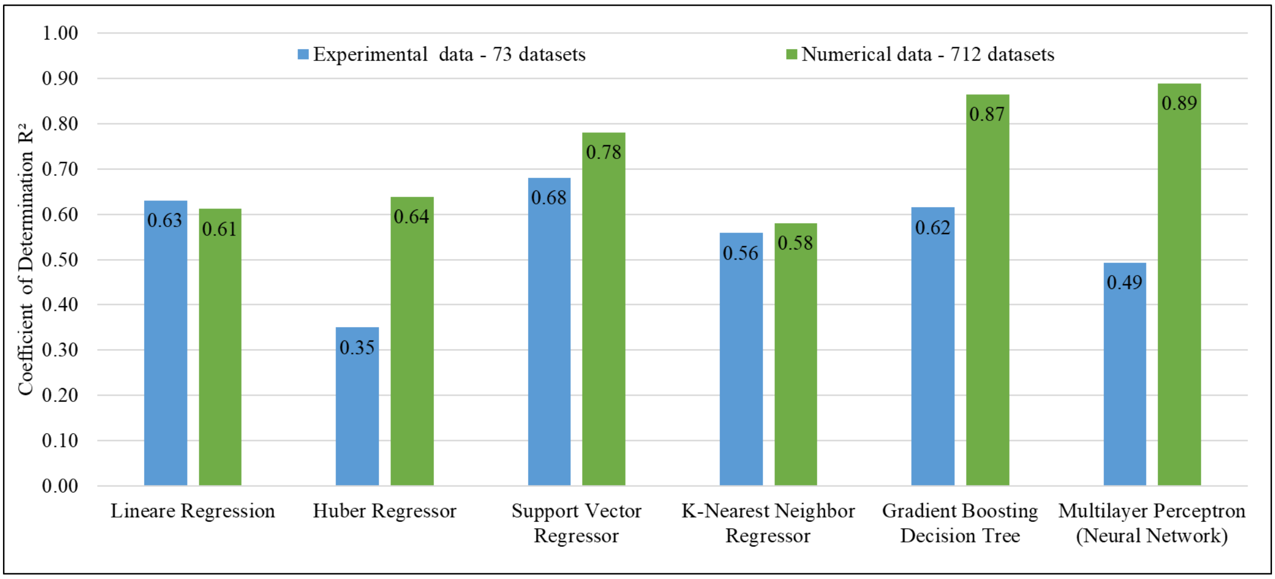


Fig. 4: Comparison of the Coefficient of prognosis R^2 for different regression algorithms trained with varying amount of data

Analytical strength prediction for Clinching

When predicting the strength with analytical formulas, it is important to know that there are two dominant failure mechanisms. The first dominant failure mode is fracture in the punch side sheet. The second failure mode is completely dominated by plastic deformation. In this case, the clinch joint will locally deform hereby reducing the interlock between both sheets eventually leading to unbuttoning of the joint. In practice, a combination of both failure modes occurs. To derive an analytical expression, however, it is mandatory to consider the most dominating failure mode. Because of these two dominating failure modes, each analytical prediction requires two analytical calculations. The dominating failure mode of the clinch is then determined by the lower bound strength. In the literature, various formulas can be found for both the top tensile strength and the shear strength. A brief summary of all models to predict failure by plastic deformation is given here.

<u>Top tensile strength</u>

The failure process during a top tensile test can be compared with that of the tube sinking process [8]. This implies that the die-side sheet can be seen as a rigid 'die'. An additional simplification that all authors rely on is that the inner diameter d of the 'tube' remains constant during the top tensile test. In a quasi-static test, there must be equilibrium between all stresses enabling the use of the slab equilibrium method to derive analytical solutions. Fig. 5 shows the simplified geometries with their most important measurements. Chan-Joo Lee et al. [9] adopt another simplification of the tube drawing process which states that $t_n << d$ enabling to arrive at Eq. 2 with $\beta = \mu/\tan\alpha$ *and* A_n *is the cross-sectional area of the tube at the neck thickness* t_n. The stress used in the equation by Chan-Joo Lee [9] is the average flow stress (AFS) in the clinched region which is rather a vague description. In this paper, the average flow stress was extracted from the numerical joining simulation (Simufact) in the neck area thereby excluding the bottom area of the punch-side sheet.

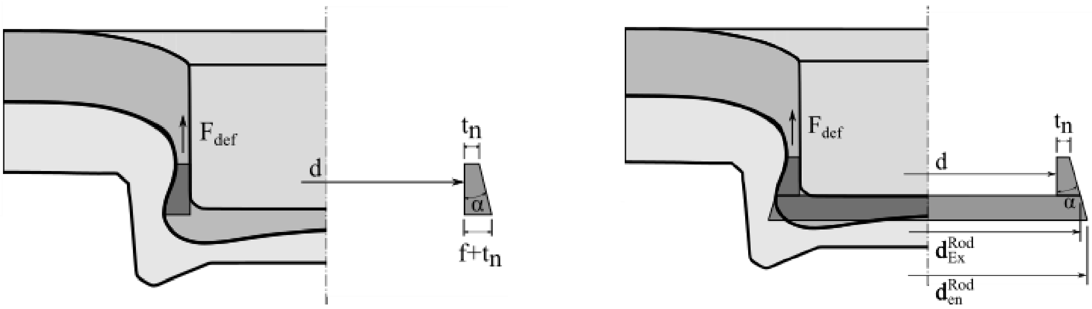


Fig. 5 The simplification of the clinch joint. Left) Tube section used by Chan-Joo Lee et al. [9] and Y. He et al. [10] Right) Tube section with the additional rod section used by Coppieters et al. [22]

Because the diameter of the punch used for clinching is much smaller than in a tube sinking process, the assumption of $t_n << d$ is questionable. He and co-workers [10] ignore this assumption leading to Eq. 3. To avoid the need for FEA-data, He et al. [10] estimate the stress based on the adopted hardening law (Swift). It must be noted that He et al. [10] employ an estimation of the engineering strain within the joint to arrive at the true stress, which is again questionable.

$$F_{def} = A_n\left(\frac{1+\beta}{\beta}\right)\left\{1-\left(\frac{t_n}{f+t_n}\right)^{\beta}\right\}\sigma_{AFS} \tag{2}$$

$$F_{def} = A_n\left(\frac{1+\beta}{\beta}\right)\left\{1-\left(\frac{A_n}{A_f}\right)^{\beta}\right\}K\left(\frac{t_1+t_2-X}{t_1+t_2}\right)^{n} \tag{3}$$

In the approaches by Chan Joo Lee et al. [9] (Eq. 2) and He et al. [10] (Eq. 3), the bottom part of the clinch was not considered. Coppieters et al. [11] argued that the bottom part contributes to the strength as it radially compressed when assuming a rigid die (i.e., the die-side sheet). Therefore, the joint was divided into a 'rod'- and 'tube'-part, more details can be found in [11]. The slab method was applied to the 'rod'-part and connected to the 'tube'-part. The latter approach leads to following equation with $\omega = 2\pi - (1+\beta)$:

$$F_{def} = A_n\left\{-\frac{4\pi}{\sqrt{3}}\sigma_{yield}^{Tube}\left(\frac{1+\beta}{\omega}\right)+\left[\frac{A_{ex}^{Rod}\sigma_{yield}^{Rod}\left(\frac{1+\beta}{\beta}\right)\left\{1-\left(\frac{A_{ex}^{Rod}}{A_{en}^{Rod}}\right)^{\beta}\right\}}{A_{en}^{Tube}}+\frac{4\pi}{\sqrt{3}}\sigma_{yield}^{Tube}\left(\frac{1+\beta}{\omega}\right)\right]\left(\frac{A_{en}^{Tube}}{A_{ex}^{Tube}}\right)^{\frac{\omega}{2\pi}}\right\} \tag{4}$$

Coppieters et al. [11] (Eq. 4) also concluded that the derived formula was only valid for i) the case that the die-side material does not deform ii) unbuttoning effects can be ignored. The former assumption relates to the strength of the lower sheet compared to the upper sheet. Regarding the latter, it can be stated that unbuttoning effects relate to the experimental set up, i.e. the clamping distance *R*. Therefore, Coppieters et al. [11] proposed an additional correction factor as to compensate for unbuttoning. This correction factor depends on the distance *R* which is the distance between the center of the clinch and the clamps. If *R*> 15 mm a reduction of about *37%* of the analytical strength prognosis is required.

Lap shear test

To calculate the lap shear strength, He et al. [10] and Coppieters et al. [12] use the von Mises criterion to convert the yield stress to the shear yield stress. Coppieters (Eq. 5) proposed to extract the stress state from a joining simulation. The stress state is equal to the AFS used in Eq. 2. He et al. resorted to a hardening law and an estimation of the equivalent plastic strain, see Eq. 6. X. C. He et al. [13] proposed Eq. 7 which requires the stress ratio (σ_x/σ_s) that can be determined by a graph provided in [11].

$$F_{def} = A_n \frac{\sigma_{AFS}}{\sqrt{3}} \tag{5}$$

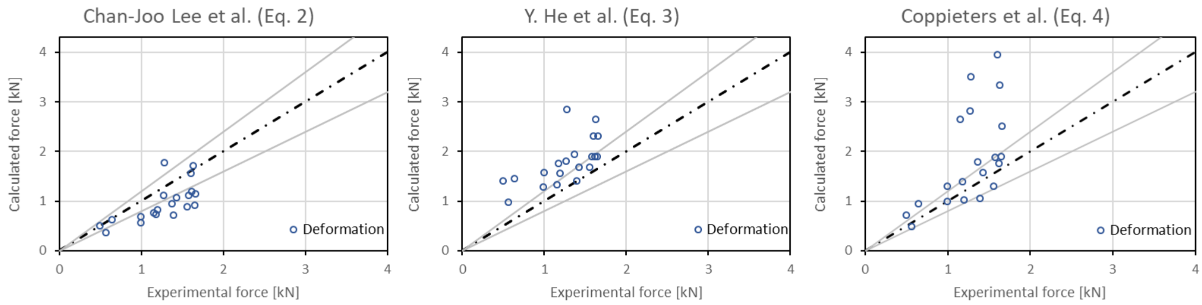
$$F_{def} = A_n \frac{k\left[\frac{t_1 - t_n}{t_1}\right]^n}{\sqrt{3}} \tag{6}$$

$$F_{def} = 0{,}9\left[1 - \frac{1 - \frac{\sigma_x}{\sigma_s}}{e^{\frac{4\mu t_b}{2{,}1d}}}\right] k \left(\frac{f}{t_b}\right)^n \frac{\pi d^2}{4} \tag{7}$$

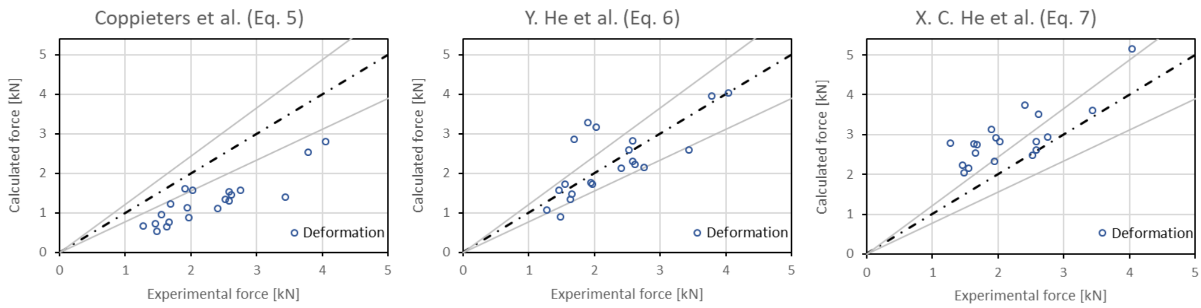
Data analysis

The predictive accuracy of the analytical strength formulas is assessed by considering 20 joints from the database (50). The selected cases were evenly distributed over four material combinations. Failure in all considered cases was dominated by plastic deformation. Fig. 6 (a) and (b) show the analytical predictions for the top tensile and lap shear strength, respectively. The figures show the 20 predictions compared to the experimentally obtained strength. The grey solid lines indicate the predictive accuracy of the numerical simulation.

It can be inferred from Fig. 6 (a) that the approach of Chan-Joo Lee and Y. He consistently underestimate and overestimate the top tensile force, respectively. This clearly indicates that the model based on tube sinking is not sufficiently accurate. Fig. 6 (a) shows that for 14 out of the 20 cases, the model by Coppieters et al. [11] has a similar predictive accuracy as the numerical simulation. Yet, for 6 out of the 20 cases the force is significantly overestimated. It was found that for these 6 cases, the necessary assumptions where violated. Indeed, a rigid die could not be assumed due to the material combination: the die-side material is much softer than the punch-side material. In addition, it is found that for cases with a large interlock f, the approach of Coppieters et al. underestimates the unbuttoning effect. It is clear that this model performs well provided that the necessary assumptions are valid.



(a)



(b)

Fig. 6: Analytical strength prediction for a deformation failure mode (a) top tensile strength (b) shear tensile strength

Fig. 6 (b) shows the analytical predictions of the shear lap strength. The tube model by Y. He et al. gives a good overall accuracy, yet it is unclear how this formula was derived. The semi-analytical tube model of Coppieters et al. consistently underestimates the shear force. The latter indicates that the failure mechanism cannot be simplified to a pure tube shearing process. Moreover, the area loaded during the lap shear test is more situated around the neck thickness where the stresses are higher than in the area where the AFS is extracted. The model by X.C. He presents an acceptable accuracy but is rather cumbersome because of the stress ratio (σ_x/σ_s) that needs to be determined as described in [13].

Summary and Outlook

The results described here show the potential of data-based and analytical prediction of joining results. In the case of the data-based models, it was shown that the forecast quality depends very strongly on the available quantity and quality of the data. Only with a larger amount of data can more complex regression models with a higher forecast quality be trained sufficiently well. If the data quantity is available and the know-how to build the models accordingly, very good predictions for clinching can be implemented with the data-based models.

The analytical models enable to predict the top tensile strength and the lap shear strength with relatively good accuracy provided that the necessary assumptions are not violated. There is clearly room for improvement, but the analytical models can be used in conjunction with joining simulations to have a quick initial guess of the mechanical strength.

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