Data-driven analysis of cold-formed pin structure characteristics in the context of versatile joining processes

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Abstract. Due to increasingly strict emission targets and regulatory requirements, especially for companies in the transport industry, the demand for multi-material-systems is continuously rising in order to lower energy consumption. In this context, mechanical joining processes offer an environmentally friendly and flexible alternative to established joining methods, especially in the field of lightweight design. For example, cold-formed cylindrical pin structures show high potentials in joining multi-material-systems without auxiliary elements. The pin structures are joined either by pressing them directly into the joining partner or by caulking with a pre-punched part. However, to evaluate the strength of the joint and to ensure the joining reliability for versatile processes, such as changing joining partners or batch variations, engineering designers currently have only limited design principles available compared to thermal joining processes. Consequently, the design of an optimal pin joint requires cost- and time-intensive experimental investigations and adjustments to design or process parameters. As a solution, data-driven methods offer procedures for structuring data and identifying dependencies between varying process parameters and resulting pin structure characteristics. Motivated by this, the paper presents an approach for the data-driven analysis of cold-formed pin structures and offers a deeper understanding of how versatile processes affect the pin characteristics. Therefore, the application of an intelligent design of experiment in combination with several machine learning methods enable the setup of a best-fitting meta-model. Resulting, the determination of a mathematical model provides the opportunity to accurately estimate the pin height considering only relevant geometrical and process parameters with a prediction quality of 95 %.

1. Introduction
More and more countries are committing to increasingly strict climate targets or striving for climate neutrality. Consequently, this accelerates the trend away from fossil fuels towards alternative energies. However, these regulatory requirements can lead to major challenges in several industries like the automotive production sector. As an example, the shifting in vehicle sales towards e-mobility is continuously increasing during the last years. In addition, emission limits for existing and future combustion engines are becoming significantly stricter. In order to comply with these limits and to decrease emissions, the reduction of vehicle weight in particular is a measure to achieve these lower emissions. Therefore, the automotive industry relies on light weight material like high-strength steel and aluminium as well as fiber-reinforced plastics, which are combined to form multi-material systems or lightweight structures. In this way, the appropriate material is used in the right place to reduce vehicle
weight. Due to the differences in the stiffness, thermal expansion coefficients or chemical incompatibilities of these material combinations, new versatile joining processes are required, as existing joining processes often reach their limits when joining multi-material systems. A promising process for joining dissimilar materials is mechanical joining using pin structures. However, manufacturing of pin structures still poses a central challenge. For this reason, various processes are already used to apply pins to the surface of components. These include the SurfScult process [1], the Cold-Metal Transfer (CMT) process [2], Metal Injection Molding (MIM) [3], subtractive processes e.g. machining processes and various additive processes, e.g. Powder Bed Fusion using a laser beam (PBF-LB) [4] or Laser Metal Deposition (LMD) [5]. The disadvantages of these processes are often long cycle times, complex process chains or a process-related limitation of the possible component size. In addition, it can be difficult to integrate them into existing industrial process chains. Therefore, the cold extrusion of pin structures from the sheet metal plane is being investigated as a manufacturing process. Therefore, the advantages are short lead times, as multiple pin structures can be formed in one stroke, an increase in strength of the pin due to work hardening, a very good surface quality and the possibility to integrate the pin extrusion directly into existing industrial process chains. Compared to most of the above-mentioned processes, no additional weight is added, as the pins are created from the base material of the component itself. Particularly for metal and continuous-fibre-reinforced plastics, several investigations have already been carried out regarding the suitability of pin structures for joining those material combinations. However, there are currently only a few publications on joining metal-to-metal using pin structures [6]. Here, components can be joined either by directly pressing the pin into an unperforated joining partner, or by caulking. The latter inserts the pin through a perforated joining partner and subsequently upsets the pin head in order to create a form-fit and force-fit joint. Previous investigations [7] described that the pin height has a significantly influence on the resulting joint strength during direct pin pressing. When investigating pins with different heights (1.08 mm, 1.45 mm and 1.86 mm) extruded from a 1.5 mm steel sheet of DP600 which are subsequently joined with a 1.5 mm aluminium sheet of EN AW-6014-T4, a 33.7 % higher shear tensile strength was obtained for the 1.86 mm pins compared to the 1.08 mm pins. Additionally, to achieve a load-bearing joint for the joining by caulking, it is necessary to create a greater pin height in comparison to the sheet thickness of the joining partner. Thus, it is important to be able to react quickly and precisely to changing process conditions, batch fluctuations or varying joining to ensure an application-specific pin height. However, due to the limited availability of design principles and the time- and cost-intensive realization of experimental studies, the determination of suitable and optimal pin structures mainly bases on a small amount of data. As a solution, the application of data-driven methods enables the identification of patterns and dependencies between varying process parameters and target product properties. Therefore, the use of meta-models provides efficient techniques to represent implicit process and design knowledge by achieving a sufficiently accurate reproduction of all related information.

Motivated by this, the aim of this contribution is to increase the versatility of the cold-formed pin structure joining process using data-driven methods for the analysis of varying process parameters. Therefore, the investigation of the resulting pin height is used as a measure to evaluate the process variation. In addition, the determination of a mathematical model provides the opportunity to estimate pin heights by only taking few experimental investigations into consideration.

2. Experimental setup and methods
In this contribution, the cold forming process of pin structures is investigated in detail using a combination of experimental data, numerical simulation and data-driven analysis. Therefore, a forward flow process from the sheet metal plane is both numerically simulated and compared with experimental data. Using this model, process-relevant parameters are varied to investigate and quantify their influence on the pin extrusion process as well as the pin height as the target value. The numerical results are then approximated and dependencies are analyzed using a meta-model. To ensure transferability and broad applicability, a typical automotive material was used.
2.1. Material characteristics
The material used in this work is a dual-phase steel HCT590X + Z (DP600). The grain structure of the steel consists out of martensite and ferrite and, due to its high strength, DP 600 is frequently used in structurally relevant components in car body constructions in the automotive industry. The flow curves and the mechanical properties of the DP600 are extrapolated for different sheet thicknesses with the Swift strain hardening approach, depicted in Figure 1.

![Flow curve and mechanical properties of DP600](image)

**Figure 1.** (a) Flow curve of DP600 from the uniaxial tensile tests extrapolated with the Swift strain-hardening model, (b) mechanical properties of the DP600 steel blank with different sheet thickness, obtained with the uniaxial tensile test in rolling direction.

2.2. Cold-forming of pin structures - Experimental setup and FE-simulation
The pin structures used for joining dissimilar materials are produced with a forward extrusion process from the sheet metal plane. This process is numerically modelled within the scope of this work and the influencing variables are varied in order to identify dependencies and influences of process parameters on the height of the pin. To ensure that there are no interactions due to the formation of multi pin structures, only a single pin is investigated. In the cold extrusion process of the pin structures a multiacting tool is used in order to control and move the punch and blank holder independently of each other. A constant blank holder pressure is applied prior to the forming process to avoid a bulging of the sheet and to reduce the material flow outwards in the direction of the sheet metal plane. After the necessary pressure has been applied, the punch moves axially downwards at a constant speed and penetrates the blank. During this process, the material is displaced by the punch both axially into the die and laterally into the sheet metal plane and die cavity. An illustration of the extrusion process and the relevant process parameters are shown in Figure 2.

![Illustration of extrusion process and parameters](image)

**Figure 2.** Schematic illustration of the pin extrusion process with the relevant process parameters.

This experimental process was then numerically modelled with the simulation software LS-Dyna. Since only a single pin structure is analyzed, the axial symmetry of the process can be utilized. The simulation model with the important parameters is shown in Figure 3. To reduce the computing time and to cover
the large parameter space, the tools were modelled as rigid bodies and the steel sheet was divided into two sections connected via tied contact. Since the inner area is mainly affected by the deformation, a remeshing is automatically triggered and the mesh is refined with an edge length of 0.02 mm reproduce the high degrees of deformation. The material card Mat24_Piecewise_linear_plasticity was used to create the material model. Thereby, the flow curves of the investigated DP600 sheet thicknesses, shown in Figure 1, were integrated. The tool was meshed to ensure at least 5 elements over the entry radius to achieve a high geometric accuracy. The simulations themselves were parameterized and automated in order to generate the large number of different simulations necessary to cover the different parameter combinations.

| FE-simulation - Relevant parameters |
|------------------------------------|
| Simulation software | LS-DYNA |
| Solver | smp_d_R920 |
| Analysis | Implicit |
| Material Blank | Mat24_Piecewise_linear_plasticity |
| Material tools | Mat_20_rigid |
| Section | Shell |
| Element formulation | 15 - Axisymmetric solid (y-axis of symmetry) |

**Figure 3.** Illustration of the FE-model and relevant simulation parameters

Since the height of the pin structure is the key parameter for the investigation in this contribution, the numerical simulation model is validated using the pin height. Figure 4 compares the simulated pin height with the experimentally measured one. In addition, the important parameters are listed. For the static friction coefficient for the blank/die pairing, a value of 0.078 was used, which was determined in [8] for a lubricated DP600/carbide combination found in the physical process. For the sheet metal/blank holder pairing, a coefficient of friction of 0.14 was used, which was measured in [9] for a DP600/DP600 combination. It can be seen that for a punch penetration depth of 0.61 mm, the simulated pin height of 1.12 mm is ~4 % higher than the experimentally determined height of 1.08 mm. At a punch penetration depth of 0.74 mm, the simulated height is ~5 % higher. Based on these data, the FE model represents a reliable analysis tool of the process.

**Figure 4.** (a) Validation of the pin height and (b) constant parameters used for the numeric model

### 2.3. Data mining and meta-modelling

According to SIEBERTZ et al. [10] meta-models provide the opportunity to approximate and examine relationships between input parameters (e.g. geometrical dimensions) and relating manufacturing or product properties (e.g. tensile strength of joints). Therefore, the methods aim to achieve a sufficiently accurate reproduction of all related information. In addition, faster calculation and computing times offer high potentials for the data-driven analysis and design of technical systems (e.g. mechanical joining processes [11]). Although, the performances of meta-modelling techniques are steadily growing, the prediction quality of particular methods significantly differs for a given scenario. Thus, to guarantee a
high reliability and to identify the best fitting model, it is advisable to evaluate several estimators. Hence, this paper includes the application of a linear and polynomial regression, a support vector machine technique and an artificial neural network. Before the meta-modelling takes place, it is necessary to define relevant parameter and target properties. Afterwards, statistical methods described by MONTGOMERY [12] and SIEBERTZ et al. [10] enable the efficient use of a design of experiment (DoE) for the following carrying out of a virtual (FEM) or physical parameter study. Then, the employment of different performance scores provide the opportunity to determine the best fitting meta-model. This includes the root mean squared error (RMSE) [13], as the subsequent formula.

\[ \text{RMSE} = \left( \frac{1}{n} \sum_{i=1}^{n} (y_p^i - y_t^i)^2 \right)^{1/2} \]  

Alternatively, the Coefficient of Prognosis (CoP) value as defined by MOST and WILL [14] offers the opportunity to automatically scale the resulting prediction qualities. This means, that a CoP value of 0.9 equals a prediction accuracy of 90%.

\[ \text{CoP} = \left( \frac{1}{n} \sum_{i=1}^{n} \left( \frac{y_p^i - y_t^i}{\sigma_p \cdot \sigma_t} \right)^2 \right)^{1/2} \]

3. Definition of parameter spaces and design of experiment
Relating to the previous section 2, it is necessary to identify relevant geometrical, process or material parameters. For this, it is crucial to take expert knowledge as well as design principles into consideration in order to avoid the exceeding of manufacturing boundaries. Following, Table 1 includes an overview of the defined minimum and maximum values for the investigation of cold-formed pin structure characteristics (see also Figure 2). Therefore, the selection of boundaries relies on empirical knowledge of previous performed experimental studies including geometrical tool parameters (e.g. punch and die diameter) as well as process factors (e.g. friction).

| Parameter | Unit | Min. | Max. |
|-----------|------|------|------|
| Punch dP | (mm) | 3.0  | 5.0  |
| Die dD  | (mm) | 0.1  | 0.8  |
| Blank holder dBH | (mm) | 0.2  | 2.0  |
| Friction σBH | (MPa) | 0.05 | 0.05 |
| µ1 | | 10   | 10   |
| µ2 | | 200  | 200  |
| µ3 | | 0.02 | 0.02 |
| Sheet t0 | (mm) | 0.02 | 0.02 |
| BH dB | (mm) | 0.74 | 1.60 |

In the next step, the design of experiment takes place. Due to experimental costs and thus often the access to only a limited number of samples, the setup of a database is entirely based on numerical simulations (FEA). Resulting, the application of a Latin Hypercube Sampling (LHS) enables the multidimensional distribution of near-randomly parameter sets based on a space-filling design and the avoidance of artificial correlations between the input factors [10]. Following the initial database includes 330 design points for the sampling of 11 input parameter.

4. Results and discussion
To evaluate the usability of data-driven methods for the analysis of cold-formed pin structure characteristics, the presented approach is demonstrated measuring the created pin height \( h_p \) as an example. For this, the DoE and the following simulation setup of the particular geometries was carried out as mentioned above. Due to the application of algorithm-based geometrical plausibility checks, the identification of error terminations or design failures reduced the database to 312 samples (loss ratio of
5.45%). Then, for the evaluation of the pin height, an algorithm loads the outlier node of each pin structure into a backend system. Based on this, the following automatic extraction of specific outlier contour nodes provide an efficient procedure to identify the required pin height characteristic. Finally, the merging of the initial DoE database and the determined heights builds the basis for the subsequent meta-modelling steps. Furthermore, for the training and evaluation of the machine learning methods, the implementation of a 10-fold cross validation enables the identification of the best fitting technique for the given scenario. Therefore, the database is randomly divided into 10 equal-sized folds. Then, the methods are trained by choosing 9 folds as the training set and monitoring the model performance by using the remaining fold as the evaluation data. Figure 5 depicts the applied machine learning methods.

![Figure 5. Performance of different machine learning methods.](image)

It can be seen, that the polynomial regression fits the training data best by showing a constant CoP value greater 0.8. Although, the use of an artificial neural network also achieved well performing results, the CoP values showed higher fluctuations. The linear regression and support vector machine algorithm obtained only poor performance qualities for the given scenario.

![Figure 6. Calculation of first- and total-order sensitivity indices.](image)

Thus, based on the identification of the best fitting meta-model, the performing of a variance-based sensitivity method, described by SOBOL [15] and SALTELLI [16], enables the determination of how varying values of an input parameter effects a particular target variable. Accordingly, it is possible to classify the input parameters based on their impact into important and irrelevant variables. In addition, the calculation of higher-order indices provides a deeper understanding of possible interactions between input parameters. Based on this, the calculation of first-order indices shows the effect of single input parameters on the target variance, while the measuring of total-order indices also includes interactions between input parameters. In summary, if total-order indices demonstrate clearly higher values in comparison to the first-order values, parameter interactions are likely occurring. Figure 6 depicts the results of the sensitivity analysis for the investigation of parameter influences on the pin height.
While the punch penetration depth and the die diameter as well as the sheet thickness are showing high sensitivity indices, one can see that the friction parameters, the sheet diameter and the blank holder parameters are having only a minor impact on the resulting pin height. Additionally, the differences between first- and total-order indices of the punch penetration depth and the sheet thickness indicate higher-order interactions between these parameters. This corresponds to the initial definition of the punch penetration depth as a proportional of the selected sheet thickness. In addition, the strong impact of the punch penetration depth on the pin height can be explained by the direct proportionality of the displaced material volume to the joining distance of the punch. Thus, with increasing penetration, more material is displaced axially as well as laterally into the die. Moreover, the dependence of the pin height on the sheet thickness can be linked to the displaceable volume. This means, the smaller the thickness gets, the less material is available for the pin extrusion. Additionally, the analyzed sheet thicknesses including different strain-hardening characteristics (Figure 1), which also affect the pin height. Furthermore, the sensitivity value of the die diameter also indicates a noticeable influence on the pin height. In this context, if the die diameter approaches the punch diameter, the pin height decreases continuously until shear cutting occurs. Compared to the previous described parameters, the sensitivity indices of the punch diameter demonstrate only a minor influence on the pin height. This belongs on the fact that a large portion of the pin structure consists of the material located directly above the die opening, as the flow resistance shows the lowest value in this area. Furthermore, the increase of the punch penetration depth and thus strain hardening effects of the surrounding materials causes a greater lateral material flow into the die, as the surrounding material acts like a reinforcement and restricts the material displacement into the sheet plane. This leads to the conclusion that the influence of the punch diameter is getting higher with increasing penetration depth and thus solidification of the material.

In the next step, based on the calculated indices, it is possible to stepwise reduce the initial database by only taking relevant parameters into consideration. Thereby, after each reduction step, the reapplication of the previous selected machine learning method monitors if the meta-model still achieves a required CoP value greater 0.8. Once this procedure is done, the final meta-model shows a sufficiently high model quality of 90% by only requiring the specification of the punch and die diameter as well as the punch penetration depth and the sheet thickness. Since the presented assumptions entirely base on numerical data, the model was evaluated on a set of 15 experimental created pin structures. For this purpose, the meta-model reached a prediction quality of 95%. Thus, it can be assumed that the presented approach ensures a sufficiently high reliability. In addition, the polynomial regression based meta-model provides the opportunity to determine a mathematical model for the description of the underlying relationships between the input and target variables. Through this, product developers have the opportunity to estimate the resulting pin height considering only relevant input parameter.

\[
Pin_{Height} = 1.003x_0-1.551x_1+6.803x_2x_3-8.288x_1^2+0.016x_0^2-0.494x_0x_1+2.081x_0x_2x_3-0.890x_0x_3+0.686x_1^2-4.413x_1x_2x_3+2.613x_1x_3+3.966(x_2x_3)^2-6.809x_2x_3^2+4.051x_3^2+3.189
\]

\[x_0 = \text{punch diameter}, x_1 = \text{die diameter}, x_2 = \text{punch penetration depth}, x_3 = \text{sheet thickness}\]

5. Summary and outlook

In the present contribution a forward flow process for forming metallic pin structures was numerically modelled and investigated using data-driven analyses. Thus, the influences of different parameters on the process were investigated with the help of a meta-model. Here, the punch penetration depth, sheet thickness, die diameter and punch diameter were identified as the significant factors influencing the target value of the pin height. The experimental results have shown that the data-driven approach is well suited to identify significant influences of process parameters on the forming process. The data furthermore suggest that a sufficient model quality can be achieved to predict experimental results with a confidence level of 95%. Due to the good performance and prediction quality of the meta-model, the versatility of the pin extrusion process and consequently of the joining process can be improved. Additionally, the determination of a mathematical model provides an accurate and fast approach for the estimation of resulting pin heights under a certain circumstance. Building on this, further parameters
and in particular other materials should be included in the evaluation in future work. In addition, based on these results, not only the manufacturing process of the pin structures but also the joining process and finally the joint characterization should be considered for a data-driven approach. This paves the way to a design supported by data-driven analysis of mechanical joining with cold-formed pin structures in versatile process chains.

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