AI

Article

Estimation of Clinch Joint Characteristics Based on Limited Input Data Using Pre-Trained Metamodels

Christoph Zirngibl [1,*], Benjamin Schleich [2] and Sandro Wartzack [1]

[1] Engineering Design (KTmfk), Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Martensstraße 9, 91058 Erlangen, Germany
[2] Product Life Cycle Management, Technical University of Darmstadt, Otto-Berndt-Straße 2, 64287 Darmstadt, Germany
* Correspondence: zirngibl@mfk.fau.de

Abstract: Given strict emission targets and legal requirements, especially in the automotive industry, environmentally friendly and simultaneously versatile applicable production technologies are gaining importance. In this regard, the use of mechanical joining processes, such as clinching, enable assembly sheet metals to achieve strength properties similar to those of established thermal joining technologies. However, to guarantee a high reliability of the generated joint connection, the selection of a best-fitting joining technology as well as the meaningful description of individual joint properties is essential. In the context of clinching, few contributions have to date investigated the metamodel-based estimation and optimization of joint characteristics, such as neck or interlock thickness, by applying machine learning and genetic algorithms. Therefore, several regression models have been trained on varying databases and amounts of input parameters. However, if product engineers can only provide limited data for a new joining task, such as incomplete information on applied joining tool dimensions, previously trained metamodels often reach their limits. This often results in a significant loss of prediction quality and leads to increasing uncertainties and inaccuracies within the metamodel-based design of a clinch joint connection. Motivated by this, the presented contribution investigates different machine learning algorithms regarding their ability to achieve a satisfying estimation accuracy on limited input data applying a statistically based feature selection method. Through this, it is possible to identify which regression models are suitable to predict clinch joint characteristics considering only a minimum set of required input features. Thus, in addition to the opportunity to decrease the training effort as well as the model complexity, the subsequent formulation of design equations can pave the way to a more versatile application and reuse of pretrained metamodels on varying tool configurations for a given clinch joining task.

Keywords: mechanical joining; clinching; machine learning; design of experiment; FEM

Citation: Zirngibl, C.; Schleich, B.; Wartzack, S. Estimation of Clinch Joint Characteristics based on limited Input Data using pre-trained Metamodels. *AI* **2022**, *3*, 990–1006. https://doi.org/10.3390/ai3040059

Academic Editors: Kenji Suzuki and José Manuel Ferreira Machado

Received: 23 September 2022
Accepted: 6 December 2022
Published: 8 December 2022

1. Introduction

Given the cost-efficiency and repeatability of clinching, the technology enables the joining of two or more sheets without the involvement of auxiliary elements, such as rivets. Furthermore, the ability to generate multimaterial assemblies involving dissimilar and coated materials is highly beneficial for use in lightweight designs. Thus, clinching represents a serious alternative to widely applied thermal joining methods, such as welding [1]. In this regard, further process [2,3] and tool developments [4] are available in the field of mechanical clinching, whereby this contribution focuses on the generation of round clinch joints. However, to guarantee a robust dimensioning of the resulting joining connection, not only is the previous selection of a suitable production technology important but the reliable design of the individual joint also needs to be focused on in more detail. For this purpose, product engineers can only refer to fewer standards, such as in [5,6], or a few experimental studies (e.g., in [7]). To face this lack of information, previous contributions introduced the utilization of data-driven or machine learning methods [8] for the accurate analysis and estimation of quality-relevant clinch joint properties as a promising solution. Because the coverage of the entire joining process mainly implies different process or tool factors, the generation of meaningful regression models consists of a wide range of input parameters. However, if not all required input data can be provided for new or changing tool configurations, pretrained metamodels often reach their prediction limits. This often results in increased uncertainties and inaccuracies within the metamodel-based design of a clinch joint connection and thus to a reduced reliability of developed products. Furthermore, the consideration of irrelevant input features can lead to a significant increase of the prediction model's complexity and thus to growing computational as well as modeling efforts. Motivated by these points, the presented contribution considers different machine learning algorithms and evaluates their ability to achieve a satisfying estimation accuracy on limited input. Therefore, the implementation of a correlation-based analysis (calculation of Pearson's correlation coefficients) as a feature-selection strategy combined with the calculation of prediction quality measurements, offers the opportunity to evaluate the performance of different machine learning algorithms on varying input data. As a result, models are available that show a significantly reduced complexity by at the same time achieving satisfying prediction qualities. This means that product engineers can achieve reliable estimations of clinch joint properties even if only a certain number of input features is provided. Thus, in addition to the decreased modeling effort, the results can pave the way to a more versatile application of pretrained regression models on varying tool configurations for a selected joining task.

2. Related Work

Given the intention of reaching a high prediction quality of clinch joint properties for a certain joining task, few contributions investigated the application of machine learning and data-driven methods. For instance, Oudjene et al. [9,10] analyzed how varying tool design parameters influence geometrical joint properties, such as the interlock and neck thicknesses. Therefore, the utilization of an adopted response surface methodology in combination with a moving least-square (MLS) approximation identified optimized tool designs (punch, die) resulting in improved joint resistances against head tensile loading.

By using these results as a fundamental, the authors in [11] set up a predictive model (Kriging metamodel) to build a response surface describing the clinching process. Finally, this method enabled a further improvement of the joint strengths regarding head tensile loading (+10%, 623 N to 834 N) in comparison to the previously introduced MLS approximation.

Because not only the clinching process affects the resulting joint properties, Roux and Bouchard [12] additionally involved ductile damages in the material behavior as an input parameter. In this context, the application of a global optimization algorithm obtained enhanced geometric joint characteristics (neck and interlock). Through this, the defined tool configurations achieved a significant change in the mechanical strengths of the joints (head tensile +13.5%, shear tensile +46.5%) compared to an initial die and punch design.

Another study [13] investigated the utilization of artificial neural networks (ANN) for the estimation of the joint strengths in a clinching process with an extensible die. Therefore, an intelligent design of experiment (DoE) using a Taguchi L27 orthogonal array represents five tool parameters divided over three levels. Following the model training and fitting process, a meaningful ANN enabled the prediction of different joint properties for varying tool configurations. In this regard, the subsequent use of a genetic algorithm (GA) identified optimal design parameters for changing blank thicknesses.

A further approach was demonstrated by Eshtayeh et al. [14]. The authors introduced a procedure for the combined use of a Taguchi-based Grey method with an analysis of variance to determine enhanced tool designs considering a dissimilar material connection. In this context, a Taguchi L27 DoE with a signal-to-noise ratio builds the basis for the subsequent obtainment of impact factors of different tool configurations on multiple clinch joint properties (interlock, neck, and bottom thickness).

Wang et al. [15] demonstrated a novel method aiming to identify an optimized contour of the joining tools through the direct communication between a genetic algorithm and a finite element simulation model. Through this, it is possible to adjust individual positioning coordinates of previously parameterized shape contour nodes based on the results of the current GA population. Finally, an optimal contour of the die shows increased clinch joint properties by improving the joint's resistance against fractures during the clinching process at the same time.

Beside the inclusion of tool design parameters, Wang et al. [16] also puts process factors for the investigation of several joint characteristics, such as the interlock and neck thickness as well as the tensile force, into consideration. Therefore, the authors used a combination of the response surface method with a nondominated sorting genetic algorithm (NSGA-II) to achieve an optimized clinching tool and process configuration for the analyzed use case.

A novel approach was introduced by Schwarz et al. [17]. Thereby, the use of a principal component analysis (PCA) characterizes individual clinching geometries through the calculation of statistical eigenmodes combined with the following setup of PCA-based metamodels. The resulting derivation of a functional relationship between the created joint contour and the particular input factor set offers the opportunity to apply a genetic algorithm for the improvement of interlock and neck thickness by simultaneously not exceeding maximum normal stress values during the joining process.

Bielak et al. [18] and Martin et al. [19] used metamodels to describe the effect of pretraining in the joining area on geometric characteristics and load capacity. In this context, validated FE simulation models combined with varying materials and sheet thicknesses were considered.

In comparison to this, the authors in [20] introduced a novel method for the definition of optimized clinching tools by using a deep reinforcement learning algorithm. For this purpose, the training of an agent represented by an artificial neural network predicts individual clinch joint characteristics without the consideration of labeled input data. Moreover, the setup of a value-based deep learning algorithm (Q-Learning) provides the opportunity to select an optimal design of joining tools in a multidimensional solution space.

3. Research Questions

Whereas available works have mainly focused on the setup and training of several data-driven or machine learning algorithms considering use case-related databases, this contribution investigates the influence of limited input data on the prediction accuracy of different regression models. In particular, if product engineers cannot provide data to all required input parameters for a new or changing joining task, pretrained and implemented metamodels often show decreasing prediction qualities. Because a poor estimation of individual target variables can result in an inaccurate or incorrect dimensioning of product components, the investigation of how pretrained regression models response on limited data is crucial. In this context, following the theoretical and methodical background, the setup of a parameterized and validated clinching FE simulation model combined with an intelligent design of experiment enables the generation of an initial set of data. Based on this, the subsequent application of a statistically based feature-selection method provides the opportunity to answer three research questions (RQ).

First, the focus is on the evaluation and comparison of different machine learning algorithms considering 330 data points and 13 input features. Therefore, the aim is to answer the question of which regression models show the best ability to estimate individual clinch joint properties for the given joining task and which methods are less suitable (RQ1). Then, Section 5.3 deals with the application of a statistically based feature selection method. In this context, the systematic reduction of input parameters provides a suitable approach to answer the question of whether the considered models are capable of achieving satisfying estimation qualities for varying input data and which parameters are at least required for this (RQ2). Simplified and less complex predictive models are available. Based on this, the subsequent Section 5.4 introduces mathematical representations of the generated models and evaluates whether these design equations are feasible and applicable for the accurate description of clinch joint characteristics (RQ3). This can then pave the way to a reliable design of clinch joining connections without the necessity to once again set up metamodels for a given joining task. To evaluate the results, an experimental study using an exemplary tool configuration is considered.

4. Method

In the following, a brief overview of the involved methods for the generation of a numerical clinching process (Section 4.2) and the definition of a suitable design of experiment (Section 4.3) is provided. In this regard, the realization of a correlation analysis combined with the application of different machine learning algorithms (Section 4.4) are presented within a statistical feature-selection method (Section 4.5). Therefore, the defined approach will be described in more detail in the subsequent Section 4.1.

4.1. General Approach

This chapter provides a brief overview of the applied general approach (cf. Figure 1), introducing the particular steps beginning with the data sampling process over carrying out a feature selection strategy to the final definition of minimum required subsets of input data considering only relevant parameters. In the context of this contribution, the focus will be on the investigation of varying joining tool configurations and thus mainly on geometrical parameters of the punch and die. The dimensions of the blank holder remain constant. Moreover, factors that are often unknown or can only hardly be specified, such as varying sheet thicknesses or material properties, are not considered in the presented work. At the beginning, the selection of a statistical DoE provides an intelligent way to investigate a large number of joining process configurations in a small number of numerical experiments. For this purpose, the specification of parameter boundaries (min./max.) combined with suitable factor distribution functions (Gaussian or uniformly distributed) enables the generation of an initial design space including 13 input features and 330 data points (Section 4.3). In this regard, an intersection between a parameterized FE clinching simulation model and the defined DoE offers the opportunity for a fast and consistent sampling and evaluation of several clinch joint connections. Additionally, an automated determination of geometrical joint characteristics (neck and interlock thickness) and the maximum transmittable shear loading as well as the applied force during the joining process is carried out in Section 4.2. Afterward, the application of a correlation-based feature selection method provides an efficient approach for the evaluation and comparison of machine learning algorithms based on their ability to describe clinch joint characteristics considering a limited number of input parameters. Therefore, the method calculates the linear influence of all input features on the investigated clinch joint properties. This allows the definition of a parameter-removing order, whereby features are sorted based on the calculated impact indices (sorting order: weak to strong impact). After this, the initial input data is iteratively reduced by the respective parameter in the removing order, while the number of available samples remains constant. However, due to high computational efforts of sampling numerical data, only a small set of 330 data points will be considered for this purpose. Based on this, and in order to reduce the occurrence of overfitting, a cross-validation method is implemented. In this context, the randomized and nonoverlapping division of the particular databases into ten equal folds (nine training and one testing fold) provides the opportunity to calculate 10 times the achieved prediction qualities (CoP values) of the considered machine learning algorithms for changing training and test configurations. In this regard and to ensure a reliable evaluation of the regression model's performance, the cross-validation method is applied for each feature removing iteration.

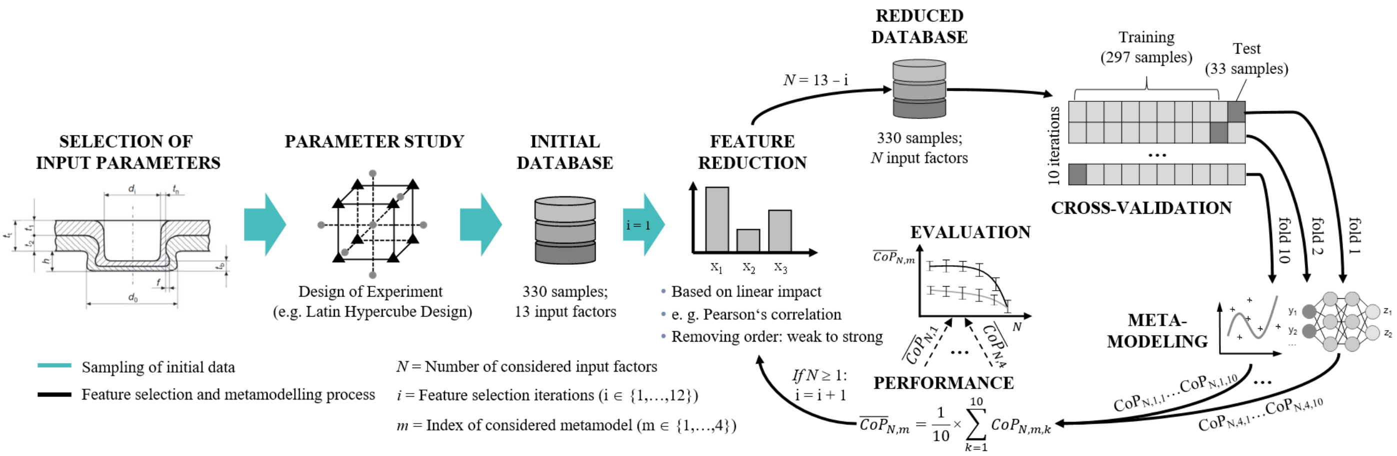
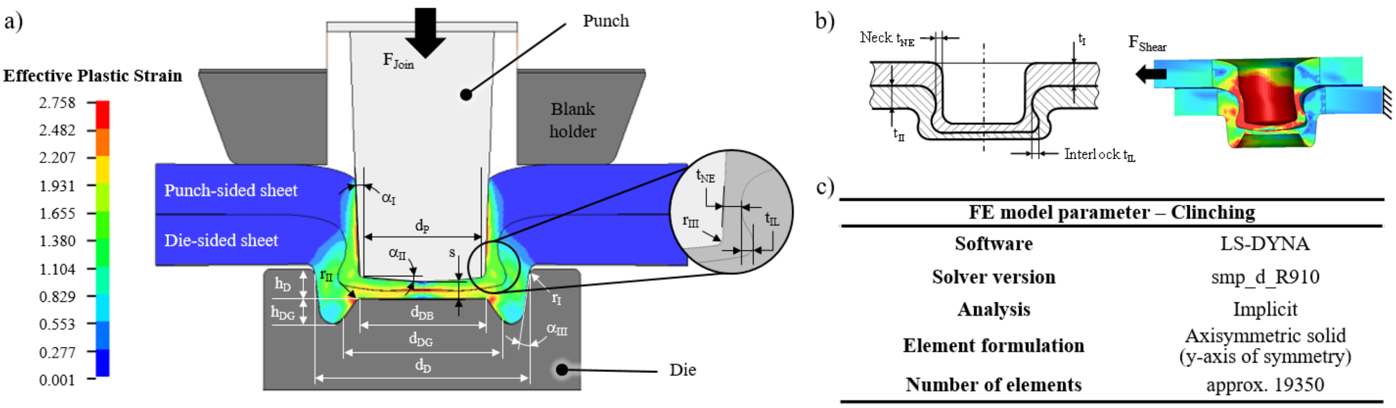


Figure 1. Illustration of the applied general approach.

In summary, the methodical approach is performed for each target variable separately and enables the identification of suitable regression models requiring only a minimum set of features to accurately estimate quality-relevant clinch joint properties. These steps will be demonstrated and carried out in Sections 5.2 and 5.3.

4.2. Numerical Clinching Process

Given the challenges of performing comprehensive experimental studies, such as a significant time- and cost-effort, the formalization of an initial database depends on the setup of a parameterized and validated finite element simulation model representing the clinch joining process. In this regard, a highly nonlinear elastic–plastic material behavior combined with strong deformations and element distortions have to be accurately covered. Therefore, the simulation software Ansys LS-DYNA (solver version: smp_d_R910) is capable of efficiently simulating a 2D-axisymmetric model configuration of the joining process including the die, punch, blank holder, and punch- and die-sided sheet. The experimental validation of the simulation model is demonstrated in [18,19]. In this context, Figure 2a illustrates the structural setup of the FE model and Figure 2b the determined quality-relevant clinch joint properties.



FE model parameter – Clinching	
Software	LS-DYNA
Solver version	smp_d_R910
Analysis	Implicit
Element formulation	Axisymmetric solid (y-axis of symmetry)
Number of elements	approx. 19350

Figure 2. Illustration of the clinch joining process (**a**), resulting joint properties (**b**) and FE model parameters (**c**).

Focusing on a realistic representation of the clinching process, the FE model consists of elastic (001-Elastic) and elastic–plastic (024-Piecewise_linear_plasticity) components. For example, whereas the die is defined as a entirely elastic part involving a fixed bearing of several bottom nodes, the punch and the blank holder are divided into elastic and fully rigid (020-Rigid) parts. Thus, the effects of an elastic tool deformation can be included in the analysis. Further settings regarding FE model parameters are summarized in Figure 2c. In addition, to demonstrate the joining process, the aluminum magnesium silicon alloy EN AW-6014-T4 (tensile strength, 245.7 MPa; yield strength, 137.8 MPa) with a nominal thickness of 2.0 mm, Young's modulus of 70 GPa, and a Poisson's ratio of v = 0.33 is used as the blank material. In contrast, the tools are represented by the material HCT590X (tensile strength, 610.8 MPa; yield strength, 397.3 MPa; Young's modulus, 210 GPa; Poisson's ratio, 0.3). Due to the occurrence of high element distortions, adaptive and automatic remeshing is activated during the simulation procedure. Because the investigation of the blank holder is not a part of this contribution, the geometrical dimensions of this tool and the related force (785 N) remain constant during the entire analysis and sampling process. Furthermore, the joining velocity of 2 mm s^{-1} causes a compression of the punch-sided material into the die-sided blank based on cold-forming. In this context, Figure 3a depicts determined experimental data compared with the results of the generated FE model. Because the values demonstrate a satisfying agreement, the numerical clinching model can be assumed as valid.

After this, the generation of a 3D FE simulation model enables the measurement of maximum shear load capacities based on the described approach in [21]. Therefore, the transfer and mapping of data, such as node coordinates as well as plastic strains and stresses, involves previous results of performed joining operations. Moreover, a constant test velocity of 10 mm/min is applied and decreases the effect of strain rates. In addition to the results in [21], the applicability of the simulation is further validated in Figure 3a,b. In this regard, the detected shear simulation curve (red) and the determined maximum transmittable shear force show a high agreement with the experimental force-displacement curves. However, no failure criteria and material damage is implemented, and the generated 3D simulation model can be assumed as sufficiently accurate.

To enable an automated and consistent carrying out of the introduced parameter study, the generated simulation models involve parameterized factors. Based on the approach in [22], an algorithm-based intersection between the design of experiment and the FE models provides the opportunity for a fast sampling of several clinching tool configurations. After this, an algorithm determines the individual clinch joint characteristics and automatically combines the DoE data with the obtained results [23]. Thus, an initial database of 330 samples will be available for the subsequent performance of a correlation-based feature-selection method.

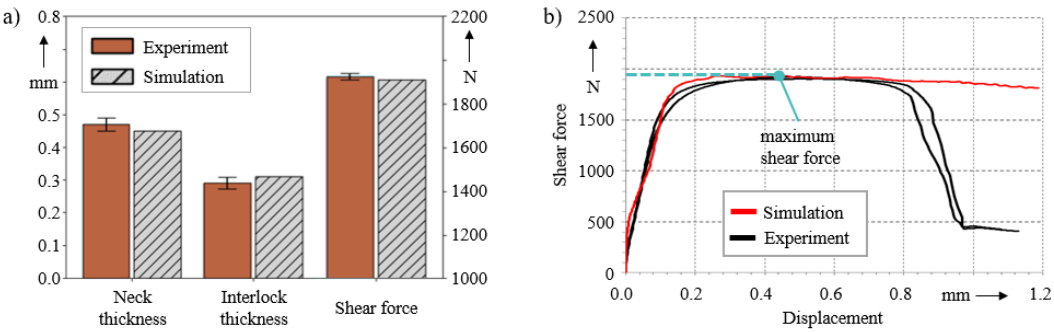


Figure 3. Experimental validation of clinch joint properties (**a**) and force-displacement shear curve (**b**).

4.3. Design of Experiments

To choose a suitable design of experiment, it is crucial to define the required input parameters of interest with relating distribution boundary values in advance. In this regard and in order to ensure a sufficient setup of parameter spaces, it is important to consider both expert knowledge based on empirical studies and manufacturing standards, such as in [5,6]. For instance, although the selection of tool dimensions often relies on preliminary numerical or experimental studies, the limitations of the punch penetration distance are mainly based on expert recommendations. In summary, Table 1 shows the chosen input parameters that represent the clinch joining process and their minimum/maximum boundaries. Furthermore, the constant settings of the blank holder and joining velocity are demonstrated.

Table 1. Input parameters and the relating minimum/maximum spaces.

Input Parameter	Unit	Min.–Max.	Input Parameter	Unit	Min.–Max.
Punch			**Die**		
Diameter d_P	mm	4.5–6.0	Diameter d_D	mm	7.5–8.5
Radius r_{III}	mm	0.1–0.6	Depth h_D	mm	0.8–1.8
Side draft angle α_I	deg	0.0–4.0	Groove depth h_{DG}	mm	0.5–1.3
Face draft angle α_{II}	deg	3.0–8.0	Bottom diameter d_{DB}	mm	3.5–4.8
Process			Groove diameter d_{DG}	mm	5.6–7.0
Punch penetration s	%	70–90 *	Corner radius I r_I	mm	0.1–0.4
Joining velocity	mm s^{-1}	2 (const.)	Corner radius II r_{II}	mm	0.1–0.4
Blank holder			Side draft angle α_{III}	deg	0.0–8.0
Force	N	785 (const.)			
Tool dimensions		const.			

* of total sheet thickness.

For the precise analysis of technical systems, often a high amount of data points are required. In this regard, the application of a statistical design of experiment provides an intelligent way to describe and represent extensive parameter spaces considering significantly fewer samples [24]. Moreover, in contrast to experimental studies, the involvement of parameterized FE models combined with the implementation of an intersection to the defined DoE enables the direct specification of tool, process, or material characteristics. Based on this, the implementation of a Latin hypercube design provides the opportunity to sample space-filling and uniformly distributed parameter values. Moreover, the statistical method ensures an efficient representation of a multidimensional design of near-randomly generated data points combined with a decreased occurrence of unwanted spurious correlations between the input factors [24]. This offers the following detection of multivariate dependencies taking the investigated input parameters and the individual clinch joint characteristics into account. As previously mentioned, the initial input dataset will consist of 330 data points and 13 input parameters.

4.4. Metamodeling

Based on [24,25] the utilization of metamodels enables a powerful method by which to approximate and analyze relationships between independent input factors, such as varying tool dimensions, and dependent product properties (e.g., shear or head loading capacity). In particular, the consideration of machine learning methods (e.g., regression functions or artificial neural networks) provides a suitable choice of useful algorithms to realize the estimation of technical systems. In this context, the purpose is to identify underlying patterns within a set of data and based on this, the accurate and fast prediction of individual target variables requiring a significantly decreased demand on computing time and resources. However, because the ability of machine learning algorithms to achieve a high prediction accuracy strongly depends on the investigated use case and input data, it is mainly recommended that one consider and evaluate the performance of various methods in order to identify the best-fitting solution. Thus, this contribution involves regression functions (linear and polynomial regression), an ensemble learner (random forest) and artificial neural networks. This also ensures the inclusion of different types of algorithms based on their structural setup. For instance, although ANNs consider hidden layers and neurons, the configuration of the random forest model is composed of several fitted and trained decision trees.

To evaluate the prediction accuracy, the application of the coefficient of prognosis [26] as a performance score (see Equation (1)) provides the opportunity for an efficient identification of the best-fitting regression models. In this regard, the CoP represents an extension of the commonly used coefficient of determination (R^2) offering an automatic scaling of the calculated results. This means that, for instance, a CoP value of 0.9 is equivalent to a regression model's prediction accuracy of 90%. To ensure a high estimation quality, only predictive models that reached a mean CoP value of at least 0.8 are defined as sufficiently precise:

$$CoP(y_p, y_t) = \left(\frac{\sum_{i=1}^{N} (y_p - \bar{y}_p) \times (y_t - \bar{y}_t)}{(N-1) \times \sigma_p \times \sigma_t} \right)^2. \quad (1)$$

4.5. Feature Selection

The following application of a statistically based feature-selection method (cf. Figure 4) allows the identification of a minimum set of input features that still allows the accurate estimation of target variables. In particular, the inclusion of irrelevant or less important factors can result in a decrease of the model's generalization ability by simultaneously leading to an increase in the overall model complexity [25]. In this regard, the aim of feature selection is to identify a set of variables that enables the utilization of useful regression models considering only relevant input data. Because this contribution deals with labeled data, it is possible to implement a correlation-based selection method. Therefore, the statistical measure determines the linear relationships between input and output parameters. Then, based on the calculated correlation coefficients and the following categorization of factors into relevant parameters and those which have only a marginal impact on resulting clinch joint properties, varying subsets of input data can be defined.

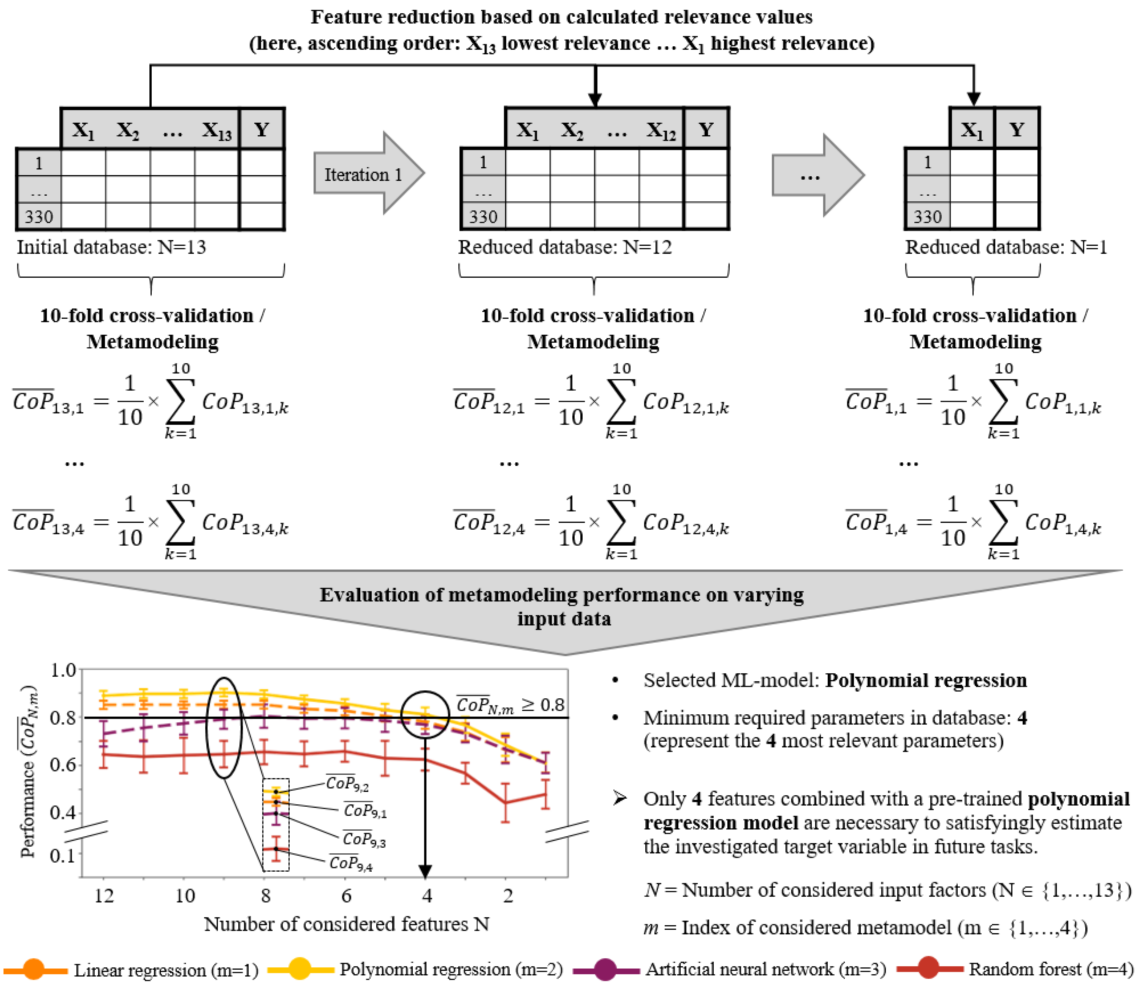


Figure 4. Process of the feature-selection approach.

In this context, features are iteratively removed from the input data based on their relevance (ascending order). This means that one additional parameter will be removed in each iteration. Moreover, the considered machine learning algorithms will be applied on each reduced subset combined with the evaluation of their ability to predict individual target variables taking the CoP into account.

As already introduced in Section 4.1, the performance of a tenfold cross-validation in each iteration run reduces the influence of overfitting models. In summary, the application of a statistically based feature selection method enables the definition of a minimum input data configuration, which is at least required for the accurate estimation of quality-relevant clinch joint characteristics. This can lead, in addition to the reduction of a computational and modeling effort, to a more versatile application of pretrained regression models despite reduced or limited input data.

5. Results

The following section describes the utilization and evaluation of different machine learning algorithms for the estimation of clinch joint properties in more detail. First, the performance of machine learning algorithms will be determined on the basis of an initial generated database and then for limited input data. In this context, the subsequent formulation of design equations enables the accurate estimation of clinch joint characteristics considering only relevant input parameters.

5.1. Performance of Machine Learning Algorithms on a Comprehensive Database

The purpose of this section is to evaluate the performance of the considered machine learning algorithms taking the entire input data (330 samples, 13 input parameters) into account. In this context, the previously explained execution of a tenfold cross-validation enables the systematic determination and comparison of the regression model's performances providing different test and training data configurations. As an overview, Figure 5 illustrates the reached mean CoP values ($\overline{CoP}_{13,m}$, where $m \in \{1, \ldots, 4\}$ and represents the particular machine learning algorithms) for the estimation of the neck and interlock thickness as well as the joining and shear force.

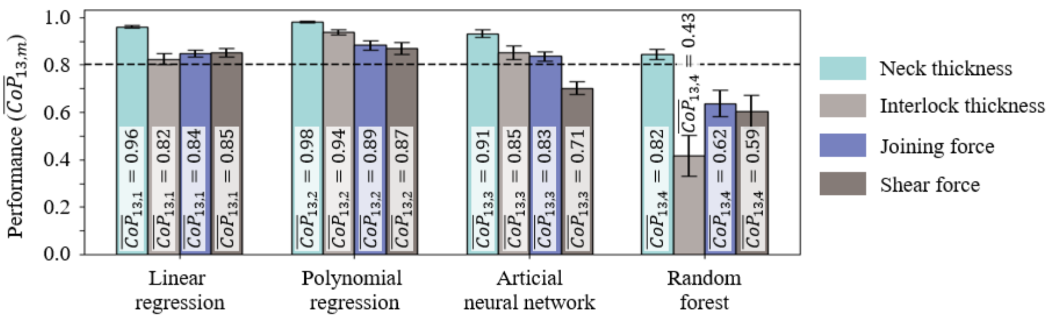


Figure 5. Performance of machine learning algorithms for the estimation of individual clinch joint characteristics

One can see that the linear and polynomial regression models achieve a constant CoP level greater 80% predicting each target variable. Especially the latter algorithm reaches the highest estimation performances showing additionally small distributions (standard deviations) of the calculated prediction quality scores. Compared to this, the application of artificial neural networks achieves only satisfying qualities for the prediction of the interlock and neck thickness as well as the joining force. In contrast, the setup of random forest models demonstrates mainly poor results, showing a sufficient prediction level for the estimation of the neck thickness. In summary, the training of regression functions (linear and polynomial) presents the highest potentials for the accurate description of clinch joint properties. Thus, these results provide the basis for the performance of a feature-selection process. In this regard, the aim is to evaluate whether and by how much the prediction qualities change compared to varying input data.

5.2. Correlation Analysis

The carrying out of a Pearson's correlation analysis within the feature selection process provides an efficient way to identify the influence of input parameters on individual target variables determining their interactions. As an overview, Figure 6 depicts the calculated correlation values for all 13 input factors demonstrating the impact on the neck and interlock thickness as well as on the joining and shear force. This step represents the initial state for the first feature selection and reduction iteration considering a constant number of 330 samples.

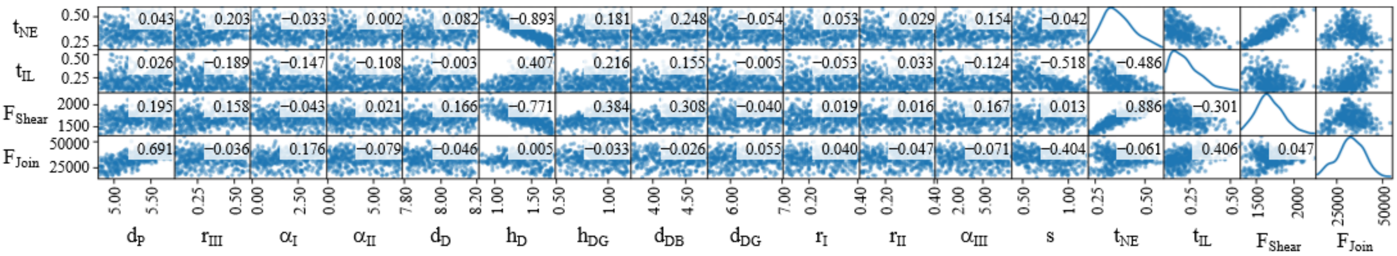


Figure 6. Illustration of the calculated Pearson's correlation coefficients.

One can see that the chosen die depth (h_D) significantly influences the formation of the neck thickness. In this context, an increase of the input parameter results in a prolonged thinning of the die- and punch-sided sheets and thus to a later beginning of the material displacement [27]. Because the correlation between the neck thickness and the achievable resistance against shear loading are commonly known and widely investigated, such as in [7], the strong impact of the die depth on the resulting shear force can be seen as a confirmation of the result's validity. Furthermore, the influence of the punch penetration depth (s) on the interlock thickness and on the joining force corresponds to a higher downward movement of the punch (total compressibility). This leads to an increased displacement of material volume and a radially material flow [28,29]. In addition to the punch penetration depth, the variation of the punch diameter (d_P) indicates a high impact on the joining force as the increase of both input factors can lead to an enlarged volume displacement into the die and thus to a growing demand on sufficiently high process forces [27]. In comparison, the tool parameters d_D, d_{DG}, r_I and r_{II} show nearly no influence on the investigated clinch joint properties. Based on these results, it is possible to define the parameters to be removed in the first feature selection iteration. Therefore, the weakest absolute correlation values closest to zero will be chosen (neck, $\alpha_{II} = |0.002|$; interlock, $d_D = |-0.003|$; shear force, $s = |0.013|$; and joining force, $h_D = |0.005|$). However, it is important to notice that the calculated indices are only valid for the defined design of experiment and the relating parameter spaces and can vary for different factor settings. Because the results show a sufficient agreement with previous works, such as [16] or [29], the correlation analysis can be assumed as having satisfying accuracy.

5.3. Performance of Machine Learning Algorithms on Varying Input Data

Based on the performance of a feature-selection method, this section investigates the ability of different machine learning algorithms to estimate individual clinch joint properties considering a varying set of input data. In this regard, the methodical approach is performed for each target variable separately. Therefore, features are filtered out step-by-step based on their calculated correlation coefficient. Thus, the fewer factors are taken into account, the less input information is available for the accurate prediction of the joint properties. In this case, the proportion of noise within the data increases in each reduction step and this complicates the approximation of relationships between input and output factors.

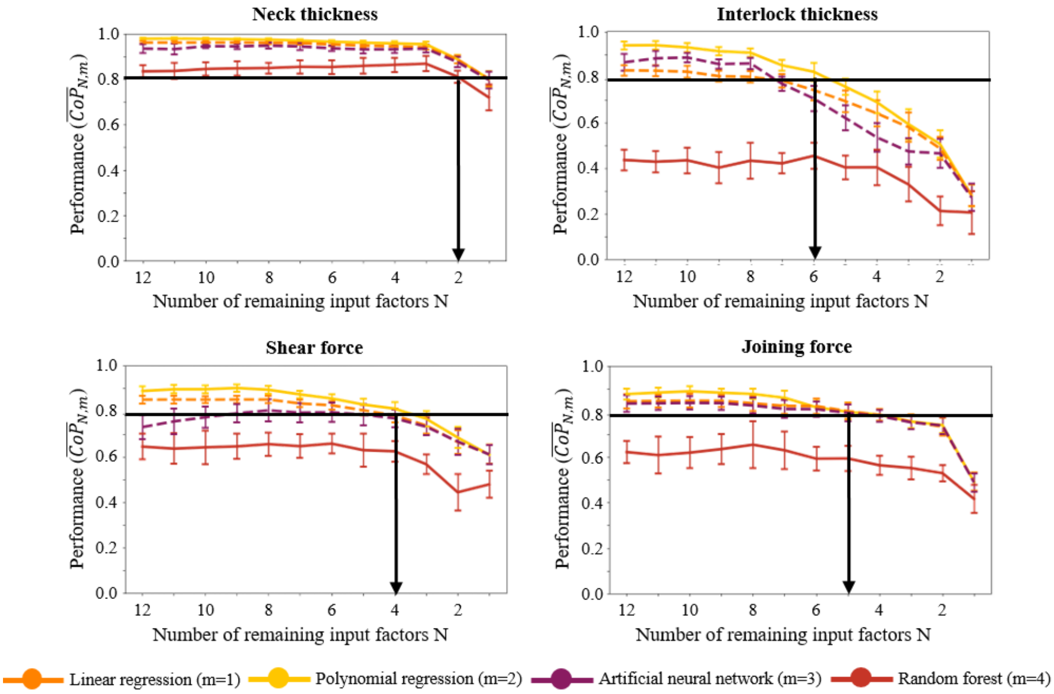


Figure 7. Performance of the machine learning algorithms on limited input data.

As mentioned in Section 4.1, the involvement of a tenfold cross-validation in each iteration provides an efficient method by which to decrease the influence of overfitting models. Therefore, the generated folds and thus the particular training- and test-data configurations build the basis for utilizing the particular machine learning algorithms. In this regard, the amount of samples within the generated dataset remain constant (330 samples, cf. Figure 1) over each feature-selection iteration, whereby only the number of considered input parameters will be reduced. As an overview, Figure 7 depicts the performance of the machine learning algorithms on varying input features. To get a deeper understanding of the generated averaged CoP values ($\overline{CoP}_{N,m}$), the additional calculation of the standard deviation demonstrates the distribution of the individual results. Furthermore, Table 2 illustrates the particular removed input parameters in each feature selection iteration as well as the determined minimum set of factors (green) that still allow the accurate estimation of the particular joint characteristic. Therefore, the removing order is based entirely on the calculated absolute correlation indices.

Table 2. Overview of the selected and removed input parameters in each feature selection iteration.

	Removed Input Parameter in Each Feature Selection Iteration												
	13 * (1 **)	**12 (2)**	**11 (3)**	**10 (4)**	**9 (5)**	**8 (6)**	**7 (7)**	**6 (8)**	**5 (9)**	**4 (10)**	**3 (11)**	**2 (12)**	**1 –**
t_{NE}	α_{II}	r_{II}	α_I	s	d_P	r_I	d_{DG}	d_D	α_{III}	h_{DG}	r_{III}	d_{DB}	h_D
t_{IL}	d_D	d_{DG}	d_P	r_{II}	r_I	α_{II}	α_{III}	α_I	d_{DB}	r_{III}	h_{DG}	h_D	s
F_{Join}	h_D	d_{DB}	h_{DG}	r_{III}	r_I	d_D	r_{II}	d_{DG}	α_{III}	α_{II}	α_I	s	d_P
F_{Shear}	s ***	r_{II}	r_I	α_{II}	d_{DG}	α_I	r_{III}	d_D	α_{III}	d_P	d_{DB}	h_{DG}	h_D

* Number of parameters in database for feature selection. ** Current feature selection iteration. *** Parameter that will be removed from the database in the present iteration.

Taking Figure 7 and Table 2 into consideration, one can see that all machine learning methods reached high prediction performances for the estimation of the neck thickness considering at least the two most relevant input parameters (d_{DB} and h_D). In particular, the linear and polynomial regression models as well as the artificial neural network almost consistently achieved a prediction accuracy greater than 90%. Thus, a reliable prediction of the neck thickness can still be reached despite limited input data. Moreover, the results also lead to a significant reduction in model complexity. In addition, although the predictive models indicate no drop in prediction quality for removing several irrelevant parameters, the estimation of the interlock thickness shows an opposite effect. In this regard, a consistent loss of the prediction performance can be obtained by focusing on the best-fitting model (polynomial regression). This means that even the parameters classified as irrelevant seem to have an effect on the target value, which is also reflected in the required number of six input features (α_I, d_{DB}, h_{DG}, r_{III}, h_D, s). For the estimation of the joint's resistance against shear loading, at least the four most relevant parameters (d_P, d_{DB}, h_{DG} and h_D) have to be taken into consideration. Although the random forest algorithm performed weakly, both linear and polynomial models, as well as the ANN, showed satisfying results. Similar findings could be observed for the prediction of the joining force. Therefore, the input features α_{III}, α_{II}, α_I, s and d_P are mostly relevant for an accurate estimation of the target variable. Because the reduction of the estimation model's complexity is targeted in this contribution, the method with a simpler structural configuration is selected in the case of a similar prediction ability between two or more machine learning algorithms. Based on this, Table 3 shows an overview of the chosen metamodeling techniques, the achieved mean CoP values and the required number of input features for the accurate prediction of individual clinch joint characteristics.

5.4. Design Equations

Because the application of linear and polynomial regression algorithms achieved the most promising results for the estimation of clinch joint properties, it is possible to define mathematical representations (design equations) of these models. This offers the possibility for a versatile and time-efficient calculation of target variables without the previous execution of an entire sampling and metamodeling process for the presented joining use case. Moreover, this can lead to a significant reduction of cost-intensive development iterations because the design equations can already be applied in the early phases of the product development process. In this context, the mathematical representations of the particular regression functions are illustrated in Table 4. Furthermore, in order to evaluate whether these functions are feasible and reliable for the accurate prediction of individual clinch joint characteristics, an experimental study considering an exemplary tool configuration for the joining of the considered aluminum alloy EN AW-6014-T4 with a nominal sheet thickness of 2.0 mm is carried out. The ranges of the determined target variables (n = 5) are also depicted in Table 4.

Table 3. Overview of the achieved mean CoP values and the minimum required number of input features for the accurate prediction of individual clinch joint characteristics.

Input Data: 330 Samples, 13 Features			**Input Data: 330 Samples, N Features**		
Target Variables	$\overline{CoP}_{13,m}$		**Metamodel**	$\overline{CoP}_{N,m}$	**Remaining Features N**
Neck	$\overline{CoP}_{13,2} = 0.98$	$\rightarrow$	Linear regression	$\overline{CoP}_{2,1} = 0.89$	2 (d_{DB}, h_D)
Interlock	$\overline{CoP}_{13,2} = 0.94$	$\rightarrow$	Poly. regression	$\overline{CoP}_{6,2} = 0.81$	6 (α_I, d_{DB}, h_{DG}, r_{III}, h_D, s)
Joining force	$\overline{CoP}_{13,2} = 0.89$	$\rightarrow$	Linear regression	$\overline{CoP}_{5,1} = 0.81$	5 (α_{III}, α_{II}, α_I, s, d_P)
Shear force	$\overline{CoP}_{13,2} = 0.87$	$\rightarrow$	Poly. regression	$\overline{CoP}_{4,2} = 0.83$	4 (d_P, d_{DB}, h_{DG}, h_D)

Table 4. Overview of the regression functions and their performances compared to experimental data.

		Regression Functions	Prediction	Exp. Study *
t_{NE}	=	$-0.267h_D + 0.055d_{DB} + 0.507$	0.46 mm	[0.45-0.49] mm
t_{IL}	=	$-0.089r_{III} - 0.001\alpha_I + 0.436h_D + 0.419h_{DG} - 0.286s$ $-0.295d_{DB} - 0.173r_{III}^2 - 0.005\alpha_I^2 - 0.088h_D^2 + 0.021s^2$ $-0.170h_{DG}^2 + 0.043d_{DG}^2 + 0.301$	0.34 mm	[0.28-0.32] mm
F_{Join}	=	$19078p_D + 928\alpha_I - 473\alpha_{II} - 285\alpha_{III} - 16888s - 54600$	29.2 kN	[31.5-35.7] kN
F_{Shear}	=	$1611p_D - 267h_D + 192h_{DG} + 221d_{DB} - 142p_D^2 - 80h_D^2$ $+7h_{DG}^2 - 6d_{DB}^2 - 3430$	1895 N	[1902-1946] N

* number of experimental data = 5.

One can see that the equations mainly achieved precise predictions of the individual target values. However, with the exception of the estimated neck thickness, the values are slightly above or below the experimental data. This can be caused by the exclusion of material or process uncertainties within the joining process, such as differing friction mechanics, in this contribution. Because different values can lead to a variation in the results [29], the inclusion of these variations in future work is recommended. Nevertheless, the results show already high potentials for the accurate estimation of clinch joint properties considering limited input data and a significantly reduced regression model complexity.

6. Discussion

Reflecting RQ1, Figure 5 illustrates the performances of different machine learning algorithms for the estimation of individual clinch joint properties considering the initially generated database (330 samples, 13 input features). In this context, the polynomial regression model achieved the best-fitting results, showing sufficient averaged CoP values for the prediction of the neck ($\overline{CoP}_{13,2} = 0.98$) and interlock ($\overline{CoP}_{13,2} = 0.94$) thickness as well as for the shear ($\overline{CoP}_{13,2} = 0.87$) and joining force ($\overline{CoP}_{13,2} = 0.89$). Furthermore, the linear regression model reached accurate performances showing slightly worse CoP values. In particular, the ability to describe relationships between input features and the interlock thickness is associated with a significantly poorer prediction quality in comparison to the polynomial model. In contrast, the involvement of an ensemble learner (random forest) achieved satisfying performances only for the estimation of the neck thickness, whereas the prediction of further joint characteristics did not reach a sufficient quality including high standard deviations. However, the performance of predictive models highly depends on the available data. Thus, the results are only valid for the investigated joining use case (similar material and sheet thickness) as well as the involved input data and can differ significantly for considering changing parameter spaces or multimaterial connection. Moreover, the implemented algorithms represent only a marginal selection of applicable machine learning algorithms. Nevertheless, it was shown that simpler regression methods, such as the linear and polynomial models, tend to be more preferable given the presented input data. In addition to this, the involvement of a hyperparameter optimization can lead to a significant increase of prediction performances, especially for the application of artificial neural networks or ensemble learner in future work.

Referring to RQ2, Figure 7 and Table 2 depict that the implementation of a statistically based filtering method enables the systematic reduction of input features regarding their impact on individual clinch joint properties. In this context, the methodical approach provides the opportunity to identify a minimum subset of input parameters, which are at least required to achieve sufficient prediction qualities for each target variable. Therefore, the highest potential reducing the model complexity was demonstrated for the estimation of the neck thickness. For this purpose, only the two most relevant input features (d_{DB}, h_D) are required to accurately describe the geometric characteristic. In summary, the application of a correlation-based feature-selection method combined with linear or polynomial regression models achieved a simplified estimation procedure taking only a few required inputs into account. However, although the reduction of features can lead to a significant decrease of the prediction model's complexity and thus to less required joining input data, the calculated prediction qualities did not reach the initial level considering all input features. This can cause varying prediction performances and thus an increase of the estimation uncertainty. For this purpose, machine learning algorithms that are able to measure their own prediction uncertainty (aleatoric and epistemic), such as Gaussian process regression models or Bayesian neural networks, can provide high potentials compared to deterministic models. If the resulting distributions are too high, the minimum number of required input features has to be increased. Furthermore, due to a high computational and time effort, only a small number of input data points (330) were generated and used for the training and testing of metamodels. Although, a tenfold cross validation is carried out for each feature selection step, it is recommended to involve more data in future work in order to further increase the reliability of the results.

Leading over to RQ3, Table 4 contains mathematical representations of the previously selected regression models (see Table 3). To evaluate the applicability of these design equations, an exemplary tool configuration was chosen to perform an experimental study ($n = 5$). Subsequently, the required input data were added to the functions and the prediction of the individual target variables was carried out. As a result, it was shown that a sufficiently accurate estimation of the clinch joint properties is possible despite a significantly reduced number of features. Thus, the provision of the mathematical functions enables a much more simplified design process of clinch joint connections, because no comprehensive representations of the metamodels are necessary for the satisfying description of the investigated use case. However, the equations are only valid for joining a similar material and sheet thickness combination (EN AW-6014; 2.0 mm). The effort and the possibility to apply or calibrate these functions to new joining task will be investigated in future work. In particular, for the description of multimaterial connections, an additional evaluation of the calculated parameter correlation coefficients is recommended. Nevertheless, the demonstrated results show that the reuse of pretrained regression models is feasible and reliable through the performance of a feature-selection method and the following formulation of design equations even for strongly limited input data. Thus, it is possible to cover a wide range of varying tool configurations for the investigated joining task. In summary, the availability of mathematical representations allows a decrease of the initial model complexity while achieving a sufficient ability to estimate individual clinch joint characteristics.

7. Conclusions

The presented work introduces a method for the estimation of clinch joint properties by using pretrained metamodels and limited input data. In this context, the investigation of different machine learning algorithms regarding their ability to predict individual clinch joint characteristics was carried out at the beginning. Then, the application of a statistically based feature selection method provided the opportunity to determine the impact of input parameters on individual target factors and based on this the systematic reduction of the considered input data. Therefore, the involvement of a Pearson's correlation analysis as feature filtering strategy combined with a prediction quality measurement (coefficient of prognosis), offered the opportunity to evaluate the performance of different metamodels on varying input data. As a result, predictive models and mathematical representations (design equations) are available that require a significantly reduced number of input features and thus provide a decreased model complexity by at the same time achieving a high prediction accuracy for the given use case. Subsequently, in order to verify and evaluate the feasibility and applicability of the results, the experimental analysis of an exemplary tool configuration combined with the determination of target variables was demonstrated. Therefore, a high level of agreement between the predicted clinch joint properties and the experimental study was determined. In summary, the demonstrated investigations within this contribution led to the following results.

- The linear and polynomial regression models achieved the highest ability to predict the investigated clinch joint properties considering comprehensive and even limited input data.
- The application of a correlation-based feature-selection method enabled the significant decrease of the model complexity based on a systematic reduction of the database. For instance, the accurate estimation of the neck thickness can be achieved by only considering a linear regression model and data regarding the applied die depth and die bottom diameter.
- The experimental evaluation of the generated results confirm a high applicability of the simplified models and design equations for the prediction of clinch joint characteristics even if only a limited number of features are available. Thus, besides the reduction of computational and modeling effort, the results can pave the way to a more versatile application of pretrained regression models on varying tool configurations for a given joining task.

Our outlook is as follows. Considering the present challenges in the field of lightweight designs, it is of high interest to also investigate multimaterial connections as well as dissimilar sheet thickness combinations. Therefore, the demonstrated results need to be evaluated regarding their transferability and applicability towards new use cases. Moreover, because this contribution only investigated varying tool configurations, the inclusion of uncertain material or process parameters combined with further machine learning algorithms, such as Gaussian process regression models, can lead to a an even better representation of the clinch joining process. This can pave the way to a more suitable and robust estimation of clinch joint characteristics and thus to a reliable design of joining connections and parts towards a high joining safety in the future.

Author Contributions: C.Z., conceptualization, methodology, software, formal analysis, investigation, writing—original draft, visualization; B.S., conceptualization, methodology, formal analysis, writing—review & editing, supervision, project administration, funding acquisition; S.W., conceptualization, writing—review & editing, supervision, project administration, funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This work was Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research 635 Foundation)—TRR 285 B05—Project-ID 418701707. We also thank the collaboration within the TRR285, especially with A01.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
CoP	Coefficient of Prognosis
DoE	Design of Experiment
FE	Finite Element
GA	Genetic Algorithm
MLS	Moving Least-Square
NSGA-II	Non-Dominated Sorting Genetic Algorithm
PCA	Principal Component Analysis
RQ	Research Questions

References

1. Kaščák, L.; Spišák, E.; Majerníková, J. Clinching and Clinch-Riveting as a Green Alternative to Resistance Spot Welding. In Proceedings of the 2019 International Council on Technologies of Environmental Protection (ICTEP), Stary Smokovec, Slovakia, 23–25 October 2019; pp. 138–142. [CrossRef]
2. Shi, C.; Li, H.; Chen, C.; Ouyang, Y.; Qin, D. Experimental investigation of the flat clinch–rivet process. *Thin-Walled Struct.* **2022**, *171*, 108612. [CrossRef]
3. Ran, X.; Chen, C.; Zhang, H.; Ouyang, Y. Investigation of the clinching process with rectangle punch. *Thin-Walled Struct.* **2021**, *166*, 108034. [CrossRef]
4. Zhang, X.; Chen, C.; Peng, H. Recent development of clinching tools and machines. *Int. J. Adv. Manuf. Technol.* **2022**, *121*, 2867–2899. [CrossRef]
5. *DVS-EFB 3470:2017-02*; Mechanisches Fügen—Konstruktion und Auslegung—Grundlagen/Überblick. DVS Media GmbH: Düsseldorf, Germany, 2017.
6. *DVS-EFB 3420*; Clinchen—Überblick—Clinching—Basics. DVS Media GmbH: Düsseldorf, Germany, 2012.
7. Neugebauer, R.; Riedel, F.; Marx, R. *Entwicklung eines Konstruktionssystems für den Rechnerischen Festigkeitsnachweis von Punktförmig Mechanisch gefüGten Bauteilen*; EFB-FB Nr. 323; Europäische Forschungsgesellschaft für Blechverarbeitung e.V.; Hannover, Germany, 2010. ISBN: 978-3-86776-359-2.
8. Zirngibl, C.; Schleich, B.; Wartzack, S. Potentiale datengestützter Methoden zur Gestaltung und Optimierung mechanischer Fügeverbindungen. *Proc. Symp. DfX* **2020**, *31*, 71–80. [CrossRef]
9. Oudjene, M.; Ben-Ayed, L. On the parametrical study of clinch joining of metallic sheets using the Taguchi method. *Eng. Struct.* **2008**, *30*, 1782–1788. [CrossRef]
10. Oudjene, M.; Ben-Ayed, L.; Delamézière, A.; Batoz, J.-L. Shape optimization of clinching tools using the response surface methodology with moving least-square approximation. *J. Mater. Process Technol.* **2009**, *209*, 289–296. j.jmatprotec.2008.02.030. [CrossRef]
11. Lebaal, N.; Oudjene, M.; Roth, S. The optimal design of sheet metal forming processes: Application to the clinching of thin sheets. *Int. J. Comput. Appl. Technol.* **2012**, *43*, 110–116. [CrossRef]
12. Roux, E.; Bouchard, P.-O. Kriging metamodel global optimization of clinching joining processes accounting for ductile damage. *J. Mater. Process Technol.* **2013**, *213*, 1038–1047. [CrossRef]
13. Lambiase, F.; Di Ilio, A. Optimization of the clinching tools by means of integrated FE modeling and artificial intelligence techniques. *Procedia CIRP* **2013**, *12*, 163–168. [CrossRef]
14. Eshtayeh, M.; Hrairi, M. Multi objective optimization of clinching joints quality using grey-based taguchi method. *Int. J. Adv. Manuf. Technol.* **2016**, *87*, 1–17. [CrossRef]
15. Wang, M.; Xiao, G.; Li, Z.; Wang, J. Shape optimization methodology of clinching tools based on Bezier curve. *Int. J. Adv. Manuf. Technol.* **2017**, *24*, 2267–2280. [CrossRef]
16. Wang, X.; Li, X.; Shen, Z.; Ma, Y.; Liu, H. Finite element simulation on ivestigations, modeling, and multiobjective optimization for linch joining process design accounting for process paramteres and design constraints. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 3481–3501. [CrossRef]
17. Schwarz, C.; Kropp, T.; Kraus, C.; Drossel, W.-G. Optimization of thick sheet clinching tools using principal component analysis. *Int. J. Adv. Manuf. Technol.* **2020**, *106*, 471–479. [CrossRef]
18. Bielak, C.R.; Böhnke, M.; Beck, R.; Bobbert, M.; Meschut, G. Numerical analysis of the robustness of clinching process considering the pre-forming of the parts. *J. Adv. Join. Process.* **2021**, *3*, 100038. [CrossRef]
19. Martin, S.; Bielak, Ch, R.; Bobbert, M.; Tröster, T.; Meschut, G. Numerical investigation of the clinched joint loadings considering the initial pre-strain in the joining area. *Prod. Eng.* **2022**, *16*, 261–273. [CrossRef]
20. Zirngibl, C.; Dworschak, F.; Schleich, B.; Wartzack, S. Application of reinforcement learning for the optimization of clinch joint characteristics. *Prod. Eng.* **2022**, *16*, 315–325. [CrossRef]
21. Bielak, C.R.; Böhnke, M.; Bobbert, M.; Meschut, G. Further Development of a Numerical Method for Analyzing the Load Capacity of Clinched Joints in Versatile Process Chains. Paper Presented at ESAFORM 2021. In Proceedings of the 24th International Conference on Material Forming, Liège, Belgique, Belgium, 14–16 April 2021. [CrossRef]
22. Zirngibl, C.; Schleich, B.; Wartzack, S. Approach for the automated and data-based design of mechanical joints. *Proc. Des. Soc.* **2021**, *1*, 521–530. [CrossRef]
23. Zirngibl, C.; Schleich, B. Approach for the Automated Analysis of Geometrical Clinch Joint Characteristics. *Key Eng. Mater.* **2020**, *883*, 105–110. [CrossRef]
24. Siebertz, K.; van Bebber, D.; Hochkirchen, T. *Statistische Versuchsplanung—Design of Experiments (DoE)*; Springer: Wiesbaden, Germany, 2017. [CrossRef]
25. Witten, I.H.; Frank, E.; Hall, M.A. *Data Mining: Practical Machine Learning Tools and Techniques*, 3rd ed.; Morgan Kaufmann: Burlington, MA, USA, 2011.
26. Most, T.; Will, J. Metamodel of Optimal Prognosis - An automatic approach for variable reduction and optimal metamodel selection. *Proc. Weimar. Optim. Stochastiktage* **2008**, *5*, 20–21.
27. Lambiase, F. Influence of process parameters in mechanical clinching with extensible dies. *Int. J. Adv. Manuf. Technol.* **2013**, *66*, 2123–2131. [CrossRef]

28. Drossel, W.-G.; Falk, T.; Israel, M.; Jesche, F. Unerring Planning of Clinching Processes through the use of Mathematical Methods. *Key Eng. Mater.* **2014**, *611–612*, 1437–1444. [CrossRef]
29. Drossel, W.-G.; Israel, M.; Falk, T. Robustness evaluation and tool optimization in forming applications. In Proceedings of the 9th Weimar Optimization and Stochastic Days, Weimar, Germany, 29–30 November 2012.