57th ICFG Plenary Meeting
Korea Institute of Materials Science (KIMS)
Busan – South Korea

Advanced friction modelling in cold forging using machine learning

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Despite the intensive development of FE simulations for cold forging applications over the last decades, they are still prone to errors due to, among other things, inaccurate material and friction modelling. The use of advanced friction models can reduce the error caused by friction modelling. [1] However, existing models for cold forging are often limited to a specific application and require extensive tribometer testing for parameter determination. This work presents a new method for efficient data collection through time series analysis, which significantly reduces the number of tribometer tests required. The new method also allows the use of deep learning algorithms for friction modelling. Using the new method, five different friction models, including one deep learning model, are trained and implemented in the FE simulation. Using two typical forming processes for validation, it is shown that the use of a feed-forward neural network friction model reduces the relative error of the FE simulation by ~59% compared to simple friction models. Compared to the state of the art method, the time series based data collection approach reduces the necessary experimental testing by 62 %. Furthermore, the advanced friction models presented are not limited to a specific process, but can be used for any type of cold forging simulation.

Keywords: cold forging, advanced friction modelling, machine learning, finite-element-simulation

1. Introduction

Ever shorter product lifecycles, increasing demands on component tolerances and ever shorter product development times increase the need for accurate FE simulations. The use of FE simulations in the design process of cold forming processes can reduce tool design time by approximately 12% [2]. Despite the intensive development of FE simulations over the last decades, they are still prone to uncertainties due to inaccurate material and friction modelling.

In this work, the effects of inaccurate friction modelling on the accuracy of the FE simulation are first demonstrated using two typical forming processes. A new method for advanced friction modelling is then presented. This includes an innovative data acquisition method that significantly reduces the number of tribometer tests required and enables the use of deep learning algorithms to model friction in cold forging. Using the presented method, five different advanced friction models, including a deep learning model, are compared and the following aspects are discussed: data efficiency, model accuracy, simulation time and their impact on the accuracy of FE simulations.

2. FE-Simulation with constant coefficient of friction

In order to capture the error of simplified friction modelling on the results of FE simulations, the forming force of two typical forming processes (Forward Rod Extrusion (FRE) and Backwards Cup Extrusion (BCE)) are both measured experimentally and calculated numerically. Figure 1 shows the two forming processes.

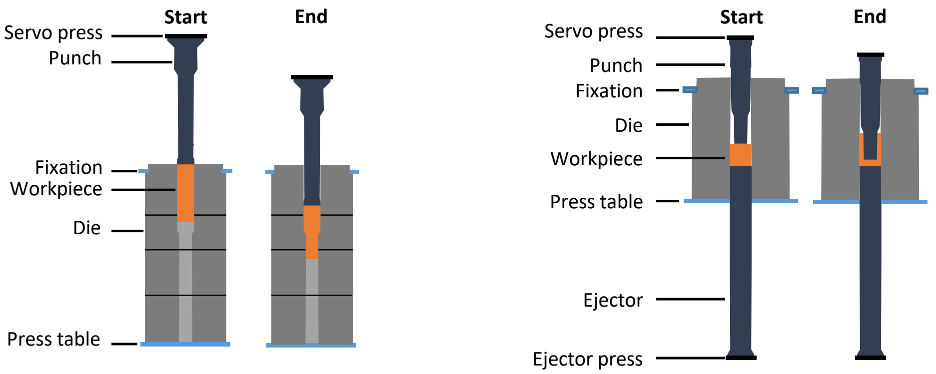


Figure 1. schematic depiction of the forming processes. left: forward rod extrusion (FRE), right: backward cup extrusion (BCE)

2.1. Experimental investigation

Both processes are carried out on a servo press with constant stroke speed. The forming force is measured in the force flow of the punch using an HBM C6 strain gauge-based load cell and a Quantum X amplifier with a sampling frequency of 1 kHz. The dies and punches are made of material 1.2379 and have a hardness of 62 HRC and a surface roughness of Ra = 0.03 µm. The workpieces are made of 16MnCr5, soft annealed at 675°C for 6 hours. The lubricants used are ZWEZ PD 5940 polymer-based lubricants in a 1:1 ratio with distilled water, applied in an immersion bath at 75 °C and dried at room temperature. The parts were blasted with F20 abrasive prior to lubricant application.

Table 1. experimental plan for forming experiments

Prameter	Amount of levels	Levels
Process	2	Forward- Rod- Extrusion (FRE), Backward- Cup- Extrusion (BCE)
Tool temperature [°C]	3	RT, 50 °C, 100 °C
Stoke speed [mm/s]	3	5 mm/s, 50 mm/s, 150 mm/s
Sum	18	
Repetitions	5	
Experiments	**90**	

Table 1 shows the test plan. The tool temperature is set by means of electric heating cartridges and a temperature control circuit.

Figure 2 shows the forming force curve for forward-rod extrusion and for backward cup extrusion. The solid line shows the average of 5 repetitions, the hatched area shows the standard deviation. The measurements clearly show the influence of extrusion speed and die temperature on the forming force.

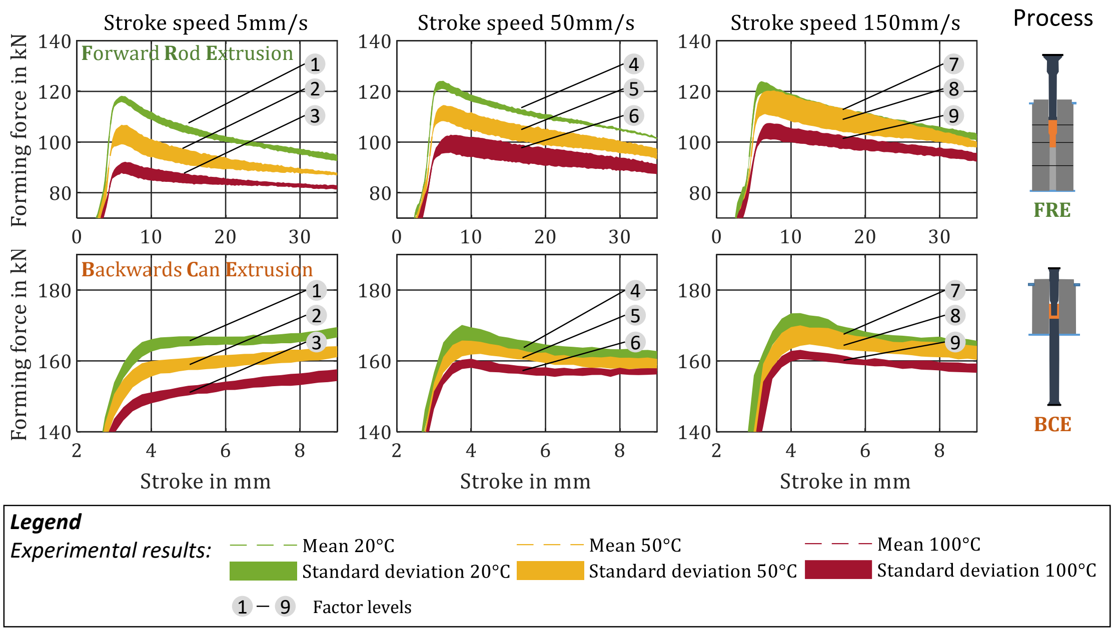


Figure 2. mean and standard deviation of experimental forming force curves for all nine factor levels. top: FRE, bottom: BCE

2.2. Numerical Simulations

The FE simulation is performed using the Simufact Forming 2022.1 software. The tools are assumed to be elastic with heat conduction; a detailed description of the material properties and simulation settings is given in the appendix. A Hensel-Spittel flow curve model is used for the workpiece; the parameters of the model are given in appendix. For both processes, nine simulations are calculated according to the factor levels listed in Table 1. A Coulomb friction model was used and the coefficient of friction µ was assumed to be a median of µ = 0.08 from 64 literature sources on cold forging [3]. Figure 3 shows the graphs of the experimental measurements from Figure 2 extended by the numerically determined force curves for simulations with µ = 0.08.

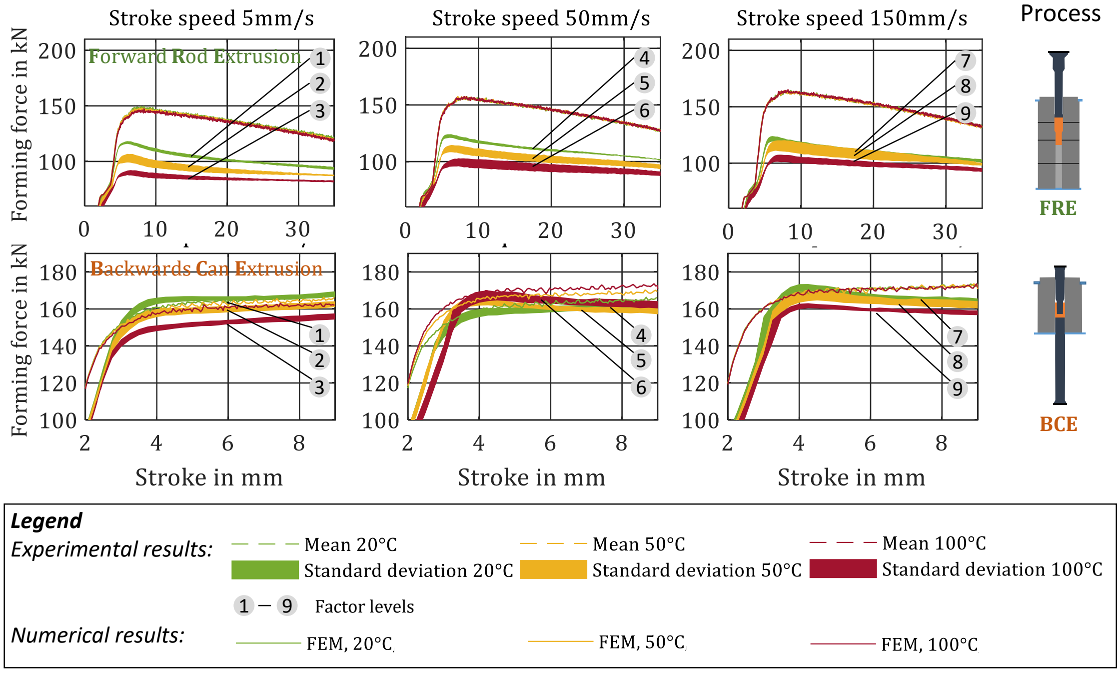


Figure 3. mean and standard deviation of experimental forming force curves and numerically calculated forming force curves for all nine factor levels. top: FRE, bottom: BCE

In this study, two metrics are used to quantify the absolute error (AE) of the numerical simulation. Firstly, the absolute difference in the forming work and secondly, the absolute difference in the maximum forming force between experiment and simulation. Referencing the difference (AE) to the maximum forming force measured in the experiments gives the absolute relative error (ARE).

Figure 4 shows the ARE of the maximum force for all factors (marked with 1- 9 according to Figure 2 and Figure 3) for both processes, FCE and BCE, assuming a constant COF of μ = 0.08. Figure 4 also shows the mean of all factor levels (mean absolute relative error, MARE) as well as the standard deviation of the MARE for the FRE (marked with B) and the BCE (marked with D). The standard deviation provides information on the scatter of the ARE while the error bars of the mean and the standard deviation are calculated by Gaussian error propagation based on the uncertainty of the experimentally measured force curves due to scatter.

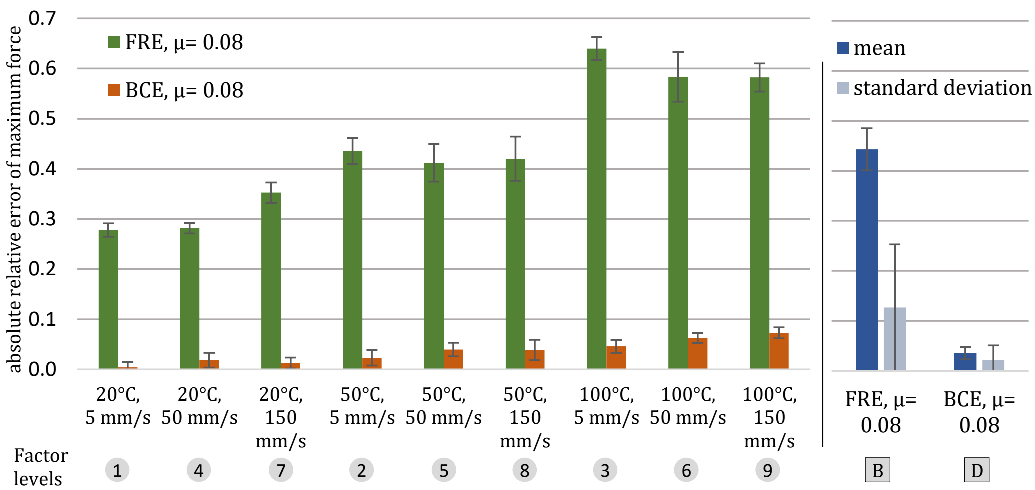


Figure 4. left: mean absolute relative error of FE simulation for all nine factorlevels 1-9 and both processes FRE and BCE. right: mean and mean standard deviation of all nince factor levels and both processes.

In order to extend this investigation the same procedure is followed for a second lubricant based on molybdenum disulfide (MoS2). The MoS2 based lubricant MD5742 was applied in a ratio of 1:1 with destilled water, in an immersion bath at 75 °C, dried at room temperature and tumbled before forming. Additionally the simulations were carried out assuming a COF of μ = 0.04, which was measured by the subgroup lubrication of the International Cold Forging Group (ICFG) in 2023 as the average COF of 13 zinc-phosphate free lubricants measured using 6 different tribometer tests [4].

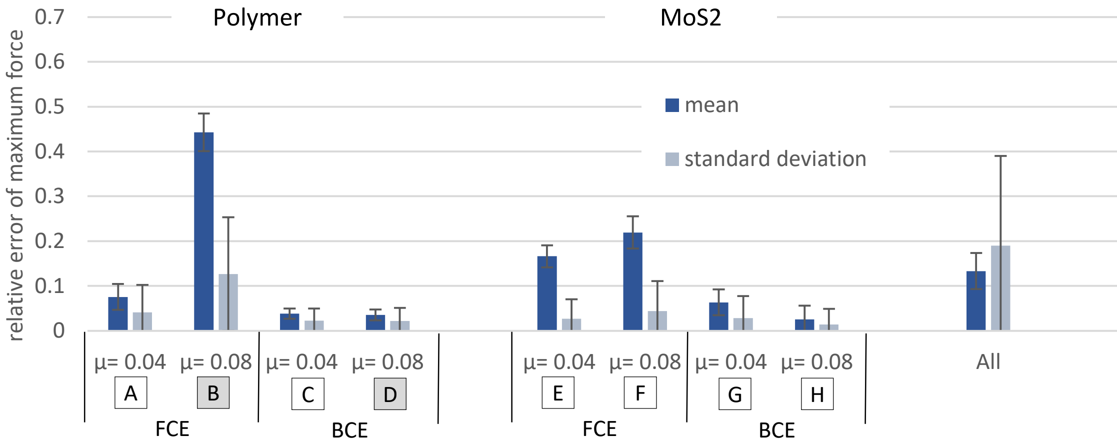


Figure 5. left: mean absolute relative error (MARE) and standard deviation for eight factors (A-H), right: average of mean and standard deviation of all eight factors (A-H) indicated by "All".

Figure 5 shows the two MARE values presented in Figure 4 (B and D) and six additional MARE values and their corresponding standard deviations for the additional lubricant and the COF investigated. Figure 5 also shows the average of all eight MARE values and their standard deviation, indicated by "All". The MARE of the maximum forming force is 13 % ± 4 % with a standard deviation of 19 ± 20 %. Considering that the forming force has a direct influence on several important die design, such as tool stress or press selection, this error seems frighteningly high, especially in the case of multi-stage processes, where the errors can add up.

To ensure that the presented error is not caused by miscalculation of the frictional stress τ_r greater than the shear yield strength k according to van Mises, the results of the FE simulations are investigated in this respect. [5] Figure 6 shows the friction stress τ_r and the contact normal pressure σ_n with respect to the flowstress Y for the assumed COF of µ = 0.08. It can be seen that for the contact pressures observed in the FE simulations presented in chapter 2 the highest τ_r is below 60 % of the shear yield strength.

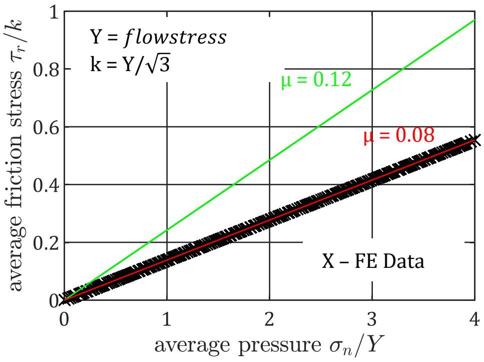


Figure 6. contact pressure and friction sheer stress in FE simulations assuming a COF of µ = 0.08

3. Advanced friction modelling

Advanced friction models are models that can be used to calculate friction forces, considering multiple influencing factors. A four-step process is required to use such models in FE simulations. These four steps are: model definition, training data acquisition, model training and testing, and model implementation. In this study, the four-step process is carried out for five different advanced friction models. Chapter 3 presents each of the four steps in detail.

Compared to the state of the art in advanced friction modelling, this study presents two new and innovative aspects. The models used include a deep learning model, which have never been used to this extent for friction modelling in cold forging (Chapter 3.1). The use of deep learning models requires a rethinking of data collection, as much larger databases are required for model training. To achieve this, a new time series based data collection method is presented in chapter 3.2.

3.1. Model definition

The influencing variables of advanced friction models can be divided into process and system parameters. Process parameters, often referred to as 'tribological loads', are locally and temporally variable variables whose value is largely dependent on the type and design of the forming process. System parameters are properties of the tribological system that depend less on the type and design of the forming process than on the properties of the lubricant, the workpiece and the tools (e.g. tool hardness, workpiece material, surface roughness, …). Existing friction models of cold forging mainly consider process variables. System parameters are generally not considered and are assumed to remain constant.

Figure 7 shows the five models used in this study. The models consider the five most commonly used process parameters x_1 – x_5 (tribological loads): x_1 = relative sliding velocity (v_{rel}), x_2 = Temperature (T), x_3 = contact normal pressure (σ_n), x_4 = sliding distance (sd), x_5 = surface expansion ratio (ψ). Details of the machine learning models and the determination of the hyperparameters are presented in chapter 3.3.

grey-box models		
linear regression model	polynomial regression model	average COF
$\mu = c_0 + \sum_{i=1}^{n} c_i \cdot x_i$	$\mu = c_0 + \sum_{i=1}^{n} c_i \cdot x_i + \sum_{i=1}^{n} c_{ii} \cdot x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} c_{ij} \cdot x_i \cdot x_j$	$\mu = \frac{1}{m} \sum_{i=1}^{m} \mu_m$
n= 5 (number of model variables, here: tribological loads), m= training datapoints		

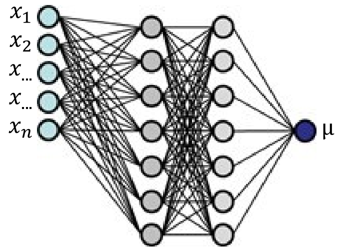
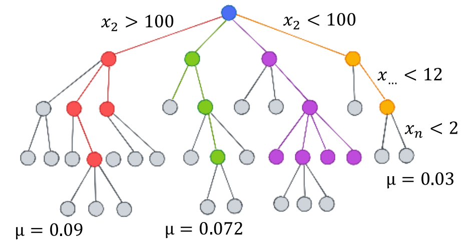
machine learning (black-box) models	
feed-forward-neural network (ffnn)	decision tree model (tree)
	

Figure 7. Overview of advanced friction models used in this study

3.2. Data collection and tribometer

The necessary training data is obtained during data collection using tribometer tests. There are many different tribometer tests for cold forging. Groche et al. present six of the most commonly used tribometer tests in cold forging, pointing out their very different set-ups, principles and flexibility. [6] Not every tribometer test can be used to train every advanced friction model, so it is important to select the correct tribometer test for data collection. As the complexity of the friction model increases (more influencing factors), the tribometer for data collection must be equally flexible in terms of controlling the influencing factors during testing. As the complexity of the friction model increases, so does the number of tribometer tests required. These two aspects hinder the use of advanced friction models in industrial practice. While the need for flexible tribometers is inevitable for successful advanced friction modelling, the amount of testing required can be reduced by efficient use of data when using direct tribometers. In this study, an efficient data acquisition is presented in section 3.2. A comparison of the new method with the state-of-the-art data acquisition method is presented in section 3.3, highlighting the significant reduction in experimental testing required. Figure 8 shows an overview of the tribometer (SCT) used in this study and the workflow of both, the state of the art and the new method of data collection.

Tribometer - Sliding Compression Test (SCT)

The SCT separates the upsetting and sliding phases. In the upsetting phase, the workpiece (cylinder, diameter = 15 mm, height = 15 mm, 16MnCr5, lubricant = ZWEZ PD 5940) is upset on the sliding plate (60 x 120 x 25 mm, 1.2379, 62 HRC, Ra = 0.01 µm) by a stationary punch with a defined force F_n. By controlling the upsetting force F_n, the contact normal stress and surface enlargement between the workpiece and the sliding plate can be adjusted. After upsetting, the die is moved over a defined sliding distance (sd) at a defined relative sliding velocity (v_{rel}). The temperature of the sliding plate T_t can be tempered using heating cartridges. During the sliding process, the following variables are measured at a sampling frequency of 1 kH: sliding distance (sd), friction force (F_r), compression force (F_n), sliding acceleration, plate temperature (T_t). The coefficient of friction (µ) is calculated as the quotient of the friction force (F_r) and the compression force (F_n).

Data Collection - State of the Art (average based)

The upper part of Figure 7 shows the state of the art of collecting data from a direct tribometer test using the SCT as an example. The values T_t, v_{rel} and µ are taken directly from the experimental tribometer test. The tribological loads: contact normal stress (σ_n) and surface expansion ratio (Ψ) cannot be measured and must be determined with the help of a FE-simulation using the compression force F_n as an input. The tribological loads are then averaged over the sliding distance, resulting in a single data point for each tribometer test. This procedure is state of the art for measuring COF considering the corresponding TLs [6].

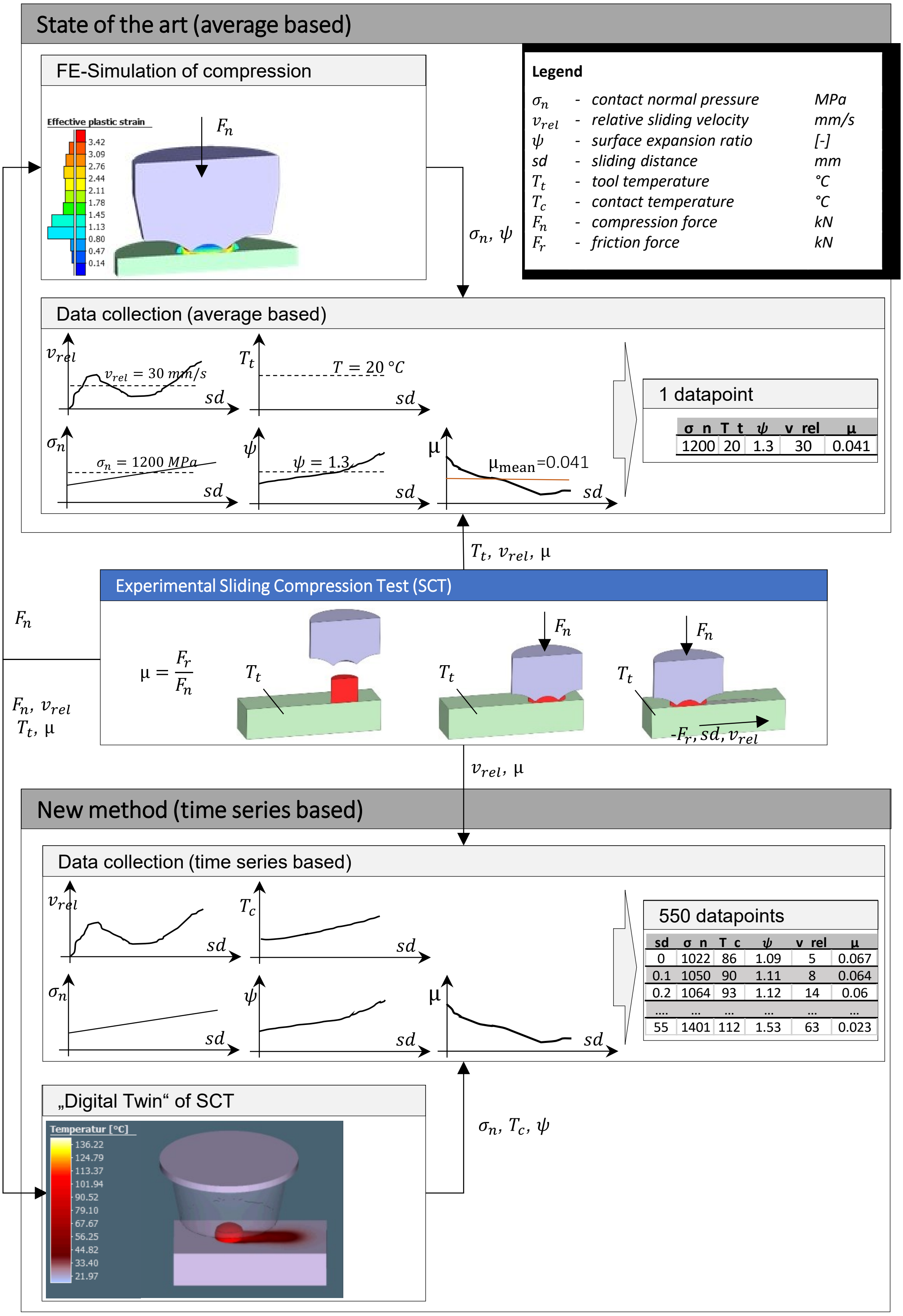


Figure 8. Schematic depiction of the sliding compression test (SCT) and the work flow for both methods presented

Data Collection - New Method (time series based)

The lower part of Figure 7 shows the new method of collecting data from tribometer tests based on time series. While the general use of time series in engineering applications is well known and described by Molitor et al (KDT-EA source), this principle has not been used in tribometer testing for cold forging until now.

In this new method, instead of averaging the measurements, the entire time series of measurements is used. The time series of relative sliding velocity (v_{rel}) and COF (μ) are taken directly from the experimental SCT data. In order to provide time series of the other tribological loads, the introduction of a "digital twin" - a 3D thermomechanically coupled FE simulation of the SCT - is necessary to calculate the contact normal pressure and the surface expansion ratio. The digital twin also allows the temperature in the contact zone to be calculated. The contact temperature time series derived from the digital twin is much more accurate than assuming that the contact temperature is equal to the constant tool temperature. To ensure the accuracy of the digital twin, the time series of the compressive force F_n, the sliding velocity v_{rel} and the COF are taken directly from the experimental SCT. This means that an individual FE simulation has to be calculated for each SCT. In this study, an equidistant distance of 0.1 mm sliding distance between data points was found to be feasible. The parameters of the FE simulation are identical to those of the forming simulations described in Chapter 2. Using this new method, a single SCT with a sliding distance of 55 mm will provide 550 data points instead of 1 data point.

Experimental plan

The full factorial test plan is designed to fully cover the tribological loads typical of cold forging [7]:

- Contact normal pressure (σ_n): 500 – 2750 MPa (500, 1750, 2750 MPa)
- Surface expansion ratio (ψ): 1.069 - 20 (1.069, 5, 20)
- Relative sliding velocity (v_{rel}): 5 – 500 mm/s (5, 200, 500 mm/s)
- Contact temperature (T): 20 – 300 °C (20, 100, 300 °C) *
- Sliding distance (sd): 0 – 60 mm (60 mm)

*) Note that the in the SCT the tool temperature is varied from 20 to 300 °C in three steps. The temperature used in the dataset is not the tool temperature but the contact temperature calculated with the help of the "digital twin".

The test plan includes a total of 81 SCTs for each of the two lubricants investigated. The time series of each SCT contains 550 data points. For the current method, the data set contains 81 data points. For the time series method, the training data set consists of 44,550 data points. In addition, 30 SCTs are performed for each lubricant to create a test data set.

3.3. Model training

To compare the data efficiency of the two data collection methods presented, all five models were trained using both methods. For FFNN training, for the hyperparameter optimisation a 5-fold cross validation using grid search was used, for which five random SCTs where chosen on the basis of whole SCTs, meaning that the whole data of an SCT is either training or validation data. During the model test, the mean absolute error (MAE) between the friction values calculated by the model and the measured friction values of all data points of the test data is calculated. To analyse the effect of the data collection method on the model performance and data efficiency, the amount of training data used for model training was successively increased. The training data was randomly selected from the entire training data set. It was found that the randomness of the training data selection had a strong effect on the MAE, especially for a small amount of training data. To account for this, the training was repeated ten times for each training set size. This results in an MAE distribution for each training data size.

Model training - State of the Art (average based)

Figure 9 a) shows the MAE for all friction models, with the line describing the 0.95 percentile value of the MAE distribution using the average-based method of data collection. It can be seen that the 0.95 percentile of the MAE distribution converges around 70 SCTs with values between 0.008 and 0.012. Linear and polynomial regression models have lower converged MAEs than the black box models. This can be attributed to the insufficient amount of training data for deep learning models.

Model training - New Method (time series based)

Figure 9 b) shows the MAE for all friction models using the time series based data collection method. It can be seen that the 0.95th percentile of the MAE distribution converges at around 30 SCTs with values between 0.007 and 0.011. Using this method, an MAE of less than 0.01 was achieved for all models, which is the typical accuracy of tribometer testing in cold forging. Compared to the average based method, the time series based method reduced the required experimental work by 73 %. With this method, 17 SCTs at random tribological loads are sufficient to train a friction model to have a 95 % probability of having an MAE below 0.01.

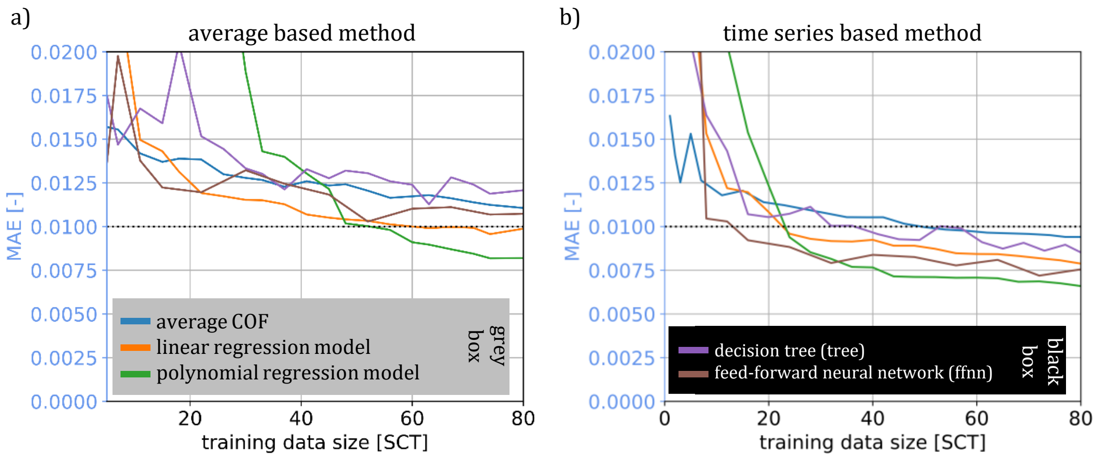


Figure 9. Comparison of the effect of training data size on the 0.95 percentil of the MAE for all models and both methods.

3.4. Model integration

To integrate the friction models into the FE simulation, the user subroutine ufric() must be used, which allows the friction coefficient μ of each individual node in the contact to be defined. To avoid convergence problems in the friction coefficient calculation, the calculation of the friction coefficient must be based on the tribological loads of the previous increment.

4. FE-Simulation results

A total of 180 forming FE-simulations were carried out using the five friction models, nine factor levels, two processes and two lubricants. Figure 10 shows the comparison of the numerically determined forming forces for the forward rod extrusion process at a die temperature of 20 °C, 50 °C and 100 °C at a constant forming speed of 5 mm/s for the models: a) constant coefficient of friction, b) linear regression and c) ffnn using the polymer lubricant. The comparison shows that the numerically calculated forming force curves using the linear friction model and the ffnn friction model agree better with the experimentally determined forming force curves than those assuming a constant COF of μ = 0.04.

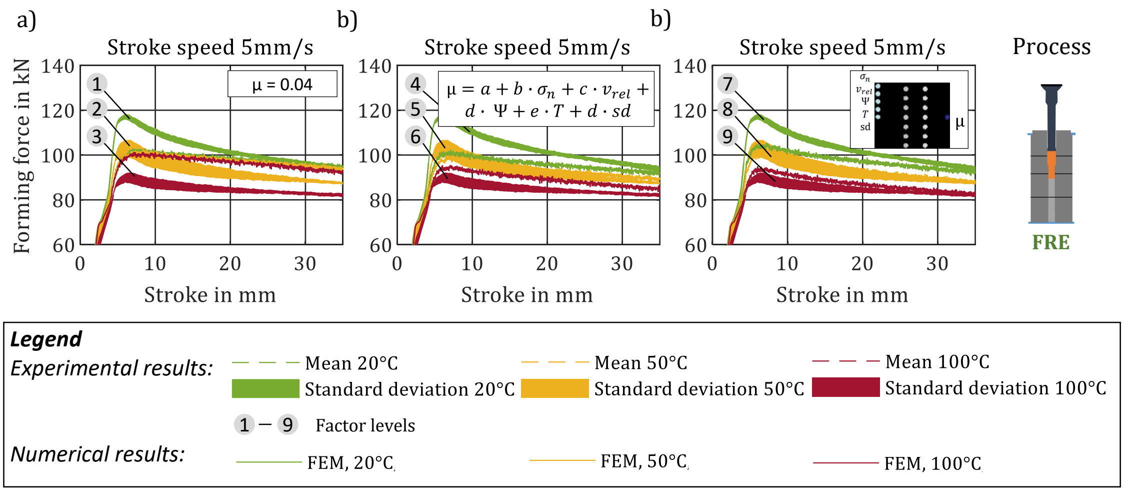


Figure 10. Experimentally and numerically determined forming force curves of the FRE at 5 mm/s for three different friction modells.

Figure 11 shows the absolute relative error of the FE simulation using the five friction models, averaged over all die temperatures and stroke speeds, both processes and both lubricants. The figure allows a comparison of the absolute relative error and its standard deviation of FE simulations assuming constant COFs (see Chapter 2) and using 'advanced friction modelling'.

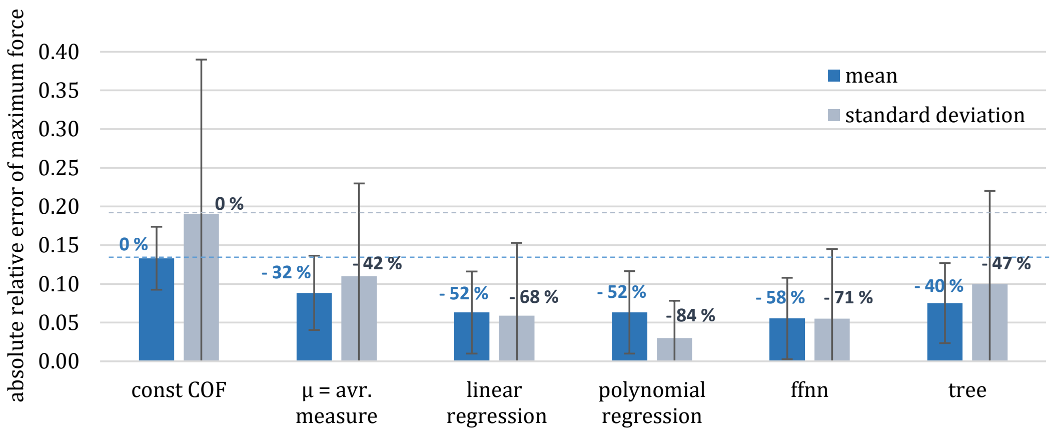


Figure 11. mean absolute relative error and standard deviation of the maximum forming force for the constant COF models and the five advanced friction modells.

All advanced friction models reduce both the mean relative error and its standard deviation. The usage of a ffnn friction model leads to the largest reduction of the relative error of 58 %. The reduction is slightly smaller for the polynomial regression friction model (-52 %), while the reduction in the standard deviation is higher (polynomial: 84% and ffnn: 71 %). The linear regression model shows similar improvements with reductions of 52 % and 68 %. For linear and polynomial regression, the simulation time increases by 18 % and for ffnn by 61 %. However, the subroutines were not optimised in this respect. Optimising the subroutines in terms of computation time could probably reduce this increase.

5. Summary and Discussion

In this study, the influence of friction modelling on the error of the FE simulation was first demonstrated using the example of two processes representative of cold forging. It is important to note that the error of the FE simulation is not only influenced by the friction modelling, but also by several other variables such as the material modelling. It can also be assumed that these influence each other. The error caused by friction modelling inaccuracies cannot be quantified in isolation. However, in order to evaluate the influence of advanced friction modelling on the accuracy of the FE simulation, the relative errors of the FE simulation using different friction models can be compared. When comparing, all other parameters of the FE simulation, such as the material modelling, must remain the same. Within this study, the absolute relative mean error of the maximum forming force of FE simulations with a constant COF was found to be: 13 % ± 4 % with a standard deviation of 19 ± 20 %.

With regard to the general validity of these results for FE simulations of cold forging, it should be noted that these investigations only examine a fraction of the tribological systems that occur in the industrial environment. Although the full range of tribological loads is investigated, system variables such as tool hardness and roughness, lubricant type or surface treatment are kept constant. However, at this stage there is no reason to believe that the results will be fundamentally different for different systems. The coefficients of friction $\mu = 0.04$ and $\mu = 0.08$ analysed in this study can be considered representative, since according to Kramer coefficients of friction between 0.05 and 0.11 are used in 50 % of the cases and between 0.01 and 0.16 in 99.3% of the cases. [3] In fact, it can be assumed that the relative errors and standard deviations are even higher when friction coefficients above 0.08 and below 0.04 are added.

By using advanced friction models, the error of the FE simulation can be significantly reduced compared to simulations with a constant friction coefficient. Based on the presented results, a polynomial regression model is recommended due to its high accuracy increase (-52 % relative error), low training data requirement (25 SCTs), low simulation time increase (18 %) and easy simulation integration. Depending on the importance of these different aspects, the FFNN can also be recommended. Its use reduces the relative error by 58 % while increasing the simulation time by 61 %. Less data is needed for model training (17 SCTs), but model integration is more challenging.

It is important to note that the structure of the training data with its inherent information influences the performance of the grey box models. Therefore, the performance of grey box models on one training data set may not be generalisable. While polynomial regression performed well on the tribological systems investigated in this study, it may not perform well on another system. Therefore, when using a grey box model, it is recommended to select an appropriate model definition for each data set individually, which is time consuming. This step is not necessary when using a deep learning model such as ffnn. Due to the hyperparameter optimisation that is part of every ffnn model training, the optimal model definition for the given training data set is found automatically.

Using the time series based data acquisition method reduces the amount of experimental work required to generate an advanced friction model with an MAE < 0.01 by 62% from 45 to 17 SCTs. It also reduces the lowest possible MAE by an average of 27 % from 0.011 to 0.008. The clearly defined scope and design of the experimental work as well as the statistically proven model accuracy presented in this study provide a great benefit for the industrial use of advanced friction models. A friction model generated by the presented method, in contrast to most models presented in the literature, can be used for all types of cold forging processes due to the large range of tribological loads included. This further enhances its industrial applicability. While the presented method greatly reduces the necessary experimental work, it increases the need for a "digital twin" for each SCT. In addition, the experimental data can only be collected using a highly flexible direct tribometer such as the SCT, which represents only a small fraction of existing tribometers.

6. Outlook

As explained in chapter 3, in addition to the process variables (tribological loads) considered in this work, numerous system variables such as tool hardness, tool material, tool roughness, workpiece material, etc. also have an influence on the coefficient of friction. In this work, all system variables were kept constant in both the tribometer test and the forming tests and were not taken into account in the friction models. In order to further improve the scope and applicability of the presented methodology and friction models for industrial use, future studies will extend them to include system variables. Two aspects will then be of great importance:

With each additional variable, the experimental effort required to collect the training data increases significantly. Therefore, time series based data collection becomes inevitable in order to progress further and create friction models with an even wider range of applications while keeping the experimental work within an industrially feasible scope. In addition, when extending the methodology to include system parameters, the use of black box models becomes increasingly necessary to account for the complexity in the tribological system.

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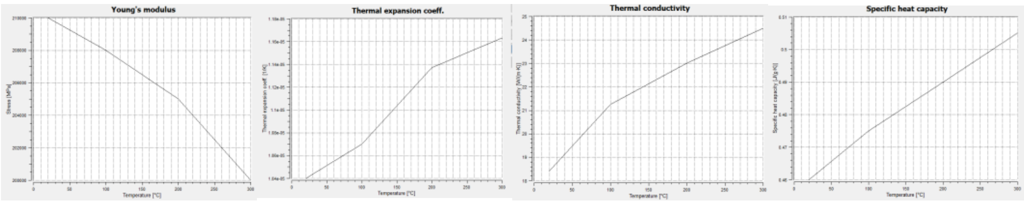
Appendix

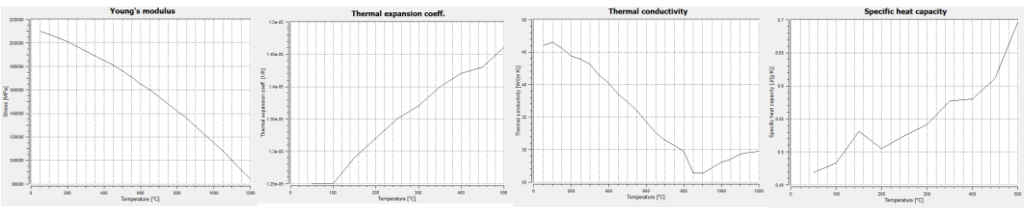
Tool properties

- elastic
- HTC: constant 35000 W/m^2K
- Emission coefficient: 0.25
- Coefficient to environment: 50 W/m^K



Workpiece properties

- Elastic plastic
- Hensel Spittel parameters: 677.443, -0.000788968, 0.103451, 0.0253737, 8.45076e-05 (assuming °C)
- Density: 7850.0 kg/m^3
- Dissipation factor: 0.9
- Poisson's ratio: 0.3



Simulation properties

- Element type 3D: Haxahedral
- Element edge length 3D: 0.5 mm
- Refinement type and level 3D: none
- Remesh: strain based (0.4)
- Contact, friction and step control: automatic
- Element type 2D: Quadtree (Quads10)
- Element edge length 2D: 0.4 mm
- Refinement type and level 2D: h-method, level 2