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Comparison of Conventional and Data-Driven Friction Models for Cold Forging on a Shear Stress Level

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Abstract

Friction modelling in finite element simulations is largely based on state-of-the-art analytical approaches, ranging from the Coulomb friction model and the shear friction model to advanced friction models that incorporate multiple influencing variables to represent the fluctuating contact conditions. This work presents a systematic benchmark of such state-of-the-art friction models, complemented by data-driven machine-learning-based approaches. A tribometer-based benchmark using sliding compression tests is conducted under identical boundary conditions and over a wide range of tribological loads. To enable a physically consistent comparison of fundamentally different friction formulations, model performance is specifically evaluated on the level of frictional shear stresses. The results show that the neural-network-based friction model consistently achieves the highest predictive accuracy, exhibiting the lowest prediction error. In comparison with the Coulomb model, which utilises standard constant values, the mean absolute error (MAE) is reduced from 51.38 MPa to 9.35 MPa. This equates to an error reduction of 81.8 %.

1 Introduction

Cold forging is widely employed in industrial production, where numerical simulation has become the dominant tool for process design and optimisation [1–3]. Among the various modelling aspects, friction at the tool–workpiece interface plays a decisive role, as it directly governs material flow and process stability [4]. In industrial practice, zinc phosphate–based lubrication systems are still predominantly used despite their ecological impact and economic cost. Consequently, environmentally benign alternatives have gained increasing attention [5]. These lubricants, however, often exhibit pronounced load-, temperature- and state-dependent friction behaviour, which fundamentally challenges the assumptions underlying conventional friction models [6]. Despite this increasing tribological complexity, friction in finite element simulations of cold forging is still commonly represented by simplified formulations, such as the Coulomb or shear friction law, which use constant coefficients [7, 8]. As a result, significant deviations between simulated and experimentally observed process behaviour can occur, particularly when modern lubricant systems are applied.

Numerous advanced friction models have been proposed in the past. However, these approaches differ substantially in terms of their formulation and the underlying assumptions. This limits their comparability and transferability. To date, there is no commonly established procedure of comparing different friction models and especially their capability to precisely calculate shear friction over a wide range of contact conditions.

Against this background, the present study aims to systematically benchmark friction models based on fundamentally different physical assumptions within a unified evaluation framework. Rather than comparing model parameters, conventional, combined, regression-based, and data-driven friction models are assessed based on their predicted frictional shear stresses under identical tribometric boundary conditions, enabling a physically consistent comparison of their predictive capabilities.

2 State of the art

In cold forging, friction is commonly described by analytical models that relate the frictional shear stress τ_R to either the contact normal stress σ_N or the material flow stress [1, 7]. Figure 1 illustrates the fundamental friction models used in cold forging, namely the Coulomb friction model, the shear friction model and combined transition models.

Coulomb friction models [9] assume a proportional relationship between frictional shear stress and contact normal stress via a constant coefficient of friction μ. While widely used in industrial practice, this formulation does not impose an upper limit on the transferable shear stress and assumes a linear dependency between σ_N and τ_R. Experimental observations under cold forging conditions, particularly at high contact pressures and for state-dependent lubricant systems, frequently deviate from this assumption [8].

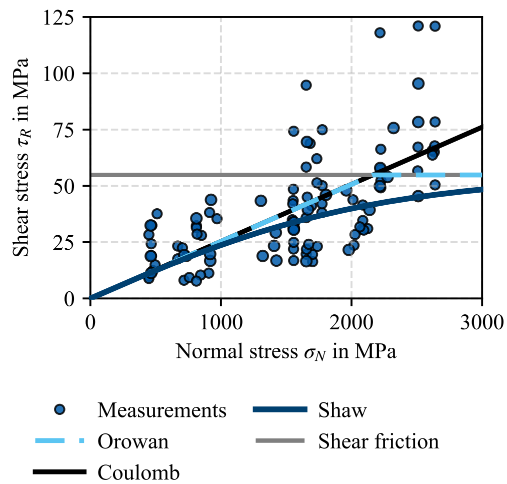

Figure 1: Application of conventional friction models to experimental data from sliding compression tests assuming identical material flow stress for all tests. Experimental range and conditions are summarized in Table 1.

Shear friction models [10] relate the frictional shear stress to the shear yield stress of the workpiece material via a friction factor m, resulting in a stress-limited friction formulation independent of the contact normal stress. While this assumption is suitable under conditions of severe plastic deformation and high contact normal pressure, it is inaccurate at low contact normal pressure and in well-lubricated tribological systems where low shear stress occurs[11].

Combined friction models have been proposed to bridge the conceptual gap between Coulomb-type and shear-stress-limited friction. The model proposed by Orowan [12] introduces a transition between the two regimes by accounting for plastic deformation within the contact zone. Continuous transition models, such as the formulation proposed by Shaw et al. [13], enable a smooth transition between the limiting cases.

Despite the refinement of these conventional models, they still show large inaccuracies when calculating shear stress for real cold forging contact conditions. To clearly highlight this, the experimental data derived within this study is displayed in Figure 1. The data shows the shear stress acting in the contact interface for different real cold forging contact conditions. The shear stresses vary considerably and are not adequately described by conventional models. While their numerical efficiency and ease of parameterisation make them attractive for industrial applications, the pronounced nonlinearity and scatter indicate the simultaneous influence of multiple interacting tribological variables, which cannot be captured by predefined analytical functional forms. A fundamentally different modelling strategy is pursued by data-driven friction models, in which friction is represented as a function of multiple influencing variables without prescribing a fixed physical relationship.

Neural-network-based friction models, such as the model proposed by Volz et al. [7], enable a consistent representation of nonlinear interactions based on tribometer-derived training data and aim at a process-independent description of friction behaviour within the load range relevant to cold forging.

3 Motivation, aim and methodology

The state of the art highlights the most industrially relevant friction models for cold forging, namely the Coulomb, shear, and Orowan models, and reveals fundamental differences in their underlying physical assumptions. Coulomb and shear friction models define frictional shear stress based on fundamentally different reference quantities, i.e., contact normal stress and material flow stress, respectively. Consequently, the coefficient of friction μ and the friction factor m represent distinct tribological concepts and cannot be uniquely converted into one another, as both reference stresses vary spatially and temporally during the forming process. Therefore, a direct comparison of model parameters is not meaningful. To enable a physically consistent comparison, friction models must instead be evaluated based on their resulting frictional shear stresses and their predictive accuracy under identical boundary conditions.

Accordingly, the objective of this study is to assess friction models at the model level rather than at the parameter level. It is acknowledged that zinc phosphate-free lubricant systems are sensitive to tribological loading; hence a polymer-based lubricant provided by ZWEZ-Chemie GmbH is used consistently throughout the investigations.

The data required for the development of the friction models are obtained from sliding compression tests in combination with finite element (FE) simulations. Based on these datasets, the friction models are trained using designated training data and subsequently evaluated on independent test data. The evaluation is conducted on the frictional shear stress level using established error metrics such as the mean absolute error (MAE) and the root mean square error (RMSE). Identical training and test datasets are employed for all investigated friction models, ensuring a high level of comparability among the model predictions.

The friction models investigated in the study are:

- Coulomb friction models with constant $\mu = 0.08$ [14], $\mu = 0.04$ [6] and mean values of μ obtained from the training data
- Shear friction models with constant $m = 0.12$ [4] and mean values of m obtained from the training data

- Orowan Model [12] with mean values of μ and m obtained from the training data
- Extended Coulomb friction model (logarithmic form) [6] including contact normal stress, surface enlargement, sliding velocity and contact temperature
- Extended Coulomb friction model (multiplicative-exponential form) [15] including contact normal stress and contact temperature
- Neural-network-based Coulomb friction model (black-box) [7] including contact normal stress, surface enlargement, contact temperature, sliding velocity and sliding distance

The constant parameter values $\mu = 0.08$, $\mu = 0.04$, and $m = 0.12$ represent commonly applied reference values in industrial cold forging practice and are therefore included as baseline cases in the benchmark.

4 Data acquisition on shear stress level

The study requires a comprehensive database with varying tribological loads for training the friction models. In particular, data-driven experiments, such as the neural network-based friction model by Volz et al. [7], require time series-based data.

Table 1: Test area of the experimental data of the sliding compression test

Process Parameters	Test Area
Normal stress σ_N in MPa	500 – 2750
Surface expansion ratio ψ [-]	1 – 20
Sliding velocity v_{rel} in mm/s	5 – 500
Tool temperature in °C	20 - 200

Therefore, the benchmark is based on sliding compression tests [16], which allow as direct tribometer an independent and systematic variation of key tribologically loads, including contact normal stress (σ_N), relative sliding velocity (v_{rel}), tool temperature (T_{Tool}), surface expansion (ψ) and sliding distance (sd). The functional principle of the test setup is shown in Figure 2, while the investigated experimental space is summarised in Table 1. The process parameters are fully factorial in three levels. Therefore, the dataset comprises 81 experiments with a total of 44,550 data points used for model training or parameter identification and 30 additional random sliding compression test experiments (16,500 data points) reserved exclusively for validation. Quantities that are difficult to measure, such as contact normal stress, material flow stress or surface enlargement, are determined by finite element simulations following the methodology of Volz et al. [7].

The friction shear stress is calculated based on the friction coefficients measured in the sliding compression test and the simulated contact normal stress according to Equation 1.

$$\tau_R = \mu_{meas} \cdot \sigma_{N,sim} = \frac{F_{R,meas}}{F_{N,meas}} \cdot \sigma_{N,sim} \quad \text{(eq. 1)}$$

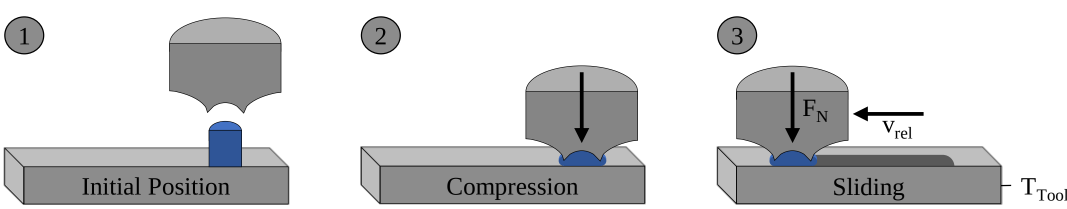

Figure 2: Functional principle of the sliding compression test

5 Training, evaluation and discussion of friction models

The training of friction models using data from the sliding compression test is described by Volz et al. [7]. All friction models are trained or parameterised in accordance with their respective formulations using the complete time series of the training experiments and are evaluated on the full-time series of the independent validation experiments. An exception is the logarithmic extended Coulomb model, whose parameter identification is computationally intensive and therefore feasible only for a limited number of data points [6]. Accordingly, the experimental data of each sliding compression test are averaged, and 54 training points are randomly selected from the training dataset.

For all investigated models, frictional shear stress τ_R is used as the sole comparison quantity. Model performance is evaluated by comparing predicted frictional shear stresses $\tau_{R,pred}$ with experimentally measured values $\tau_{R,meas}$ according to Equation 2 and 3. Using identical datasets and boundary conditions for all models ensures that observed differences in predictive accuracy can be attributed exclusively to the respective friction model formulations.

$$\mathrm{MAE}_{\tau_R} = \frac{1}{N}\sum_{i=1}^{N}\left|\tau_{R,meas,i} - \tau_{R,pred,i}\right| \qquad \text{(eq. 2)}$$

$$\mathrm{RMSE}_{\tau_R} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\tau_{R,meas,i} - \tau_{R,pred,i}\right)^2} \qquad \text{(eq. 3)}$$

$$\mathrm{Residues} = \tau_{R,meas,i} - \tau_{R,pred,i} \qquad \text{(eq. 4)}$$

Figure 3 presents the residuals (eq. 4) between measured and predicted frictional shear stresses together with their probability density distributions for all investigated friction models.

Constant Coulomb friction models exhibit pronounced systematic deviations across the entire stress range, with residuals increasing monotonically at higher frictional shear stresses. This indicates that a linear proportionality between contact normal stress and frictional shear stress is insufficient to represent the experimental data. Parameter adjustment reduces the overall error magnitude but does not eliminate the systematic bias. Shear friction and combined models, including the Orowan formulation, further reduce MAE and RMSE compared to constant Coulomb models. While these approaches are conceptually well suited to represent stress-limited friction at high contact pressures, structured residual patterns persist, particularly at medium and high stress levels. This indicates that a single, predefined saturation mechanism is insufficient to capture the state-dependent variability of frictional shear stresses observed in the experiments. Extended analytical Coulomb models provide an additional improvement in predictive accuracy and show a more uniform residual distribution. Nevertheless, residual trends persist, reflecting constraints imposed by predefined functional relationships. The neural-network-based friction model achieves the lowest MAE (9.35 MPa) and RMSE among all investigated approaches and exhibits an almost structure-free residual distribution across the entire range of frictional shear stresses. This demonstrates its ability to represent highly nonlinear friction behaviour under simultaneously varying tribological loads. Across all investigated friction models, a clear effect of targeted parameter identification or training can be observed. Compared to constant reference values, model calibration leads to a substantial reduction of systematic bias, with the mean of the residual distributions shifting towards zero. Accordingly, the peak of the probability density becomes increasingly centred around zero frictional shear stress deviation. However, while calibration effectively corrects the expected value of the prediction error, it does not eliminate structured, load-dependent residual patterns inherent to predefined analytical formulations. As a result, improvements in bias are not necessarily accompanied by a comparable reduction in residual scatter.

Overall, the tribometer-based benchmark establishes a clear performance hierarchy among the investigated friction models. While targeted calibration improves the performance of all approaches by reducing systematic bias, data-driven friction modelling uniquely succeeds in minimising both bias and structured residuals. Consequently, it consistently outperforms conventional analytical formulations in terms of predictive accuracy, providing a robust and physically consistent basis for the subsequent process-based evaluation.

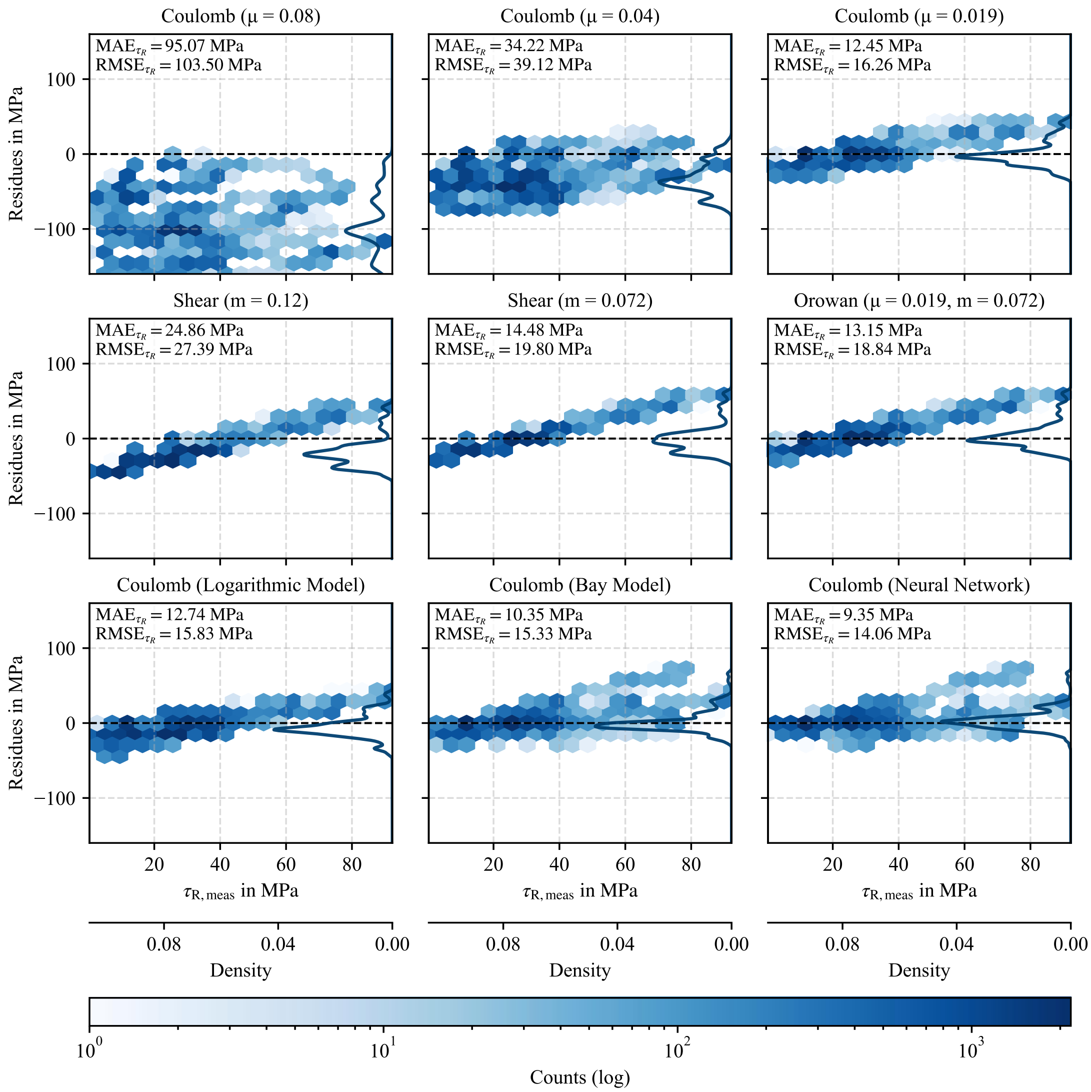

Figure 3: Residual-plots of tribometer-based benchmark of friction models

Despite the clear performance differences observed in this benchmark, several limitations of the present study must be acknowledged. First, the training and evaluation of all friction models are based exclusively on data obtained from sliding compression tests under controlled laboratory conditions. While this ensures high internal consistency and comparability, the transferability of the observed performance hierarchy to other forming operations, geometries, or loading paths cannot be assumed without further validation.

Second, the neural-network-based friction model, although exhibiting superior predictive accuracy, relies on the availability of sufficiently rich and representative training data. Its black-box nature limits physical interpretability and may reduce robustness when extrapolated beyond the range of tribological conditions covered by the training dataset. In contrast, analytical friction models retain advantages in terms of transparency, parameter interpretability, and ease of implementation in industrial simulation workflows.

Finally, the present benchmark focuses on a single lubricant system and material combination. Since friction behaviour is strongly system-dependent, the general validity of the conclusions must be assessed through additional studies covering a broader range of materials, lubricants, and surface conditions.

6 Conclusion and Outlook

This study presents a systematic benchmark of conventional analytical and data-driven friction models for cold forging at the model level. By evaluating different approaches based on frictional shear stresses under identical boundary conditions, a physically consistent comparison of fundamentally different friction formulations is achieved.

The results demonstrate that classical Coulomb, shear, and combined friction models are limited in their ability to represent the nonlinear and load-dependent friction behaviour of modern, environmentally benign lubricant systems. Even after targeted parameter calibration, these analytical models exhibit pronounced structured residuals and comparatively high prediction errors, with mean absolute errors typically exceeding 12 – 20 MPa, depending on the formulation and loading regime.

In contrast, the neural-network-based friction model achieves the highest predictive accuracy among all investigated approaches, yielding a minimum MAE of 9.35 MPa and the lowest RMSE across the entire range of frictional shear stresses. In addition, its residual distribution is nearly structure-free, indicating a robust representation of highly nonlinear friction behaviour under simultaneously varying contact pressure, surface enlargement, temperature, and sliding conditions.

The key findings of this study can be summarised as follows:

- A direct comparison of friction model parameters (μ, m) is not meaningful due to fundamentally different physical reference quantities and spatially and temporally evolving contact conditions during forming.
- Evaluating friction models at the frictional shear stress level enables a physically consistent and model-independent benchmark.
- Targeted parameter identification reduces systematic bias for all analytical models, shifting the mean of the residual distributions towards zero, but does not eliminate structured, load-dependent deviations.
- Using commonly applied industrial reference values ($\mu = 0.08$, $\mu = 0.04$, and $m = 0.12$) leads to systematic deviations with a MAE between 24 to 95 MPa.
- Calibration of the constant model parameters reduces the systematic bias and thus the error to 12 to 15 MPa.
- Data-driven friction modelling reduces both systematic bias and residual scatter simultaneously, achieving up to ≈ 25–40 % lower MAE compared to constant reference models and consistently outperforming all analytical formulations.

Overall, the results highlight the strong potential of data-driven friction models as a powerful complement to classical analytical formulations, particularly for modern cold forging applications involving complex tribological loading and zinc phosphate-free lubricant systems.

The methodological basis established in this study provides a foundation for future work. Subsequent investigations will focus on extending the benchmark to different lubricant systems and material combinations to assess the generality of the observed performance hierarchy. Furthermore, a process-based benchmark of the shown friction models to industrially relevant forming processes with complex geometries and loading paths will enable a comprehensive validation under near-production conditions. Such studies are essential for evaluating the robustness, extrapolation capability, and industrial applicability of advanced friction modelling approaches. This, in turn, supports the reliable integration of such approaches into industrial cold forging process design and simulation workflows.

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