

Integration of material simulation to extend the accuracy of FEM results for metallic forming processes

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Abstract. Nowadays, almost all metallic forming processes can be mapped by FEM simulation. Demands on FEM simulation are becoming increasingly higher with regard to the representation of very fine tolerances, whether in terms of temperature or dimensional accuracy. The combination of a FEM software suitable for the forming process and a connected materials database are a great potential to enlarge these precision figures. In the article, real simulation examples with QForm UK are used to show how this combination positively affects the accuracy of simulation results. For this purpose, several material data – such as flow curves, temperature-dependent properties or CCT diagrams – and material models – such as the recrystallization or phase transformation model – from the materials database MatILDa® are applied. Hereby, the possibilities of material simulation are demonstrated and practical methods to improve individual simulation projects are given.

Keywords: material simulation, FEM simulation, flow curves, recrystallization model, phase transformation model.

1 Interconnection of material data and forming simulation

During hot forming processes, metallic materials are formed with tools like rolls or dies to get final dimensions and properties and undergo fundamental microstructural changes. Each forming process possesses unique challenges, which is why the representation of individualized industrial processes within a FEM simulation is becoming increasingly attractive. In recent years, considerable effort was invested to reach realistic simulation results and FEM software has been significantly improved. But often the stored material data is not questioned. In practice, similar alloys or standard values are applied without knowing the experimental test setting or the validity range. However, there is great potential in the use of accurate material data and models tailored to the industrial process (see Fig. 1). Thus, the influence of material data sets developed to be included into FEM simulation, for example temperature-dependent properties, flow curves, microstructural models and CCT diagrams or phase transformation models, is described in the following sections.

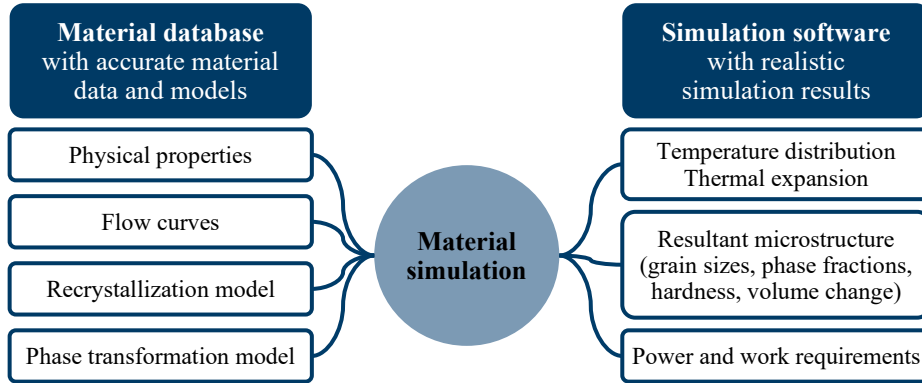


Fig. 1. The use of material data and models in material and FEM simulation.

At best, these material datasets are implemented in FEM or individual process software through a direct interface. In the simulation software, the user simply selects the alloy for the workpiece and tool and the material data and models are loaded from the materials database in the background.

The application of material datasets within a FEM simulation can be demonstrated using the example of simulating the temperature distribution. The material datasets are imported from the materials database into the simulation software. The boundary conditions of the forming process are defined in the simulation software. The software contains a temperature model for simulating the time-temperature curve during forming. The required temperature-dependent material properties are chosen from the initially provided material datasets. These properties are applied according to the condition of each node during the FEM simulation. This results in the temperature distribution in the component or die.

2 Material data for the calculation of the flow behaviour

The flow behaviour of a metal alloy is essential to simulate a forming process. Therefore, flow curves are often used to include the flow behaviour in a FEM simulation. Flow curves can be affected by the chemical composition, the experimental setting (such as tensile, compressive or torsion test), forming parameters (such as temperature, true strain and strain rate) as well as the heat treatment condition (such as as-rolled or heat-treated) [1]. Validated material datasets obtained from practical material investigations tailored to match the forming parameters and the main stress state in the forming process can enhance the accuracy of simulation results. For example, the effects of huge deformation on the dynamic and static recrystallization behaviour of Inconel 718 were investigated by Borowikow et al. [2] by using flow curves from torsion experiments. Significant improvements in the accuracy of simulation results can be achieved on the basis of accurate material data regarding the calculation of temperature distribution, thermal expansion, force and work requirements, microstructure as well as phase fractions and resulting final properties.

The next question at hand is: what occurs if you unintentionally or even unknowingly use flow curves that are not applicable to the specific forming process? How does it affect the accuracy of FEM results?

To investigate this, a FEM simulation was conducted using QForm UK to map a standard compressive test for the metallic alloys Ti6AlV4 (ASTM grade 5), 41Cr4 (AISI 5140), S420N (StE 420) and 100Cr6 (AISI 52100) with a sample size of $d_0 = 8$ mm, $h_0 = 16$ mm and $h_1 = 6,5$ mm (see Fig. 2). Based on this, the forming parameters true strain $\phi = 0.9$ and strain rate $\dot{\phi} = 0.1$ s⁻¹ were calculated.

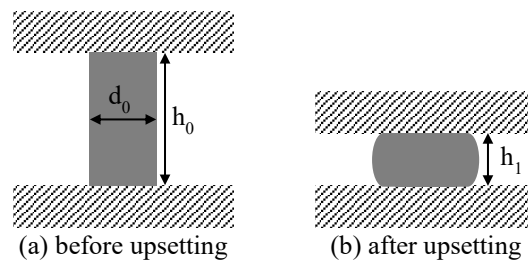


Fig. 2. Parameters for the compressive test within the FEM simulation.

The process parameters explained above were kept constant for all FEM simulation projects. But, for the same process parameters, flow curves with different validity ranges were used to see the impact on the resulting force (see Fig. 3). For example, the compressive test in Fig. 3(a) was conducted at a simulation temperature T_{sim} of 1000 °C but two different flow curves were used: the first one is valid for the temperature range of 200 to 500 °C, whereas the second one is valid in between 800 and 1200 °C. Even though it is obvious that the temperature range of the flow curve should match the temperature range of the forming process, the temperature results are the most remarkable. However, it is important to note that information on the temperature range's validity is crucial.

In the next example, two flow curves for one steel alloy were available: for a lower and an upper analysis limit (see Fig. 3(b)). Also, the difference in the calculated force is visible for variations of the chemical composition, even though they belong to the same steel grade. From this result, it can be inferred how significant the difference in resulting force can be when using a flow curve for a completely different alloy.

The experiment's setting is also influencing the simulation results (see Fig. 3(c)): adding flow curves conducted through compressive and torsion test, the resulting force differs clearly. Obviously, simulating a compressive test, the flow curve should have been recorded within a compression test. In addition, the results are affected by different heat treatment conditions, which can be seen in Fig. 3(d).

The presented examples in Fig. 3 clearly highlight the crucial role of aligning the flow curve with process parameters, such as temperature, chemical composition, experimental setting and heat treatment conditions. It is evident that validated materials datasets obtained from practical material investigations that are consistent with the parameters and the main stress state in the forming process can substantially impact the simulation results and enhance their accuracy.

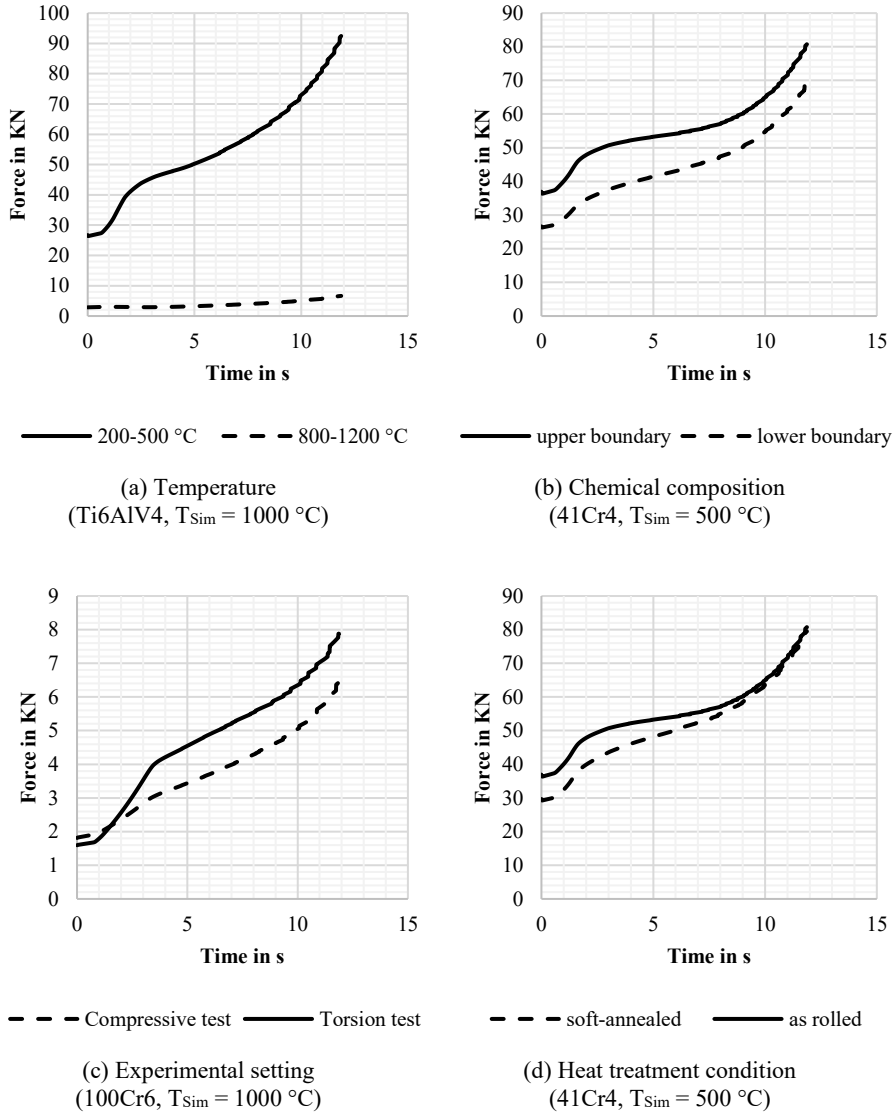


Fig. 3. FEM results for a compressive test using flow curves with different validity ranges regarding (a) temperature, (b) chemical composition, (c) experimental setting and (d) heat treatment condition.

3 Recrystallization model to calculate grain size evolution

One topic many FEM users are not aware of is the inclusion of microstructural or recrystallization models for the calculation of grain size distribution and grain growth. This is accomplished by calculating the static and dynamic recrystallization processes. The results of the recrystallized fractions and the grain size distribution are among others essential for the calculation of the mechanical properties.

There are numerous microstructural models and approaches, which have been recently summarized in [3]. As the authors describe, there are on the one hand empirical plasticity models, which do not show a high accuracy between process and simulation results and require a lot of experimental data. On the other hand, there are physical plasticity and microstructural evolution models as well as computational approaches which show good results with high agreement between simulation and industrial results and are easy to implement into FEM simulation. Also, Hallberg [4] provides a comprehensive review of different approaches to modelling recrystallization in metals and discusses the challenges in developing accurate recrystallization models, such as the need for experimental data for model validation and the difficulty of incorporating complex physical processes. Overall, the importance of accurately predicting recrystallization for improving the performance of materials is highlighted. Especially for industrial applications, microstructural or recrystallization models should not be very time-consuming to implement and use in the FEM simulation.

Well, the recrystallization model described in this contribution is a physically based microstructural model which is designed for hot forming processes. The semi-empirical model is based on Sellars and Whiteman [5][6] with modifications of Lehnert/Cuong [7]. A more detailed insight into the assumptions is shown in [8].

For now, the focus will be on the application of the recrystallization model. Biba et al. [8] validated the accuracy of the recrystallization model in QForm UK by comparing the predicted with experimentally measured grain sizes for an Inconel 718 (see Fig. 4). Thus, 3-step manufacturing process (nosing, flattening and closed-die forging) for a structural component was simulated to predict the grain size. The authors conclude that this approach can provide useful insights into the recrystallization behaviour and help optimize forming processes to reach a better product quality.

For the same nickel-based alloy, the accuracy of the recrystallization model was demonstrated in [9] within the optimization of the manufacturing process of a turbine disk, which is characterized by four cylindrical upsetting operations and a final shaping in the closed-die with subsequent trimming to the contour of the finished part.

Also, in [10] an entire open-die forging process was simulated using FEM simulation to optimize the process sequence. The FEM results were validated by comparing them with metallographically determined grain sizes and thermographic images. Additionally, the microstructure model was utilized for temperature control optimization in a bar mill, as well as for bar tempering.

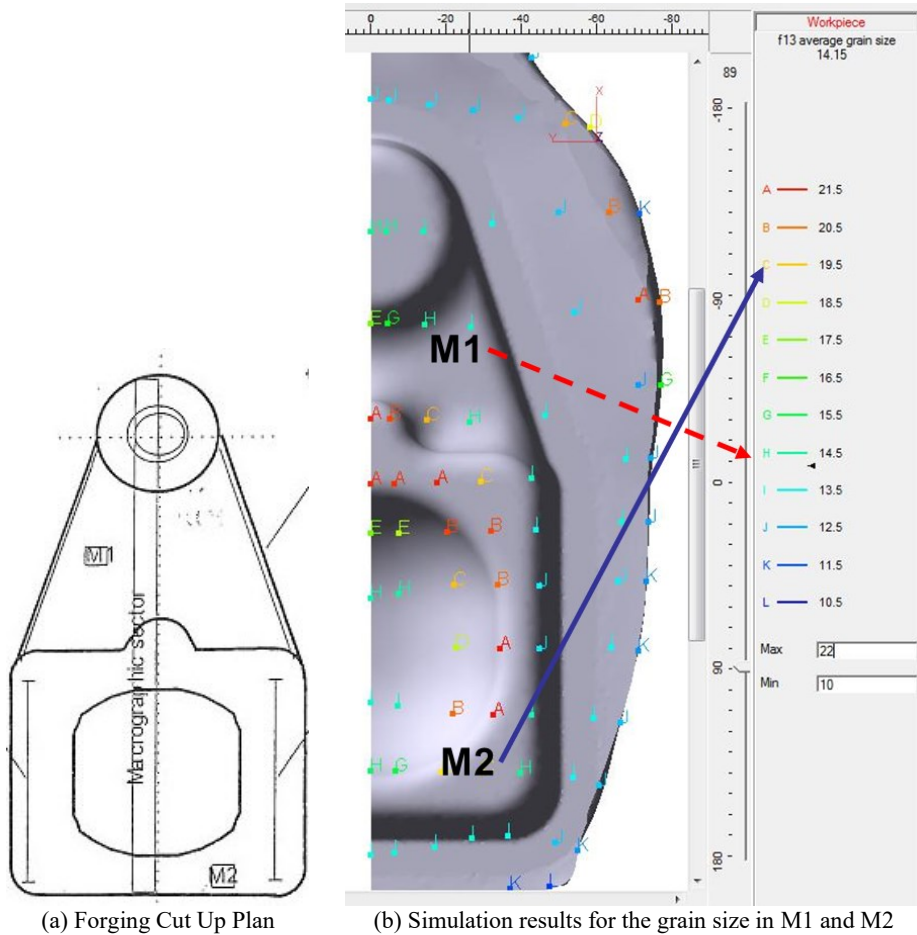


Fig. 4. Comparison of the grain size evolution for a real forming process and FEM simulation according to [8].

4 Calculation of phase transformation

CCT diagrams are well-known for the prediction of phase transformation. Sometimes the required material dataset is unavailable. In this context, neuronal networks can be used for the calculation of phase transformation based on an extensive data evaluation of CCT diagrams. This so-called transformation model from the materials database MatILDa[®] is used to describe the transformation behaviour and is applicable to a selected range of analyses of a steel grade or limited steel group and can be described as a function of chemical analysis, cooling rate, and austenitizing temperature.

The simulation of the transformation behaviour of a low-alloyed NiCrMo-forged steel (BS S154) using the QForm UK software is shown in [11]. As first, the available experimental data was analysed, including dilatometric measurements and metallography. Based on this data, a material model was developed using a combination of empirical and physical approaches, which could predict the transformation behaviour of the steel during heat treatment. The model was validated and tested for a forged fork from the aerospace industry: the tensile strength from experiments in the range of 925 and 990 N/mm² showed good agreement compared to the mean value of 950 N/mm² from FEM simulation. Thus, the developed transformation model showed a high level of prediction quality.

Furthermore, this neuronal network calculating phase transformation is utilized in the temperature and microstructure simulation to realistically determine the distribution of forming intensity in a KOCKS-3-roll RSB[®] block [12].

5 Summary

Material data and models can be used for the simulation of any forming and heat treatment process. Several examples involving real forming processes and process chains were given illustrating the diverse application fields of material and FEM simulation. The shown results highlight the benefits of precise material data and models in FEM simulation projects. In future, accurate and validated material datasets selected for the specific metallic alloy should be established as standard in FEM simulation.

Finally, the authors provide a summary of factors – decisive for a high standard in simulation – that users must consider in order to achieve a high level of agreement between simulation and experimental results. These factors include:

- using material data and models for your specific alloy,
- verifying the validity ranges and recording conditions of material data sets to ensure they are appropriate for the specific forming process (such as temperature, true strain, strain rate or stress state),
- integrating all aspects of material simulation to achieve realistic simulation results and
- expanding the functions and models according to process parameters with appropriate materials expertise.

References

1. A. Borowikow, M. D. Bambach, D. Wehage: Einfluss von Fließkurven auf die Berechnung des Kraft- und Arbeitsbedarfs bei der Simulation von Warmumformprozessen. *massivUMFORMUNG*, pp. 24-29 (March 2021)
2. A. Borowikow, H. Schafstall, H. Blei, D. Wehage, M. Borowikow: Integrierte Gefügemodellierung bei der FEM-Simulation mit Hilfe der Werkstoffdatenbank "MatILDa®". Kompetenzzentrum Neue Materialien Bayreuth (November 2004).
3. S. Y. Jo, S. Hong, H. N. Han, M. G. Lee: Modeling and Simulation of Steel Rolling with Microstructure Evolution: An Overview. *Steel research international* 94, pp. 1–21 (2023).
4. H. Hallberg: Approaches to modeling of recrystallization. *Metals*, Vol. 1, No. 1, pp. 16-48 (2011).
5. C. M. Sellars, J. A. Whiteman: Controlled rolling processing of HSLA-steels. *Proc. Product Technology Conf. York* (1976).
6. C. M. Sellars, J. A. Whiteman: Recrystallization and Grain Growth in Hot Rolling. *Metal Science* 13, pp. 187–194 (1979).
7. N. D Cuong: Mathematische Modellierung und Simulierung der Gefügebildungsvorgänge beim Warmwalzen in Kalibern, vorzugsweise beim Walzen von Stabstahl und Draht. *Dissertation TU Bergakademie Freiberg* (1991).
8. N. Biba, A. Borowikow, D. Wehage: Simulation of Recrystallisation and Grain Size Evolution in Hot Metal Forming. *American Institute of Physics AIP Conference Proceedings*, Vol. 1353, No. 1, pp. 127–132 (2011).
9. N. Biba, A. Borowikow, D. Wehage: Möglichkeiten und Grenzen der simulationsbasierten Prozesskettenoptimierung. Dargestellt am Beispiel eines Schmiedeerzeugnisses aus einer Nickel-Basislegierung. *Internationale Konferenz „Neuere Entwicklungen in der Massivumformung“*. Fellbach bei Stuttgart (May 2015).
10. A. Borowikow, D. Wehage, H. Blei: Modell zur Gefüge- und Eigenschaftsberechnung für online und offline Anwendungen. *XXVI. Verformungskundliches Kolloquium, Planeralm, AT*, pp. 123-137 (March 2007).
11. A. Doktorowski, N. Biba, A. Borowikow, D. Wehage: Simulation of the Transformation Behaviour of Low-Alloyed NiCrMo-Forged Steels-from Data Analysis to Material Model (2011).
12. M. Kruse, M. Schuck, A. Borowikow: Innovations in simulation of microstructure developments. *Materials Science Forum Vols. 706-709*, pp. 2170-2175 (2012).