Toward Holistic Digital Material Description During Press-Hardening

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Abstract

Press hardening of manganese-boron steels is one of the most widely used production processes for high-strength automotive components. The low residual formability of these parts is a decisive disadvantage. The low formability originates from a strong, but brittle martensitic microstructure transformed

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during quenching in the press-hardening tool. In contrast, medium manganese steels (MMnS) contain high fractions of ductile retained austenite improving press-hardened parts toward promising candidates for crash-relevant car body components. Disadvantages include a more complex alloy design, a highly sensitive production process, and more demanding requirements on the tool due to higher strength during press-hardening.

A detailed description of the entire production process along the process chain including the material and the press-hardening tool is important for tailoring the properties. Combined information is required to enable a precise control of the production process and its influences on the final properties of the part. Maximum economic use of the material is achieved by digitally describing MMnS as well as the tool along the entire process chain (casting, forging, hot rolling, cold rolling, galvanizing and press hardening including Q&P). To link the process steps and to describe the changes of the material, a new material database structure (idCarl) was developed. All production parameters are recorded and processed as a digital material twin. Ultimately, deviations occurring during production process can be deduced from in-line data analysis and counteracted. These can then be counteracted by adapted process control and the product can be brought back into the required parameter field of properties. Clear identification of the component and the used material allows conclusions about steps responsible for errors in the production process that become apparent during use.

8.1 Introduction

Producing high-strength press-hardened components is complex, imposing high demands on the material but equally on the press-hardening tools. Interconnected production processes for press-hardening influence each other and provide a complex interplay between material and production tools. Capturing microstructural parameters can be understood as key to understand this complex interplay. In the context of Internet of Production (IoP) the material description constitutes a bridging between the various production technologies.

In contrast to conventional alloy concepts for press hardening parts, Medium-Manganese-Steels (MMnS), a relatively new steel grade, offer promising improvements of the final properties of components produced. In order to ensure that these beneficial properties can be transferred to relevant industrial use cases such as b-pillar production, the material must be able to tolerate the necessary forming operation without material failure during manufacturing. Consequently, the material undergoes a number of treatment steps before press-hardening (casting, forging, hot- and cold-rolling, and galvanizing) that affect the microstructure. During press-hardening a precisely controlled interplay of the microstructure and the process parameters is of highest importance to achieve consistent and high-quality output. To achieve these goals, a cross-process chain description of materials was developed that captures and links all materials encountered in the process. In order to describe the process chain, it is necessary to analyze the individual process steps, to transfer the relevant parameters into a data-based form and to link them with each other. In the following, individual steps of the process chain have been highlighted. The individual chapters deal with:

- Digital description of the material for press-hardening and the database structures set up for this purpose
- The digitalization of the material behavior during deformation and improvements to achieve optimal properties
- Digitalized press-hardening tools and their additive manufacturing
- Data-driven material description of press-hardening tools in the form of representative volume elements

8.2 Digital Description of Material for Press-Hardening

Since its introduction, *Digital Twin* has drawn the attention of both industry and scientific field and has been researched and applied in numerous fields (Qi and Tao 2018; Fuller et al. 2020; Liu et al. 2019; Boschert and Rosen 2016; He et al. 2019). The digital twin was defined as a digital representation of its physical counterpart (Grieves 2015), which can be physical object, system, or process. However, implementation of the Digital Twin in practice is barely feasible due to its requirement of massive amount of data and complexity of description models, which is also impossible to deploy for monitoring and prediction purpose for production in real time. Therefore, in IOP, the *Digital Shadow* is proposed as a light version of the Digital Twin, meaning that it is "a set of contextual datatraces and their aggregation and abstraction collected concerning a system for a specific purpose with respect to the original system" (Becker et al. 2021) and represents only a particular aspect of the real object (Brauner et al. 2022). Thus, digital shadows provide a reduced amount of data sets as compared to digital twins, but capable of describing a system's state and history for a certain purpose and, therefore, make the deployment of the *Digital Shadow* in real production feasible.

However, materials are so far barely mentioned during the digitalization of production processes. Therefore, two new concepts for material digital description, *Digital Material Twin* for material state description and *Digital Material Shadow* for material processing, are proposed. In the present investigation, the focus is set on the digital description of material current state solution (Digital Material Shadow) with examples and a concept is proposed on the Digital Material Shadow for Press-Hardening.

Firstly, one workpiece is described as a collection of intrinsic and extrinsic properties. An extrinsic property can be a shape, roughness, or stiffness of a workpiece, which is the reflection of the material property, but not material property itself. With intrinsic or material-inherent properties (e.g., chemical composition, yield strength), however, the material characteristic can be completely presented. Thus, intrinsic properties of materials are defined as components for the Digital

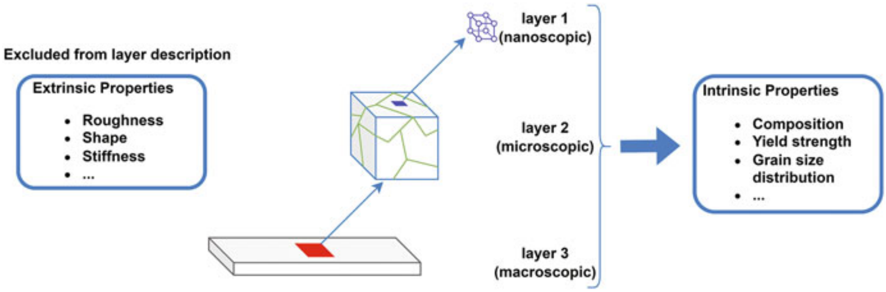


Fig. 8.1 Three-layer description of the Digital Material Twin

Material Twin. Here, we divide intrinsic properties into three layers: nanoscopic (layer 1), microscopic (layer 2), and macroscopic (layer 3). Layer 1 describes the material from atomic point of view, in which the crystal structure and the crystal defects, distribution, and diffusion of foreign atoms are described, whereas layer 2 describes phase and microstructural characteristics of material, e.g., phase fraction. In layer 3, the statistical summary (e.g., UTS, yield strength) of all the units of layer 2 will be presented. With the intrinsic properties and 3-layer description, a comprehensive Digital Material Twin can be deployed (Fig. 8.1).

Moreover, the Digital Material Twin description is extended by its correlated process step since the material state change along the process chain. With extended Digital Material Twin, each material state description can be connected and presented as a digital processing chain for one material.

Furthermore, for IoP, four components are of interest for implementing the approach into the IoP infrastructure: *Smart Human Interfaces*, *Model-Integrated AI*, *Data Modelling*, and *interconnected Infrastructure* (Brauner et al. 2022). Thus, with the concept of Digital Material Twin, a containerized Web Application with the name *intelligent digital Computational advanced research laboratory* (idCarl) is developed and deployed within the IoP. The structure of idCarl is presented in Fig. 8.2. In this approach, researchers have the possibility to create a Digital Material Twin with its chemical composition, and the extension of the Digital Material Twin (process step with core parameters). The information of the Digital Material Twin is stored in each *material card*, along with predefined, user-depended, unique *Material ID*. The information of the Digital Material Twin extension will then be stored in a *treatment card* with its *Treatment ID*. For the subsequent *material card*, the *Material ID* of its previous material state will also be stored, so that the material state can be described in chain. With the defined *Material ID*, users can also append subsequent or previous processes for expansion of the processing chain. Moreover, within the idCarl structure, a *material card* is considered as a node for testing data input and realize the *interconnected infrastructure* (Brauner et al. 2022). The user can initially test the material state with the testing machine, and the key value will then be retrieved with the designed app from the raw data output file from the machine and stored into designated *material card*. Currently, the key value of material state,

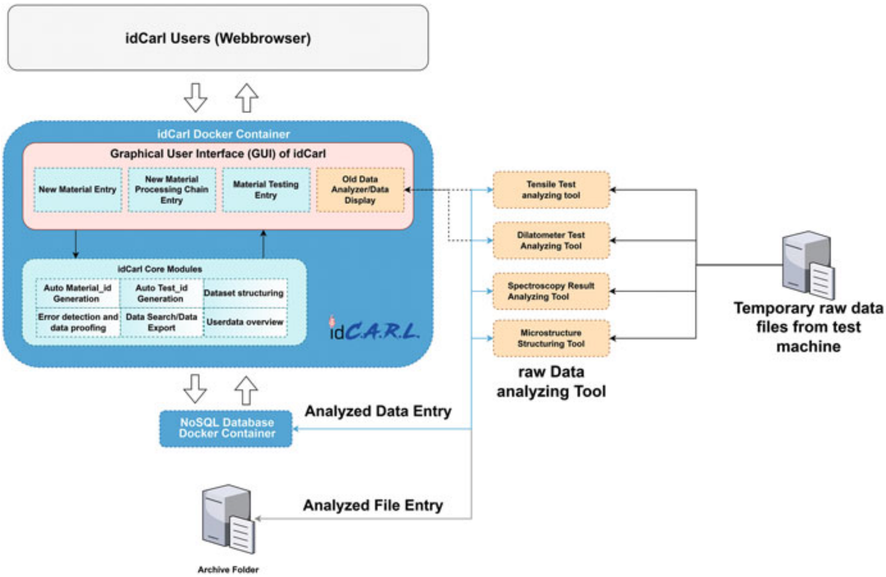


Fig. 8.2 Schematic representation of the organizational structure of idCarl and its essential components

e.g., chemical composition (with optical emission spectrometer, OES), ultimate tensile strength, yield strength and Young's modulus (with tensile machine), and martensitic start and finish transformation temperatures (with dilatometer), which represent the third layer in Digital Material Twin structure (Fig. 8.1), can be stored in a database with the developed tool box.

Since the deployment of idCarl and its core database – MongoDB is based on the concept containerization, the decentralized web application idCarl can be deployed on various platforms or operation systems which support Docker, with configuration to designated NoSQL Database Container. Moreover, with the containerization solution, further data analyzing models, data processing models, or physical models can then be appended to the idCarl structure, which also expands the functionality of idCarl and provides a comprehensive three-layer Digital Material Twin.

Moreover, the core concept of IoP is based on the Digital Shadow, which is defined as a reduced model/model collection for processing from a specific aspect in real-time.

One example of applying idCarl in the IoP is the press-hardening process. For press-hardening as use case, the development of mechanical properties, e.g., yield strength, ultimate tensile strength, and phase transformation temperatures along the process chain, from casted material to press-hardened component, are of great interest to identify necessary (real time) adjustments of subsequent process steps. Therefore, the structured datasets within idCarl, models for description of target intrinsic property and parameters correlation (see Fig. 8.3), and data collected from sensors will be applied for the *Digital Material Shadow* development. The Digital

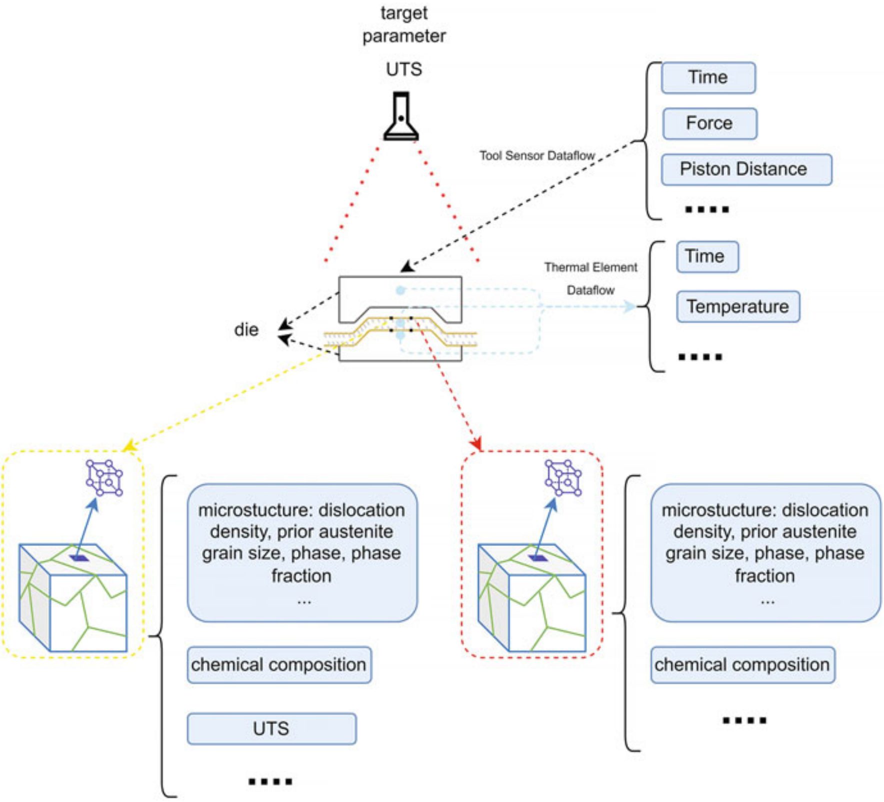


Fig. 8.3 Schematic illustration of the Digital Material Shadow of press hardening: target property monitoring through reduced extended Digital Material Twin and dataflow collected by sensors

Material Shadow can then be applied for target property monitoring and prediction along with the press-hardening process. With containerized approaches of *Digital Material Shadow* of MMnS for press-hardening, a *worker pod* or even *worker node* which contains relevant containers can be established with selected Container Orchestration tools (e.g., *Kubernetes*) into the IoP framework.

The description and monitoring of the built-up process chain of press-hardening of MMnS in the IOP begins with sheet material production including melting of the material, hot rolling, soft annealing, and cold rolling. After melting, the chemical composition of every ingot is analyzed by OES and stored into its *Material Card.* Additionally, for every above-mentioned process step a subsequent *Material ID* and related unique *Treatment ID* with most important treatment parameter, like type of treatment (e.g., hot rolling, cold rolling, heat treatment), deformation grade, deformation rate as well as temperature and time, is generated. Following each process step, the material is tested by tensile testing and investigated by dilatometry. The resulting third layer intrinsic properties are stored into the corresponding

Material Card using associated apps. The development of the characteristic values along the process chain can be displayed by a tree view in idCarl whereby necessary process adjustments of the subsequent process steps can be easily identified. For example, from the detected brittleness of a specific hot-rolled material, idCarl may recommend the need for soft annealing before cold rolling. A suitable annealing temperature could be defined on the basis of the in idCarl stored phase transformation temperatures from dilatometer experiments.

To improve mechanical property combinations of high strength and high residual forming capacity of press-hardened MMnS components, the performed press-hardening process was extended by an integration of quenching and partitioning (Q&P) treatment. Instead of quenching to room temperature after pressing, the material is quenched to a temperature between martensite start and martensite finish temperature, provided by idCarl. Given that martensitic transformation is not completed, retained austenite can be stabilized by subsequent partitioning. Hence, this heat treatment leads to a combination of soft (austenitic) and hard (martensitic) microstructural components to be set sensitively by Q&P parameters, especially quenching temperature, partitioning temperature, and partitioning time (Blankart et al. 2021; Edmonds et al. 2006).

As the phase fractions strongly influence the mechanical properties, accurate temperature control and monitoring during press-hardening and Q&P process is essential (Yang and Bhadeshia 2009; Clément et al. 2015). Since cooling is performed in the closed tempered press hardening tool, various thermocouples were integrated onto the tool and work piece to monitor the current component's temperature in real time. Time for opening the tool and transferring the work piece to the partitioning furnace is always tracked. In case of handling problems the desired properties can still be achieved within certain limits by extending the scheduled partitioning time (Clément et al. 2015; Blankart et al. 2021). For these real-time process adjustments, a fast estimation of the resulting second layer properties depending on the Q&P parameters is required. Based on dilatometric data of cold rolled material, an empirical approach in accordance with Koistinen-Marburger equation was developed for the here investigated Fe-0.3%C-5%Mn-1.5%Si MMnS and can be used to estimate rapidly the austenite fraction and hence martensite phase fractions (Blankart et al. 2021). Additional apps to store surface pressure force and pressing time into idCarl is going to be developed shortly as well as an app for saving Q&P parameter out of measured time-temperature raw data.

8.3 Digitalization of Material Behavior During Deformation

During press hardening, sheet metal forming operations, such as deep drawing or stretch forming, formability of the material plays a major role when assessing the suitability for its use in this forming process. The materials formability characterizes its ability to tolerate plastic deformation without the creation of defects like fractures or excessive thinning. A Forming Limit Curve diagram (FLC), schematically shown in Fig. 8.4, is often used to assess a materials formability. The FLC displays the

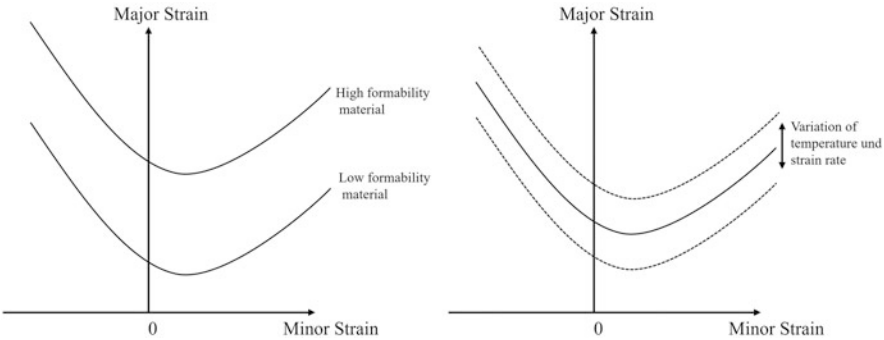


Fig. 8.4 Schematic example of a forming limit curve

point of material failure for different ratios of major and minor strains. A material's formability is therefore higher when greater strains can be tolerated before failure. As the forming during press hardening takes place at elevated temperatures, the formability is also affected by processing temperature and strain rate (Karbasian and Tekkaya 2010).

While testing methods for FLC determination are well established for cold forming conditions, for example, Nakajima testing, methods usable for hot stamping conditions are currently only investigated (Mori et al. 2017).

As can be seen from the FLC, a press hardening process can only be assumed to be robust in term of formability if the strains occurring in the formed component sufficiently lower than the strains leading to failure according the FLC. The design of the pressing tool and therefore the magnitude of strains and ratio of major and minor strains are mostly predetermined by the desired geometry of the finished product. As the geometry of press hardened components, for example in the automotive application, is strongly dependent on the overall chassis design, there is little possibility to adapt the process to compensate for an insufficient formability of the processed material. The choice of a suitable initial sheet geometry can optimize the material flow during forming and reduce the risk of material failure.

To assess the formability of the material designed in the use case a press hardening tool for manufacturing a miniaturized b-pillar is used. Figure 8.2 shows the influence of the initial sheet geometry on the manufacturability of a simplified b-pillar part. Figure 8.5 (a) shows an overlay of the two different sheet geometries along the symmetry axis of the sheet. Figure 8.5 (b) shows the result of a finite element analysis using the software *AutoForm.* Again, the results of the two sheet geometries are overlaid along the symmetry axis. The geometry presented on the left side results in material flow during forming that causes excessive thinning in the top and bottom part of the b-pillar walls. The calculated thinning exceeds values of −0.25, therefore the occurrence of cracks during press hardening is very likely. In comparison the geometry presented on the right shows a more complex sheet geometry design that results in optimized material flow and no cracks are expected according to the

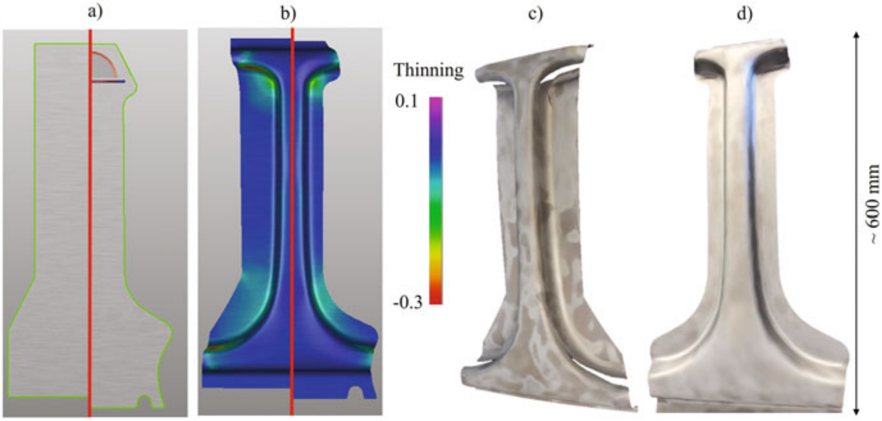


Fig. 8.5 Influence of initial sheet geometry on material failure during forming

simulation result. Figure 8.5 (c) and (d) shows the produced b-pillars for both sheet geometries. In the experiment the material displays the expected behavior and cracks occur for the simple sheet geometry on the left side. The complex sheet geometry results in a defect free part. Using an optimized sheet geometry, the influence of a suboptimal sheet geometry on the occurring forming limits of the process can be reduced. Therefore, the influence of material inherent formability is easier to investigate when conducting experiments using the b-pillar tool.

As mentioned, the determination of an FLC for the press hardening process is currently not standardized. As a first method of assessing the material formability hot tensile tests are performed. The resulting values for uniform elongation and maximum elongation are used to approximate the formability of different material batches that pass the process chain.

To correlate the results of the formability assessment to the chemical composition and parameters of previous processing steps along the process chain presented in the use case press hardening data received from FEA (predicted maximum thinning, strain distribution at points of maximum thinning), hot tensile tests (uniform elongation, maximum elongation) and experimental b-pillar production (machine force/displacement, measurement of sheet thickness after forming) are aggregated in json format and stored in a document-oriented database (Fig. 8.6). This data can then be integrated into the idCarl environment.

8.4 Digitalized Press-Hardening Tool

To form the sheets during press hardening new tools need to be developed to meet the increasing demands for individualized cooling channels and complex geometries that can be achieved by additive manufacturing. Additive manufacturing of metals is a production technology that involves manufacturing tools to form metallic

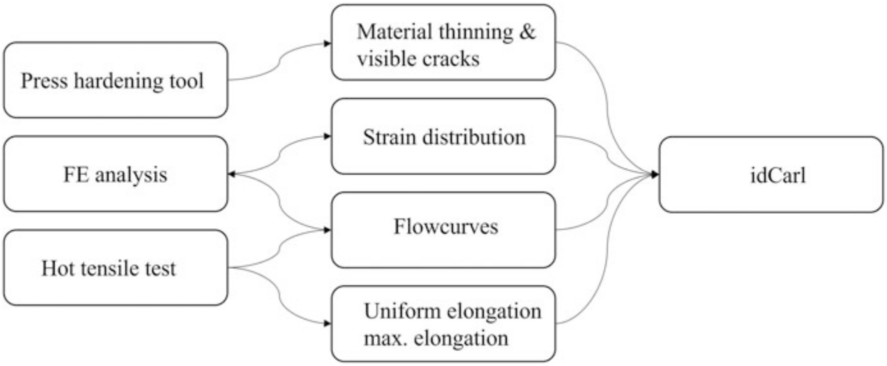


Fig. 8.6 Data transfer of formability experiments, simulation, and b-pillar production to the idCarl environment

materials layer-by-layer. The Laser Powder Bed Fusion (LPBF) process is one of the most industrially relevant additive manufacturing processes, where the component is built up with thin layers of powder by a laser. The LPBF process combines digital design and high freedom of manufacturing, which opens the possibility for new product-functionality and reduces the process chain for development. The main current applications of this technology involve medicine (Javaid and Haleem 2018), aviation and aerospace (Gisario et al. 2019), and automotive (Chantzis et al. 2020).

In industry, creating tooling requires fast product development, low cost, and high efficiency. To meet these challenges and requirements, additive manufacturing as rather novel technology has been applied and developed, which provides the potential to revolutionize completely the process of manufacturing (Rosochowski and Matuszak 2000). Opposed to conventional subtractive manufacturing, additive manufacturing possesses advantages, e.g., production of complex geometries, low material waste, flexible design, and low tooling costs.

We proposed an integrated digital process chain for the process optimization of the tools with the help of the material database idCarl, as illustrated in Fig. 8.7. The data infrastructure is organized: the data from each step in the manufacturing line are collected. The data collection procedure can be performed either manually using human-machine interface or automatically by different sensors. With these sensors, it is possible to monitor the process in real-time. The abundant data realize a detailed process description. After the data acquisition, the data will be processed firstly by idCarl database. Then the data will be analyzed and implemented to simulation for the process optimization.

The production and application of the Press Hardening (PH) tool is an excellent good example of the above process chain. Press tools and molds are commonly designed with internal cooling channels. Conventional manufacturing methods, such as drilling or casting, have the challenge that the cooling channels cannot follow the best designed geometry, which is normally in complex shape (Chantzis et al. 2020).

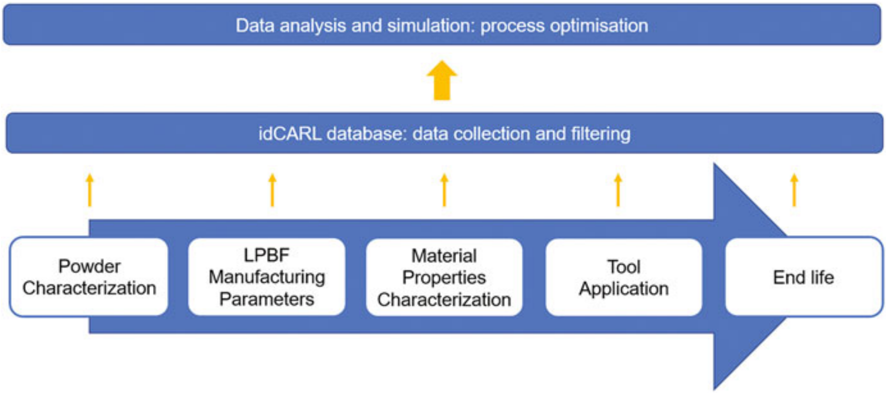
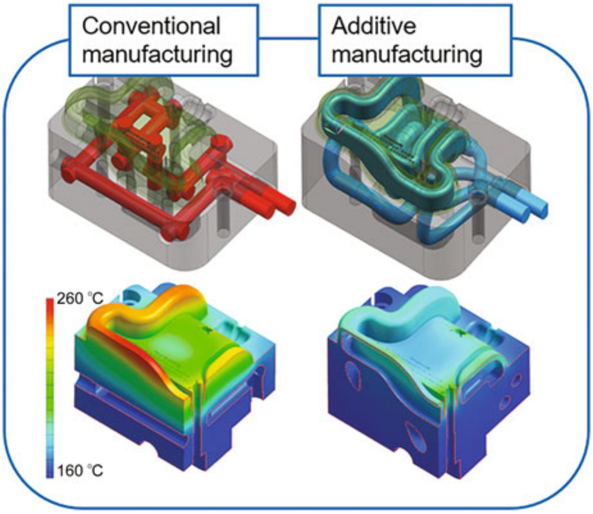


Fig. 8.7 Data infrastructure for the integrated digital process chain of a powder metallurgy (PM) tool production

Fig. 8.8 The comparison of temperature distribution of tools produced by conventional manufacturing and additive manufacturing. The conformal cooling channels realized by additive manufacturing decreases the thermal gradient and leads to a better temperature distribution on the tool surface. (Adapted from https://www.plasticstoday.com/injection-molding/milacrons-dme-partners-linear-ams-develop-3d-printed-conformal-cooling-technology)



LPBF provides flexibility for designers that is unachievable under conventional manufacturing methods, especially for the tools that will not be massively produced.

The production of press hardening tools by LPBF exemplifies one implementation of AM for tooling production. The press hardening integrates the forming and quenching into one step for producing high-strength automobile body panels (Neugebauer et al. 2012). AM enables the new design of conformal cooling channels of the PH tools, which cannot be manufactured by conventional methods. These conformal cooling channels improve the cooling efficiency, and as a result, the manufacturing cycle time of PH process is reduced and the quality of products is enhanced (Hoffmann et al. 2007). Figure 8.8 illustrates how conformal cooling channels produced by AM can optimize the temperature distribution.

Overall, the manufacturing of tools by AM is one of the incorporating elements of Industry 4.0 and Internet of Production (IoP). AM contributes to the smart factories through customization and topology optimization, which are limited by conventional manufacturing systems (Dilberoglu et al. 2017). On the other hand, AM shortens the optimization and development procedure. In the process chain, every step can be monitored for data collection in order to achieve instant feedback, continuous optimization, and traceability of the whole life cycle (Moshiri et al. 2020).

8.5 Data-Driven Material Description of Press-Hardening Tools

For the accompaniment of the process chain through means of digital shadows/twins, several parameters must be analyzed and characterized. Our goal is to digitally replicate the microstructure of the final press hardening tool to allow such characterization. This is done via so-called statistically representative volume elements (sRVE). With the help of these sRVE the influence of different microstructures, and thus different manufacturing parameters can be examined. Specifically, the influence of voids or inclusions can be examined by the application of the sRVE. Firstly, it is mandatory to achieve an extremely close statistical representation of the material in question and the microstructure that is aimed at. This step is particularly important, as later steps aim at estimating a realistic microstructure representation using only process parameters as input. Thus, the statistical description of the parameters needed to characterize the microstructure, such as grain size or grain elongation need to be done with attention to detail.

Commonly, statistical procedures to describe a materials' microstructural parameters employ simple histograms, to which distribution functions are fitted (Fig. 8.9). There are, however, two key issues with this practice: For histograms, the continuous parameters are put into buckets which can be shifted in size, which in turn significantly alters the resulting distribution function. It is therefore a lot more accurate to apply Kernel Density Estimations (KDE) to these statistical descriptions.

The second key problem is that the histograms and distribution functions are created separately from all other parameters. Thus, these parameters are not interconnected. However, the parameters of the microstructure are commonly interdependent as was shown in a study (Pütz et al. 2020). In the same study the fitting solution to this issue was presented with the application of a deep learning method. For this method input data was collected from multiple microstructure analyses in the form of data sheets where the grain sizes, the grain shapes, and the grain orientations in relation to the rolling direction were collected. This set of data was subsequently applied as the input data of a deep learning approach, called Wasserstein generative adversarial network. This approach pits two networks

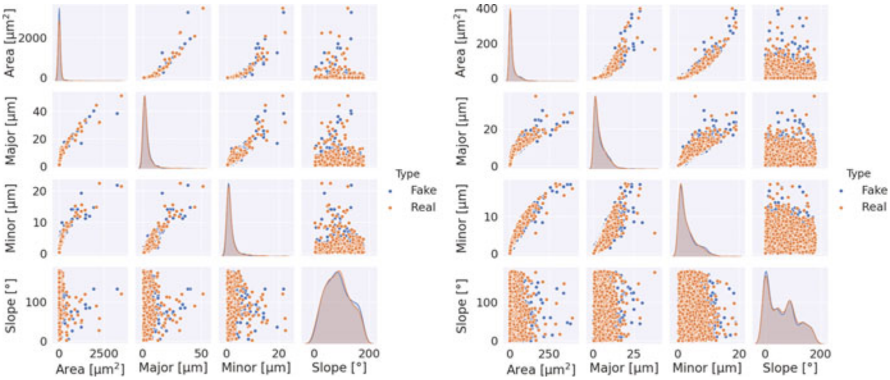


Fig. 8.9 Comparison of microstructure features (left) and inclusion features (right). (From: Fehlemann et al. 2021).

against each other, where one generates data that resembles the input data as closely as possible, while the other learns to distinguish real data from generated. Via the competition of these networks, the generator network improves significantly and is able to reproduce not only the statistical distributions of singular microstructural features, such as grain size, but also the present interdependencies.

Further extensions made to this deep learning approach changed the loss function to include a gradient penalty. Additionally, a conditional part was added to train multiple features with the same network (N. Fehlemann et al.). This is especially important for the implementation of inclusions to the network. Inclusions are a predefined breaking point, especially during cyclic loading which is present for the press hardening tool. Thus, the characterization of the inclusions is equally important to maintain the representativeness of the overall virtual microstructure. In Fig. 8.1 a trained deep learning so-called CWGAN-GP (Conditional Wasserstein generative adversarial network with gradient penalty) network can be seen. In this network, the relevant parameters of both the steel phase and the inclusions were trained within the same architecture.

The trained network then returns a virtual unlimited amount of unique input data that could all be present in the real microstructure. With the help of these extremely close statistical representations and a novel sRVE generator that utilizes discrete generation and grain growth (Henrich et al. 2020), very realistic microstructure representations can be created (Fig. 8.10). When load paths from real applications are applied to these virtual microstructures, the effect of the microstructure on the material properties can be closely examined. This leads to a quantitative estimation of the influence of individual features on the properties of the whole material and can in turn be used to make sure the produced part's quality lies within the required performance range.

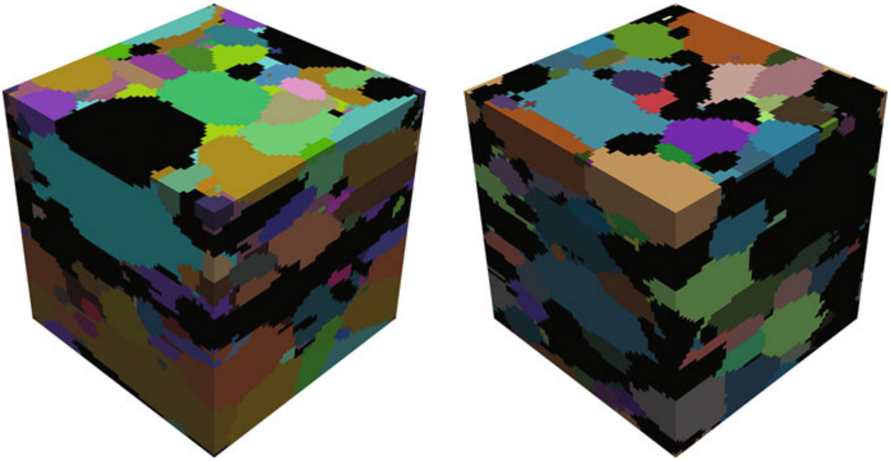


Fig. 8.10 Generated sRVE that show different microstructure features and complexities

8.6 Conclusions

Within this chapter we further developed the previously introduced concepts of digital twin and digital shadow toward Digital Material Twin for material state description and Digital Material Shadow for material processing. These were applied to the press-hardening process of steel, where we identified medium manganese steels (MMnS) as a promising candidate to surpass the mechanical properties of conventionally used manganese-boron steels. We introduced idCarl, a web application for describing material changes on different length-scales along the process chain. Only with tracking these changes in dependence of processing parameters, e.g., on the microstructural level, the full potential of relatively unexploited alloys as MMnS for press-hardening can be reached. We provide an underlying database structure for the digital description and process behavior of (i) materials during press-hardening and (ii) materials for additively manufactured press-hardening tools. For the latter, a data-driven 3D microstructure generator was described providing realistic representative volume elements. Information extracted from introduced digital material shadows enables the identification of in-line production errors and thus allows direct measures of (real time) process adjustment during press-hardening.

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