Virtual Product Development Using Simulation Methods and AI

Increased material diversity and higher component requirements along with shorter development cycles increase the complexity and development effort of today's lightweight solutions. Scientists at KIT are investigating new opportunities to combine simulations and machine learning to accelerate development processes.

Research and development have been paving the way for increasingly capable material and design solutions using fiber-reinforced polymers (FRPs) for many decades. However, the enormous effort required for a manufacturable component design and process set-up hinders the potential to achieve lightweight design. Using efficient design methods is the only way to realize the significant potential of FRPs in the final product in an economically viable manner, thereby justifying higher material costs. This holds in particular for medium- and large-scale production processes where the interaction between component performance and commercial requirements is particularly strong, Figure 1 (left). The growing use of FRPs and numerous research findings over recent decades have allowed industry and research institutes to accumulate an in-depth understanding of materials, processes and simulation [1, 2]. The full exploitation of existing lightweight construction potential can only be achieved by an optimal adjustment of material, quality-oriented production and system-oriented design - a challenging optimization task. Classical development processes involve a considerable experimental effort, conceptual variants and revisions, iterations and – in some cases – a complete restart. A continuously digitalized product development offers far-reaching opportunities to increase lightweight construction potentials, economic efficiency and sustainability within development processes in lightweight construction. The virtual process chain can then be supplemented with real-time data and Machine Learning (ML) methods to assist product development.

Continuous Virtual Process Chain

A virtual process chain provides a direct link between the design and the final FRP part, considering the interactions between material and process during manufacturing. For example, internal stress can arise as a result

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of chemothermo-mechanical effects during curing and cooling.

This can significantly influence the load-bearing capacity of a structure and must therefore be taken into consideration in a coupled process and component design. Furthermore, the process-related microstructure in heterogeneous materials such as FRPs has a key impact on final component performance. The physical interactions between material and process are to be described by means of multi-scale and multi-physics-based simulation approaches and coupled within continuous virtual CAE chains, Figure 1 (right). The establishment of standardized and neutral exchange formats between different simulation codes, such as in the ITEA project VMAP, helps to avoid user-specific stand-alone solutions.

> Virtual prediction of material- and process-specific interactions for a reliable and efficient design.

Multiphysical Interaction

Increasing demands on the reliability and complexity of components, along with ever-shorter development and production times, raise the development effort in hybrid lightweight constructions. Reliable, virtual predictions of material- and process-specific interactions are key to ensure a fundamental understanding of the system and a safe and efficient design. Insufficient modelling approaches can lead to erroneous predictions. Especially, when a high utilization of material, process or structure is desired, only little space for uncertainties is allowed. The following examples illustrate that the simulation approach is critical to reliably predict material and manufacturing effects and the resulting load bearing capacities.

Local Separation Effects in Ribs

During the production of long-fiber-reinforced Sheet Molding Compound (SMC) components, local separation of fibers and matrix can occur at narrow cross-sections and joining welds. Conventional, homogenized simulation models use the fiber orientation tensor to describe material anisotropy and other effects on the mesoscale. These homogenized approaches cannot capture separation processes. This would result in rib stiffness being overestimated in a classic design with homogenized material parameters. A promising approach is the explicit modelling of the deformable fiber bundles Figure 2 (right) including their interaction

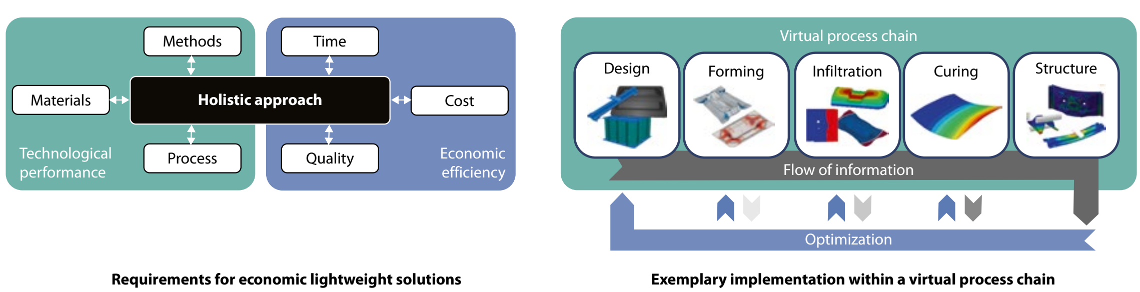

Figure 1 Technological and economic requirements for an efficient FRP solution [1] (left) and example of an end-to-end virtual CAE process chain [2] (right) (© KIT|FAST)

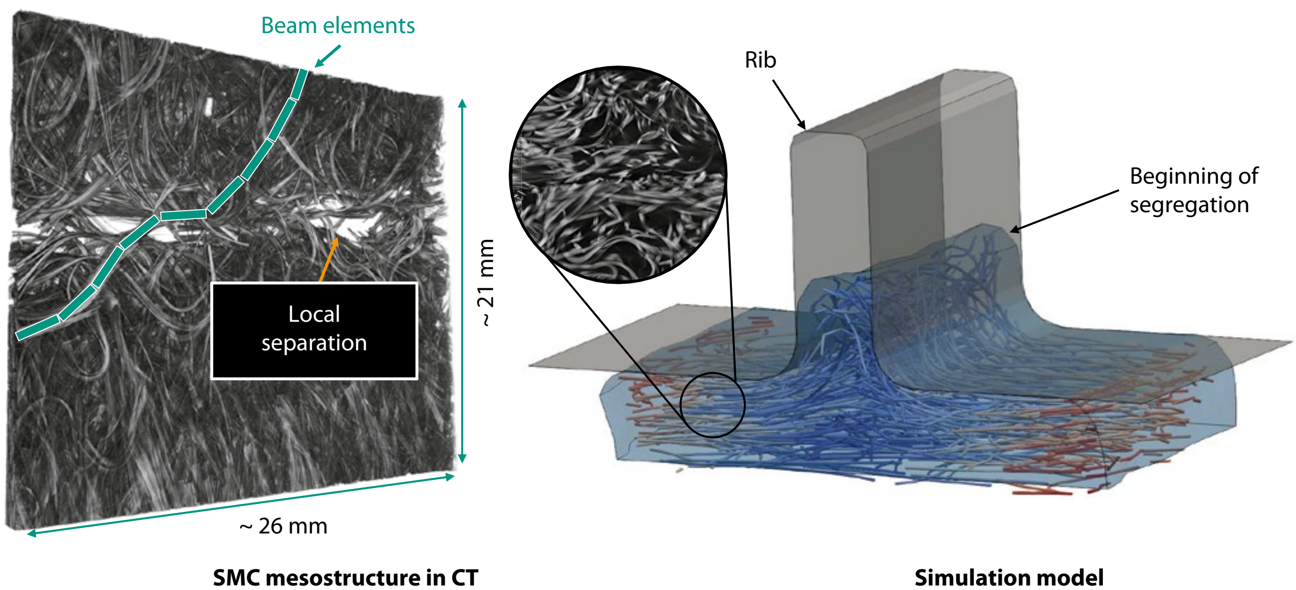

Figure 2 Mesostructure of an SMC test specimen in a CT scan (left) and flow simulation of the matrix material with embedded fiber bundles in a rib during compression molding [3] (right) (©KIT|FAST)

with the hydrodynamic fluid forces of the matrix flow – a fluid structure interaction comes into being.

The direct simulation of the bundles does not require any parameter and closure approaches to determine the fiber orientation. Moreover, the coupled approach covers anisotropic flow of the fiber suspension. This method is currently being developed in a research project as part of the Graduate School DFG-GRK 2078, funded by the German Research Foundation (DFG). This new simulation approach makes it possible to investigate the influence of relevant process parameters such as tool allocation, closing profile or rib geometry on the mesostructure in the final component and to take it into account in the structural design.

Draping and simultaneous infiltration

Complex interactions between material and process are characteristic of hybrid lightweight design, including wet compression molding (WCM). In this process, which is used in automotive large-scale production as an alternative to Resin Transfer Molding (RTM), molding (draping), mold filling

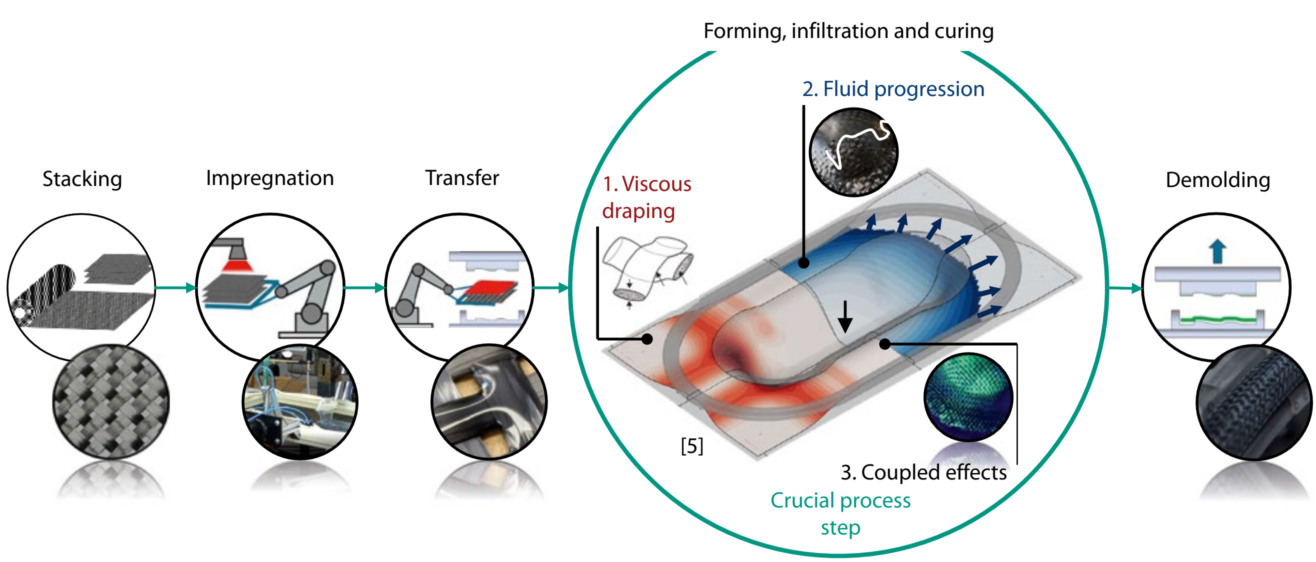

Figure 3 Illustration of the wet compression process chain from blank cutting to demoulding with particular emphasis on the simulation of simultaneous forming (shear angle in red) and infiltration (pressure distribution in blue) [4] (© KIT|FAST and Fraunhofer ICT)

(infiltration) and curing are carried out in a single process step, Figure 3. By this means, one process step can be avoided compared to the conventional RTM process and cycle times in the range of 60 to 90 s can be achieved. The key process dynamics in WCM can only be described with a coupled simulation approach for draping and mold-filling. [4]

Existing models cannot address these multiphysics-effects. Consequently, virtual tool design and sealing concepts is currently

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not supported. In the " Forschungsbrücke"-project, the physical mechanisms and application limits of wet compression molding are investigated on the basis of continuously fiber-reinforced composite parts in cooperation between KIT-FAST, IFB Stuttgart and Fraunhofer ICT.

The key mechanisms during WCM are:

- viscous draping of semi-finished part layers
- simultaneous fluid progression and curing
- fluid structure Interaction between semi-finished fiber parts and the matrix.

This inseparable interplay of effects is of crucial importance for the final component quality [5]. An isolated examination and optimization of individual effects during process design is not possible. Therefore, modelling approaches are developed, which allow a simultaneous simulation of the occurring effects, here in particular draping and mold-filling. [4] Research is currently being carried out on a three-dimensional approach that enables the prediction of measurable process variables such as cavity internal pressures and quality-relevant manufacturing effects – such as dry spots or fiber washout – to be predicted.

Manufacturing-related imperfections

Influences of production on the component are inevitable. Their impact on the load-bearing capacity of the structure must therefore be taken into account during design. This also makes it possible to use design principles that take into account manufacturing imperfections of the material, such as fiber waviness, gap formation or roving compaction, Figure 4. This requires data from previous process steps. In order to distinguish between relevant defects and negligible effects they must be taken into account in the material behaviour of the structure simulation.

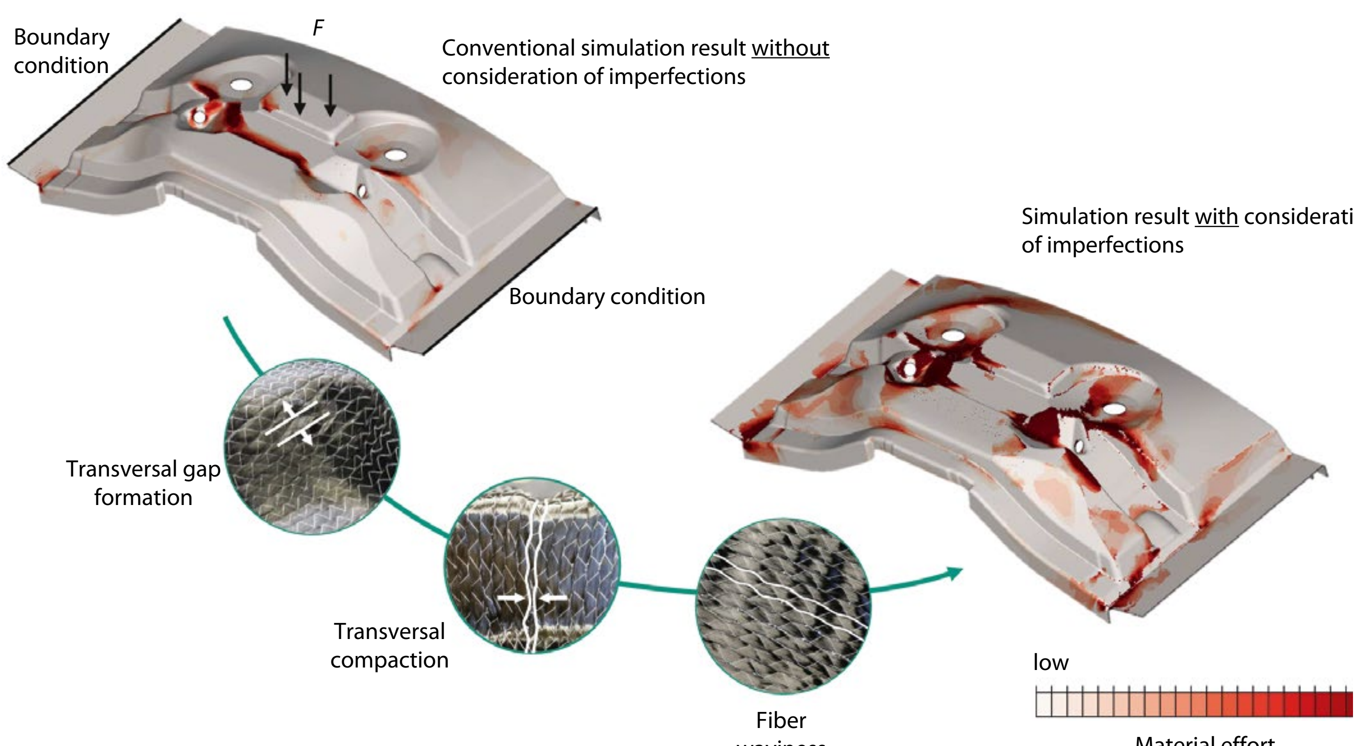

Figure 4 Illustrative example of the influence of manufacturing imperfections on the prediction of material effort related to inter-fiber failure. (© KIT|FAST)

Classical design guidelines assume a defect free, idealized fiber reinforcement in the matrix and hence often overestimate the material performance. The aim of a DFG-funded research project is to describe and quantify such manufacturing effects across different scales and to take them into account when designing components made of FRP [6]. Figure 4 shows that potential inter-fiber breaks can be predicted with greater accuracy and resolution. If the imperfections are mapped properly in addition to the local fiber orientations, not only the locations of increased material strain differ by more than 60 %, but also their characteristics at some locations. Such high-resolution approaches allow a well-founded evaluation of the consequences of imperfections in the final component structure.

Organizing Complexities and Making them Comprehensive

The presented research examples clearly demonstrate that future lightweight design solutions will benefit significantly from improved mutual adjustment of material, process and structural requirements. Hence, the full potential of future lightweight design solutions can only be harnessed using a continuous flow of information, which reflects all specific material and process aspects at the earliest possible stage of the design phase.

Higher standards for simulation techniques and expertise also bring up new challenges in product development processes. First, access to powerful computing equipment and costly simulation software may prove prohibitively costly, especially for Small- and Medium-sized businesses. Second, growing material diversity, multi-stage manufacturing processes and demanding structural requirements pose a significant challenge for optimization. Under these conditions, classical methods of mathematical optimization soon reach their limits. Often, the algorithms get stuck in local minima or require numerous iterations, which leads to inacceptable computation times – possibly days or weeks.

Thus, in practice, many companies rely on empirical best-practice-guidelines and employee experience instead of accurate simulations. Such knowledge on material or process behaviour may help narrow the range of variants to options that are technologically promising, but may not necessarily be strictly optimum or defect-free. This often results in significant costs for error correction, fine-tuning and rework.

It is therefore desirable to combine the reproducibility and reliability of simulation methods with the physical understanding and technical knowledge of engineers. Machine learning methods offer significant potential in this area. The general idea is to link ML-algorithms with simulations in order to guide the optimiser in the parameter space and overall accelerate the development process.

Neural Networks Support Optimizations

In general, the term ML refers to statistical techniques which extract correlations from data sets to give predictions in new situations. This includes various techniques ranging from classical polynomial regression or

Machine Learning

Machine learning refers to all artificial intelligence techniques that enable software or a machine to perform a previously defined task without being explicitly programmed for that task. The machine must autonomously extract suitable strategies to perform the task only from supplied data. [7]

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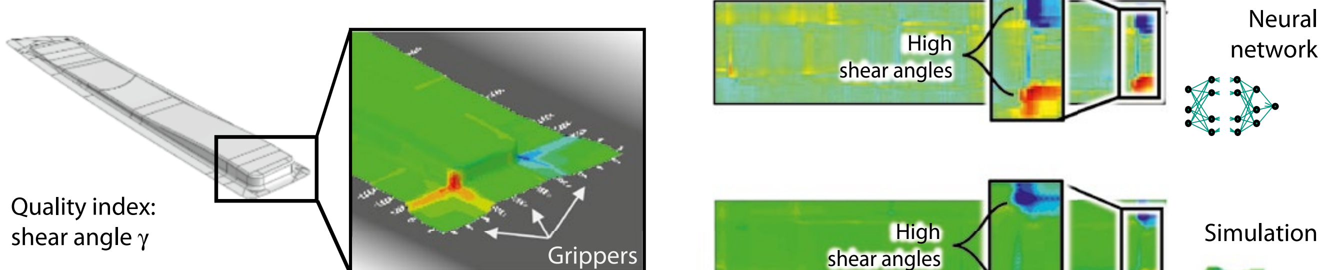

Figure 5 Schematic sketch of gripper-assisted textile forming (left) and comparison of the shear angle distribution depending on gripper-forces according to ML-estimation and simulation (right) [8] (© KIT|FAST)

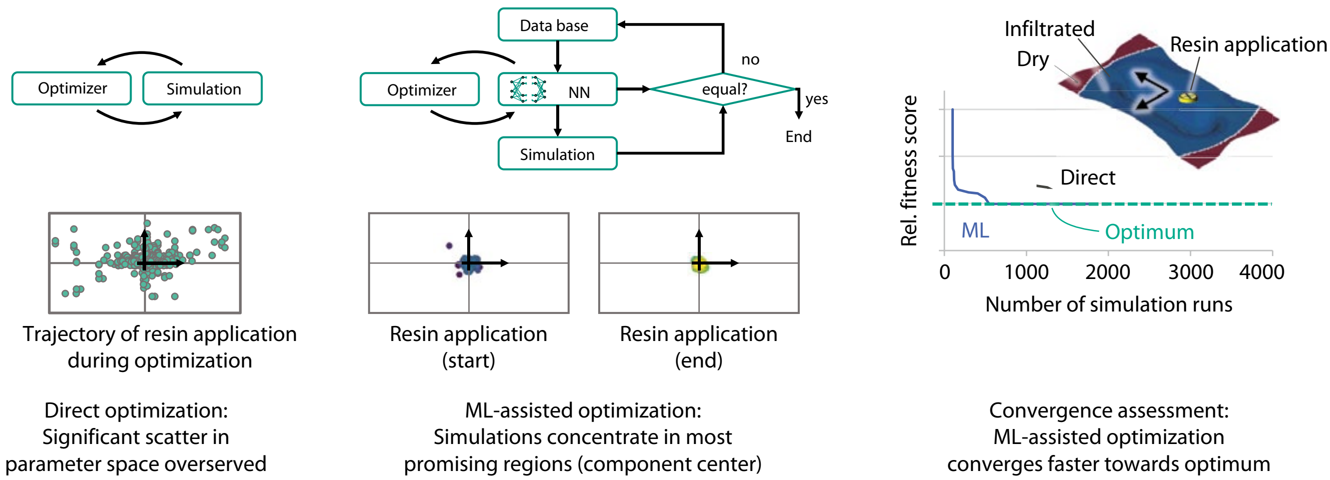

Figure 6 Schematic sketch and convergence comparison of direct and ML-assisted optimization of the resin application in wet compression molding (© KIT|FAST)

Gaussian process regression to artifical neural networks. As part of the "Forschungsbrücke" project (German for "Research Bridge"), scientists at KIT-FAST study in which way ML-techniques can support the development of complex manufacturing processes using the example of wet compression molding.

Preliminary investigations show that deep artificial neural networks (NNs) are particularly well-suited for learning complex interactions like they occur in manufacturing processes [8]. For instance, they do not just make higher-quality predictions compared to other ML techniques, they also enable a spatially resolved prediction of manufacturing effects, Figure 2. This makes it easier for engineers to evaluate different process results and deduce suitable means for process improvements.

Integrating Existing Knowledge into Optimization

Direct couplings of optimization algorithms with simulation models usually results in a widespread search across the available parameter space, Figure 3 (left). ML-techniques can be used to accelerate the process by excluding unfavourable variants from the beginning and concentrate time-consuming simulations on the most promising parameter combinations.

To this, neural networks are pre-trained using sample simulations so that they estimate the result of a new process variant within few seconds, for example the mold-filling time required at each point of the resin application, Figure 3. Optimization on the neural network then takes only a few minutes and provides a first process recommendation. By iterative integration of simulation results, the network gradually refines its prediction quality for more reliable process recommendations, Figure 3 (center). Overall, the computational effort can be reduced by 30 to 70 %, depending on the specific application, Figure 3 (right).

Geometry Assessment through Machine Learning

Current research work aims to integrate the capabilities of ML-methods into the development process at an even earlier stage. Recent findings show that neural networks specialized in image-processing ("convolutional neural networks") can interpret component geometries and assess their manufacturability. Using an extensive data record comprising variable geometries and according process simulations - specifically forming simulations, Figure 4 (right) – an algorithm learns which component features are relevant for forming processes. Based on this 'experience' it can then quickly assess the formability of a new component design and identify potentially manufacturing-critical component regions [9].

Comparable to a "virtual process expert", such an algorithm can give the designer rapid feedback on the component design – without further simulation effort after initial training, reproducible and portable in a software. Coupled with optimization algorithms, rapid changes of the geometry for improved drapability are also possible [10].

AI Generates Ideas and Assists

Further ideas describe the transition from a passive-reactive feedback tool to a proactive

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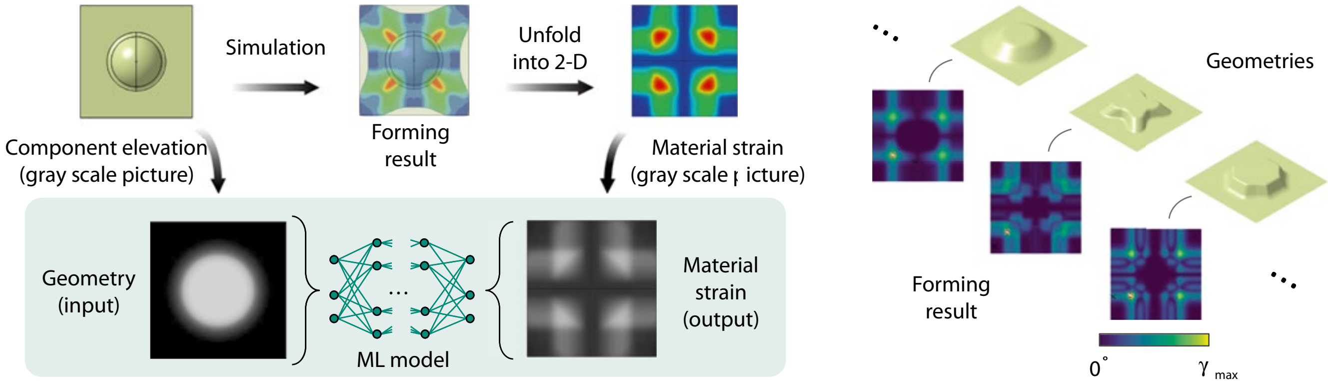

Figure 7 Image-based data pre-processing for convolutional neural networks (left) and sample geometries with according process results from the training data base [9] (© KIT|FAST)

"advisor". Latest developments indicate that advanced AI techniques can actively provide suggestions for material, component or process configurations, given certain design constraints, e.g. boundary conditions, design space or structural requirements [10, 11].

Machine-learning algorithms guide the optimizer in the parameter space.

Thereby, it is possible for the algorithms to compare numerous variants that a single human being would be unable to process. Engineers can evaluate AI-generated suggestions, combine promising options or use them for general inspiration in the parameter and variant space.

Being supported by such tools, engineers can shift away from routine work such as recurrent designs and material variations, and refocus instead on value-adding and creative activities. For instance, simulation specialists could concentrate more on the actual development of simulation techniques, while their models are made accessible to a broad range of users by means of AI.

Such tools are currently being developed, tested and focus on demonstrator tasks. Overall however, prospects for future fields of business are emerging, e.g. cloud-based AI engineering services.

Over the next decade, such methods will become increasingly significant in product development processes and provide new engineering tools (Figure 5), which assist engineers in their work. In this regard, AI-methods will not replace but complement numeric simulations and increase their accessibility.

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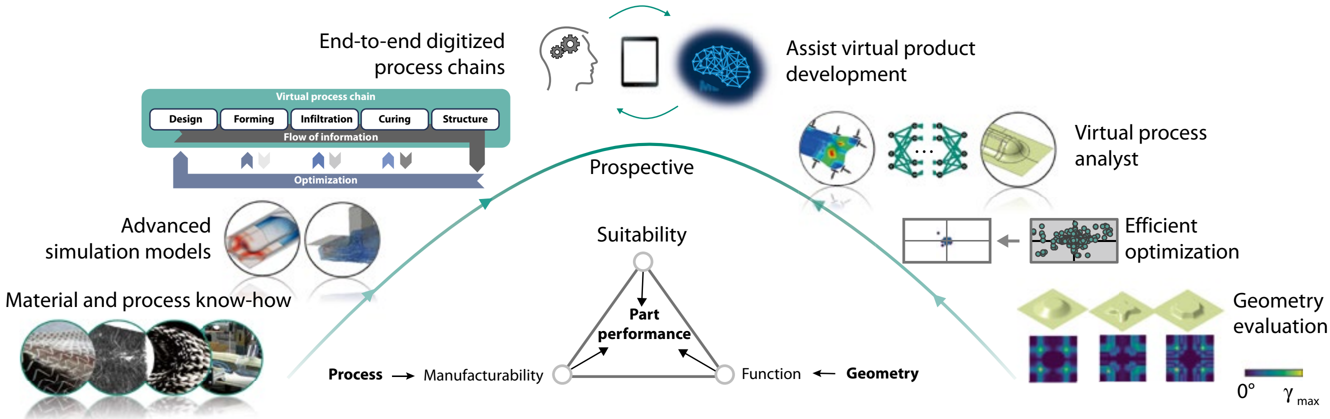

Figure 8 Future, AI-assisted, fully digitalized product development (© KIT|FAST)

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