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Challenges and Potentials of Digital Twins and Industry 4.0 in Product Design and Production for High Performance Products

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Abstract

Digital twins offer great opportunities in various domains of the product engineering process. However, current approaches to the use of digital twins only focus on different separated disciplines. In contrast to that, it is expected that the holistic use of digital twin models in product development and production will dominate future product generations, because they allow to create high-performance products competitively. This paper explores important challenges and future potentials of digital twins and Industry 4.0 for the seamless integration of product specification and production. In this regard, approaches of linking digital twins to other domains open up new possibilities in tolerance allocation and production integration. Thereby, the most efficient product specifications in technical and economic terms are achieved for the manufacturer. In addition, the connectivity of Industry 4.0 broadens the scope and enables the evaluation of alternative approaches in production planning and control. Approaches at the organizational level, product functions with specifications beyond the technological limits and production control strategies (e.g. order dispatching) ensure high performance operations. Simulations with a digital production twin with integrated digital product twin allow early estimations even before the actual ramp-up of the product. The future challenge addressed in this paper is to define a consistent framework for the holistic use of digital twins in the entire product development process, which requires the integration of product designers and production planner concepts.

Keywords: Product development; Production planning; Information

1. Introduction

Increasing product requirements and rapidly changing markets require highly precise product developments in ever shorter cycles. Dependencies and boundary conditions of the later production have to be considered already in the early phases of the product design to ensure the product function. This leads to increasing requirements in the product engineering process. Precise designs with increasing complexity and many variables must be derived. This results in increasingly complex product specifications with regard to the quality requirements. Also the production of new, highly precise products faces the challenge of producing high quality requirements and interacting features cost-effectively. Often, manufacturing processes are already reaching their technological limits.

The current developments in information technologies open up great possibilities for support in the product engineering process through increased computing power, new simulation and analysis tools, as wells as connected data. Digital twins of the product or production are already being modelled in the individual domains in order to derive optimal solutions. The increased data availability and traceability of products also allows the modeling of data-driven models using artificial intelligence methods.

2. Definition and Applications of the Digital Twin

Driven by the ambition for shifting problem identification and solving to early stages of product and process development, known as “front-loading” [1], sophisticated and highly realistic virtual models gain increasing attention in

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research and industry. This is because such models allow the time- and cost-efficient simulation of the effects of product and process design changes on the quality and function of technical products. However, the full benefit of such high-fidelity simulation models can only be exploited when feeding them with data from the physical world, leading to a digital twin of physical assets.

2.1. Definitions of the Digital Twin

In fact, a lot of different definitions for such a digital twin can be found in literature, mainly caused by various application areas. What most of them have in common is that a digital twin consists of three main parts: physical product, virtual product, and connected data that tie and indissolubly connect the physical and virtual product [2–6]. Probably the first definition of it was given by NASA in their integrated technology roadmap (Technology Area 11: Modeling, Simulation, Information Technology & Processing Roadmap; 2010), which has been slightly adapted in [5]: “A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin” (see Figure 1). With some similarity to this, Grieves et al. define a Digital Twin as “a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level” [6].

However, a digital twin is not just limited to products, it also can be a complex production system that is represented in a digital twin [7].

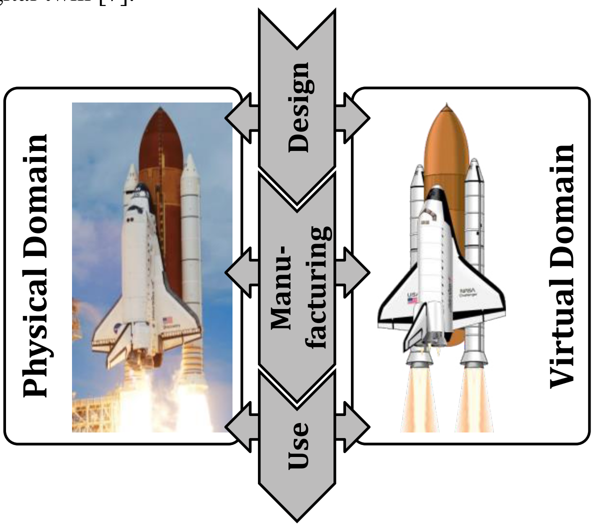

Figure 1: The vision of the Digital Twin throughout the product life-cycle in analogy to [6]

Developments within the framework of "Industry 4.0", such as increased computing power, real-time information systems, the Internet of Things, cheaper and more precise sensors and individual component traceability open up new possibilities. An exact allocation of production data of an individual product to information from product usage, for example, becomes possible. New insights for product development can be derived from this. [8–10]

More and more detailed digital twins can also be created for production by means of the increasing spread of inline measurements and operating data. In this way, it is possible to react quickly to deviations and malfunctions, or the systems themselves initiate countermeasures as cyber physical production systems [11, 12]. Through organizational approaches and order planning, increased robustness and more demanding quality requirements and product specifications become economically possible. This in turn gives product development new opportunities to design more efficient, more powerful products [13]. It is also possible that alternative working principles for the realization of functions will be made possible.

The use of digital twins opens huge opportunities to increase productivity and effectiveness, which are briefly highlighted in the following section.

2.2. Application Examples of Digital Twins

Various existing concepts of digital twins do not only vary by the width of their scope, but also by the focused use of the digital twin during the product life-cycle. There are differences if the digital twin is already used for the conceptional design and detailed design phase of the product or just in terms of production. Today, data from many previous generation product realizations are merged into a common digital twin of the product to gain more product knowledge in the early stages of a new product generation. [14]

In this regard, the application of digital twins in the product design stages allows for providing a quantitative design tool for efficient and optimal design decisions by using data from previous product generations. In this context, data from digital twins of previous product design can be analyzed and used for optimizing new designs [14].

Digital twins have also been making their way into production for some time now. Simulations of production systems can help to ensure a proper behavior and help to predict the outcome, optimize, correct and evaluate. The digital production twin combines this with an ongoing data collection. [7]

By modelling manufacturing steps and entire machine tools, the effects of tool behavior and process parameters are determined and optimized. Optimum tool geometries and process parameters for surface conditioning, for example, can be determined by using digital twins of a cutting tool to achieve advanced products. [7]

Also in additive manufacturing a digital twin is used in an approach to evaluate 3D printed metallic components. The goals are to reduce the number of trial and error tests in order to obtain the desired product attributes and shorten the time between design and production. [15]

Moreover, complex productions systems (as interlinkage of manufacturing, quality control and logistics processes) consist of multiple stochastic and dynamic processes with mostly non-linear dependencies. Analytical methods are not capable to cover all processes and dependencies and hence simulation models are used. Digital twins of the production systems can be combined with existing optimization programs, for e.g. selective part assembly to achieve cutting edge products, scheduling to build robust production schedules or predict the effect of counter measurements in case of disturbances [16–19]. In some cases, even human resources systems are considered in the digital twin [16].

Furthermore, human interaction is modelled in the digital twins as well. A developed digital twin of human robot collaboration helps to gain insights and makes it possible to test new operating policies before implementing them in the actual production setting. [20]

Significant benefits in development time and costs can be achieved using virtual experiments and validation of production systems. Insights into complex productions systems can be gained and operating policies can be tested before implementing them in the real world, as well. [20]

However, current approaches to the use of digital twins mainly focus on different separated disciplines. Consequently, product design and product specification takes place without possibly knowing more favorable possibilities in production, on the one hand. On the other, the production of highly precise products does not take into account previously acquired product knowledge and interactions of individual features. In contrast to that, it is expected that the holistic use of digital twin models in product development and production will open up new possibilities in the product engineering process with the use of domain-linking, holistic digital twins.

3. Digital Twin Applications Linking Different Domains

In this regard, approaches of linking digital twins to other domains open up new possibilities in tolerance allocation and production integration. The following section gives a selection of approaches linking digital twins to other domains, which open up new possibilities for product design and production planning.

3.1. Digital Product Twins with Integrated Production Knowledge

In order to allow the cost- and time-efficient manufacturing of physical artefacts, product designers are asked to comprehensively consider manufacturing knowledge already in early stages of product design. However, particularly for manufacturing processes with little available knowledge, this can be challenging. In order to tackle this challenge, approaches for the knowledge discovery in databases can be used to extract manufacturing knowledge from manufacturing process simulations or digital twins (see Figure 2). This production knowledge can then be used for optimizing part design with respect to manufacturability. [21]

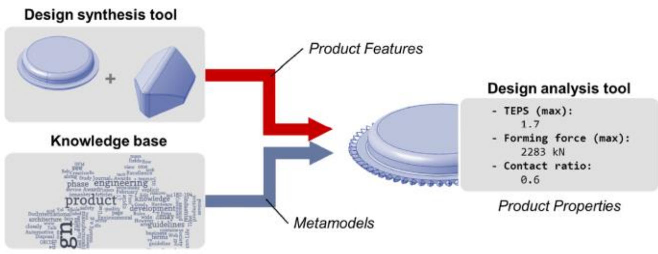

Figure 2: Visualization of a self-learning engineering workbench concept “SLASSY” for enhanced product design [21]

Beside this, production knowledge from digital twins can be used for sophisticated tolerance simulations considering characteristic manufacturing signatures in the tolerance analysis. By doing so, the knowledge about typical part deviations from previous product data allows a more realistic prediction of the effects of these part deviations on the product performance [22]. The quantitative results from such tolerance simulations based on digital twins can then guide designers in the cost-efficient tolerance specification and thus support geometrical variations management [10].

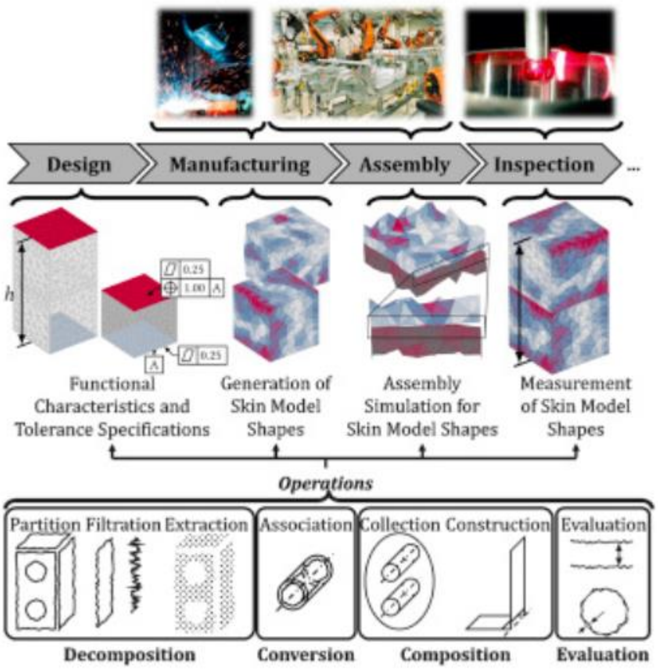

Figure 3: Digital twin for geometrical variations management based on skin model shapes [2]

Moreover, such tolerance simulations may also support computer-aided process planning and fixture design in deriving suitable process designs [10].

3.2. Digital Production Twins with Integrated Product Knowledge

The concept of function-oriented production control presented in Wagner et al. [17] introduces a digital production twin with application of control cycles for quality improvement at the organizational level. Using the example of high-pressure injection systems production, a digital twin of the value stream is modeled. In this example, the product consists of several high-precision subsystems, related to different disciplines. Specific product requirements are close to or even beyond the technological production limits for the economical manufacture of components. The digital twin models the uncertainty of manufacturing processes (P) and production-integrated inline metrology (Q), as well as inventories (I) and assembly processes (A) (see Figure 2).

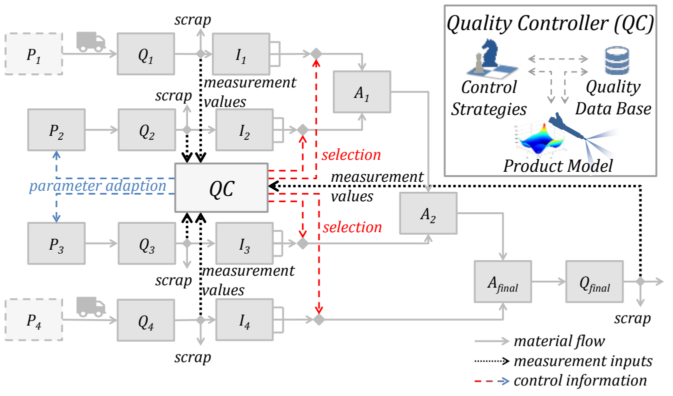

Figure 4: Visualization of the digital production twin with integrated quality controller comprising control strategies, measurement data and functional product model [17]

The approach aims at achieving critical quality requirements for products individually through control strategies of adaptive manufacturing and selective assembly, if the conventional assembly does not meet the quality requirements [23, 24]. The integration of a digital product twin of the interested product enables to quantify manufacturing deviations of product characteristics to the products function. With the integrated product twin, it is possible to apply new function-oriented strategies for quality control in production. Optimal sequential selections and adaptations can be evaluated in very complex production systems through production twin simulations and the integrated product twin. Thus, a technical and economic assessment of varying function-oriented control loops becomes possible. Subsequently, the integrated product twin in the production twin allows early estimations even before the actual ramp-up of new product generations. The use of linking the digital twins is the central enabler to consider new possibilities for the manufacture of high-precision products beyond technological limits for manufacturers, not only in the automotive sector but also in other business fields such as medical technology and drive technology. [17]

For the implementation of effective production strategies using a digital twin, methods of artificial intelligence provide great potential. For industrial applications in the semiconductor industry, Stricker et al. [25] and Waschneck et al. [26], for instance, facilitate digital twins in complex front-end wafer production systems. The job-shop system contains complex order flow due to limited, capital intensive machinery and multiple, recurrent process steps "building" the wafer layer-by-layer [27]. The complexity on the production system level is the consequence of high-tech performance characteristics of the product. The functional semiconductor-structures, e.g. architectures in the range of nanometers, are close to technological and physical limits. So, semiconductor manufacturers focus mainly on the optimization of yield management and clustering final products in multiple quality classes [27]. The aim of the production simulations is to take the product properties into consideration in order to achieve a high quality level. For example, product-individual order and history of production steps is included within the production schedule planning. In particular, waiting time in between two consecutive processes meaning time exposed to contamination despite the clean room environment causes degeneration of the product. With the digital twin, suitable production schedules are learnt by means of a reinforcement learning algorithm based on Q-learning [25].

3.3. Digital Twins of Product Use with Integrated Production Knowledge

For the industrial application of high-precision micro-gears Haefner et al. [28] develope a digital twin of the micro-gear function for lifetime prognosis dependent on their measured shape deviations. For the implementation of the digital twin, a mathematical model based on Bayes Weibull regression is created representing the relationship between the measured shape deviations and the lifetime of a pair of micro-gears (see Figure 5).

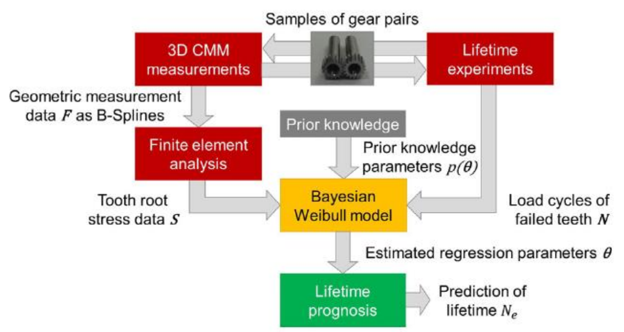

Figure 5: Method for digital twin of micro-gears enabling lifetime prognosis dependant on areal measurements [28]

Both existing prior knowledge and highly precise experimental data from lifetime experiments as well as areal geometrical measurements of the respective gear type are considered as inputs of the digital twin. Lifetime experiments are conducted on a specifically developed test rig for micro-gears. The geometry of the gears to be analysed is measured over the entire gear surface with a very high density of the data points. From these measurements, geometrical representations of the real gear topographies are created by means of B-Spline interpolation. Based on these, the tooth root stresses of the individual tooth geometries are calculated using finite element analysis. Additionally, prior knowledge about the lifetime of the gear type is integrated in the Bayes Weibull regression model, which can be parametrized by means of the Markov

Chain Monte Carlo method. Moreover, the uncertainty of the lifetime model implemented in the digital twin is evaluated according to the Guide to the Expression of Uncertainty in Measurement GUM). Altogether, all available data are integrated within the developed digital twin. [28] Finally, it can be used to predict the lifetime of individual micro gears on the basis of their measured shape deviations. To enable a real time application during production from the time-consuming finite elements analysis a meta-model based on an artificial neural network was derived (see Figure 6). [29]

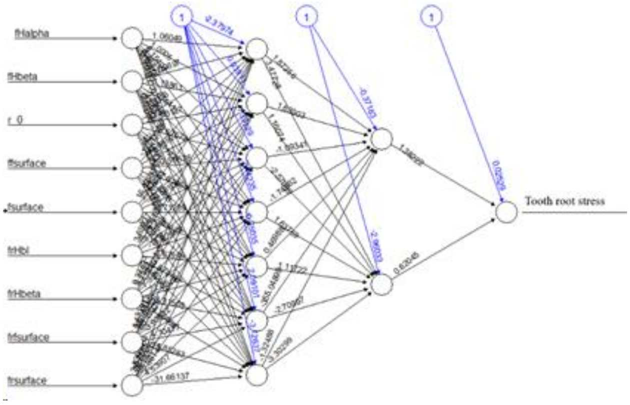

Figure 6: Artificial neural network as meta-model for real-time application of the digital twin of micro-gears in production [29]

The presented examples show first approaches for the integration of production knowledge or product twins into the respective other domain. Already in these first approaches, the potentials for both product engineering and production of products with high-tech specifications nearby or even beyond technological borders become visible. [17, 21, 22, 25, 28] Therefore, the linkage of product and production twins into digital production twins is key to achieve further improvement of the operational excellence and maintaining the competitiveness within the industry of precision products. The relevance of the approaches also applies to other areas such as for instance medical equipment and machinery as well as the biological or chemical process industry. However, the approaches shown are to be seen as industrial demonstrators, since there are still further challenges to be explored for the holistic linking of digital twins through the entire product engineering process. The future research challenges will be explained in the next chapter.

4. Future Research Challenges

As shown in the previous sections, the provision of information and digital twins throughout the entire product engineering process is advantageous. It is expected that the holistic use of digital twin models in product development and production will dominate future product generations, because they allow to create high-performance products competitively. For example, changes in product design (product co-design) or operational approaches of production control (e.g. adaptive manufacturing and selective assembly) can be developed and selected by simulating product and production twins (see Figure 7).

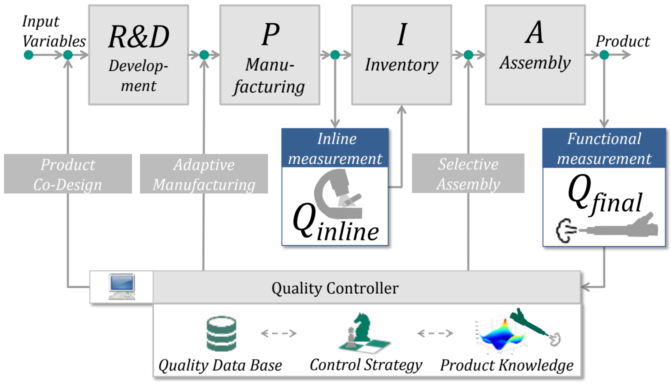

Figure 7: Schematic representation of digital twins for robust and cost-efficient product design and production control [17]

For the consequent linking of digital twins in the industrial environment, however, further challenges still need to be researched and standardized. A consistent framework for the holistic use of digital twins in the entire product development has to be defined which covers the topics of mutual understanding, interfaces and standardization, as well efficient information flow, to bring the approaches to a broad industrial application.

4.1. Mutual Understanding and Integration of Different Domains in the Product Engineering Process in Digital Twin

The basic prerequisite for successful use and providing information in digital twins is the integration of product designers, production planner and application engineers concepts. They need to have a common understanding of the respective requirements and goals of the other domains. In each phase of the product engineering process, there are different boundary conditions and concepts for optimization, without possibly being able to estimate the interaction and impact on previous or subsequent activities. The abilities and scope of action must also be clarified in order to come closer a common optimum.

4.2. Interfaces for Standardized Information Exchange

Once a common understanding has been reached and the requirements of the other domain have been identified, the common interfaces for the exchange of information must be defined. The uniform exchange of information over the entire product engineering process is enabled. During the development of a digital product twin, for example, the requirements for later use in production or application can be planned and implemented directly. This ensures compatibility of the digital twin models via the product development process and its subsequent integration. Industrial formats for structured data exchange already exist, for example in drive technology or in the semiconductor industry. The introduced gear data exchange format [30], for example, has been successfully introduced into the development, design, production, measurement and functional testing of gear wheels of various types. Closed loops for the feedback of measurement result in manufacturing processes and the simulation of digital twins are defined in a standardized manner and thus implemented and updated more quickly.

4.3. Efficient Design of Information Flow

The linking of different domains offers the risk of causing a flood of information. Therefore, information flows have to be designed efficiently and the amount of information has to be tailored to the domains. This ensures that the necessary information is accessible in a detailed manner and ability for changes, but that no misuse is possible. Cross working teams may be required to interpret significant simulation results and secure change decisions.

5. Conclusion

Digital twins offer great opportunities in various domains of the product engineering process. Presented examples, linking product and production twins into digital production twins, show first approaches for the integration of production knowledge or product twins into the respective other domain. The continuous linking of digital twins is the key to achieve further improvement of the operational excellence and maintaining the competitiveness within the industry of precision products. The main future challenge is to define a consistent framework for the holistic use of digital twins in the entire product engineering process, which covers the topics of common understanding interfaces and standardization, as well as efficient information flow. This particularly requires the integration of product designers and production planner concepts in future research.

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