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Plastics Industry 4.0

Christian Hopmann and Mauritius Schmitz

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Preface

The digital age has just begun. Computer science is penetrating production and processing technology, digitization and 3D printing are disruptively changing the methodology of product development, and digital materials are attracting scientific interest. Biologically inspired computing supports humans in discovering patterns, relationships, and correlation in a vast amount of data, and new algorithms lead to improved and entirely new models of complex systems. Quantum computing will soon provide a substantial increase in computing power. It is inevitable and obvious that these technologies will affect plastics technology tremendously – and challenge engineers to discover opportunities that come along with those technologies in plastics technology and processing. The breakthrough of those technologies is just a matter of time – the race for innovation is yet open.

Digitization and Plastics Industry 4.0 are not ready-made solutions or products which may be chosen out of a catalogue. It is rather a sort of a mindset or a philosophy to entirely think plastics technology from a digital perspective to stimulate innovation. In this sense, this book provides stimuli and impulses to connect with Plastics Industry 4.0 and to develop strategies to tackle Plastics Industry 4.0 in a specific environment rather than just offering a list of tools that may be used in a plastics processing company. The reader may enjoy the diversity and versatility and take it as a source for inspiration.

The authors would like to thank Dr. Mark Smith from Hanser for persistent encouragement to write this book and for great support on this exciting journey. Great thanks go to the DFG – German Research Foundation, which provides considerable funding for the cluster of excellence “Internet of Production” at RWTH Aachen University and thus enables us to do the research on which this book is mainly built. We also thank all the colleagues contributing to and cooperating in this cluster of excellence. The cross-domain collaboration with excellent researchers is a rich source of inspiration and has been of invaluable importance for our research and this book. We also greatly thank the scientists at the IKV – Institute for Plastics Processing at RWTH Aachen University for excellent research in digitization and Plastics Industry 4.0 and for contributing to this book.

Aachen, October 2020

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University Professor Dr.-Ing. Christian Hopmann, born 1968, studied Mechanical Engineering with particular focus on Plastics Processing at RWTH Aachen University, Germany. Following his diploma in 1996, he received his doctoral degree (Dr.-Ing.) with a thesis on injection molding in 2000. From 2001 to 2004 he was Chief Engineer and Senior Vice Director of the institute.

After several years in the plastics processing industry, since 2011 he is Head of the IKV – Institute for Plastics Processing in Industry and Craft at RWTH Aachen University and Managing Director of the IKV's Association of Sponsors. He also holds the Chair of Plastics Processing at the Faculty of Mechanical Engineering at RWTH Aachen University. In 2014 he received the innovation award of the federal state of North Rhine-Westfalia (NRW). Hopmann is Fellow of the Society of Plastics Engineers (SPE).

One of his core research interests is digitalization in plastics processing and Industry 4.0. Since 2019 he is one of the Principal Investigators in the Federal Cluster of Excellence "Internet of Production", funded by the DFG. Under his lead, the IKV is building up a fully interconnected production environment according to the principles of a smart factory. The so called "Plastics Innovation Center 4.0" is funded by the federal state of North Rhine-Westphalia and the European Regional Development Fund (EFRE).

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Mauritius Schmitz, born in 1985, studied Computational Engineering Science with particular focus on structural mechanics and fluid dynamics at RWTH Aachen University. Following his diploma, in 2014 he joined the IKV as a project engineer for process simulation in the Department of Injection Moulding. In 2015 he became a doctoral student and head of the working group for Process Simulation in the Department of Injection Moulding, focusing on applications and further development of injection molding simulation. Furthermore, he focused on model predictive control strategies for novel mold tempering techniques, considering the local part properties during the injection molding process.

In 2019 Mauritius Schmitz joined the institute management as Scientific Director at the Institute for Plastics Processing. In this position he is responsible for the research and development in the field of digitalization and Industry 4.0 as well as the internationalization strategy of the institute. Since 2019, he is a Cluster Research Domain Coordinator in the research domain “Production Technology” of the Cluster of Excellence “Internet of Production”, funded by the DFG.

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1 Introduction

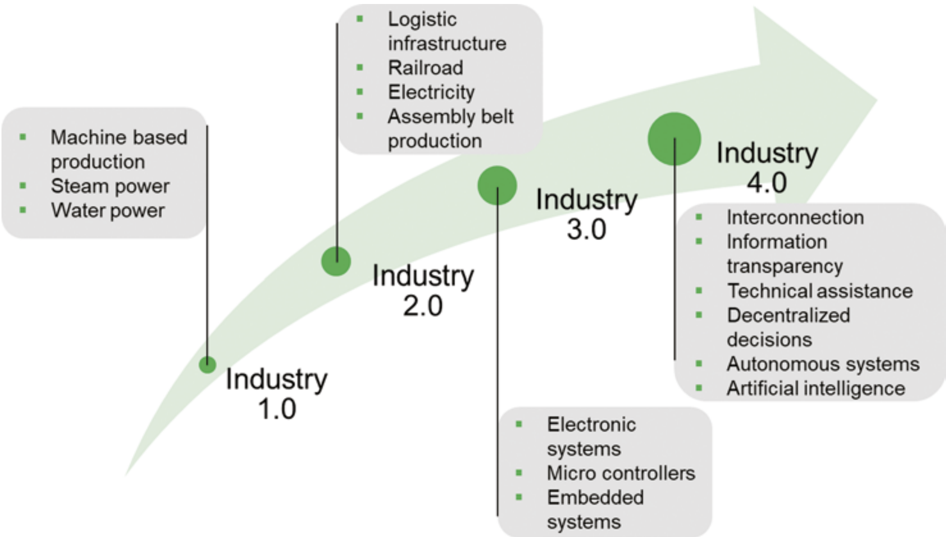

Figure 1.1 First to Fourth Industrial Revolutions

The term "Industry 4.0" describes a holistic digitalization of industrial production to achieve improvement in terms of quality, efficiency, robustness, and flexibility. This shall be achieved using modern information infrastructure and communication techniques with the aim of creating intelligent self-organizing production systems. It is not only related to a single production machine or device, but aims for connection of all essential parts of the value chain and therefore enables a holistic optimization. Additionally, the interaction between humans, machines, production systems, logistics, and products is an essential component of Industry 4.0.

For Industry 4.0, four major design principles have been defined [1]:

- Interconnection: People, machines, devices, and sensors are connected and communicate with each other.

- Information transparency: Data, which is obtained by the interconnected devices throughout the production and along the value chain, is made available, where it delivers added value.
- Technical assistance: Modern systems, which support humans either by assisted decision making using processed information or by taking over non-creative or unsafe tasks, are employed.
- Decentralized decisions: Systems are enabled to fulfill tasks autonomously and only rely on centralized decision making if conflicting goals are present.

The term “Industry 4.0” originates from a report of an advisory committee to the German government, presented in 2013 [1]. Furthermore, it originates from a project within the high-tech strategy of the German government in the year 2014. It is also referred to as the “Fourth Industrial Revolution”, a term first introduced in 2015 by Klaus Schwab, chairman of the World Economic Forum. It refers to the consequent evolution of industrialization [2]. Thereby, the four stages of industrialization are stated as follows:

- The First Industrial Revolution refers to the transition of hand production to machine-based production using steam power and water power between 1760 and 1840.
- The Second Industrial Revolution was characterized by the introduction of logistic infrastructure like railroad and telegraph networks between 1871 and 1914. Being able to provide resources and information more efficiently and using electricity in production allowed a drastic economic growth and increase in productivity.
- The Third Industrial Revolution, which occurred in the late 20th century, was mainly characterized by the introduction of electronic systems and micro-controllers into machine control systems, which extended the effects of the Second Industrial Revolution and allowed more efficient and well-controlled production.

Therefore, the Fourth Industrial Revolution defines the even further development of industrial production, extending the capabilities of production systems by enabling interconnection and developing more complex and flexible systems, which results in a smartification of the production. The benefit is higher quality and efficiency. This is to a great degree achieved by digitization, meaning that formerly analog information is transformed into digital information, enabling it to be reproducible, available anywhere, and automatically interpretable. Nevertheless, to a large extent it is achieved by digitalization, which extends digitization by the aspect of added value and transforming businesses or processes by innovative and creative new approaches instead of transferring traditional methods into a digital format. It is also referred to as “digital transformation”. Due to the rising complexity of production systems in the interconnected context, the direct benefits, which lead to increased efficiency, are manifold.

This book aims, on the one hand, to deliver basic knowledge about the acquisition and dependencies of data, industrial devices, processes, and digital infrastructures to provide a general understanding how various systems in the context of Industry 4.0 interact and how new systems can be designed and implemented. On the other hand, established as well as new applications in the field of plastics processing are illustrated to present benefits and potential new applications.

Since all applications rely on inputs in form of information, in Chapter 2 “Data Acquisition and Process Monitoring as Enabler for Industry 4.0”, the basic knowledge regarding data acquisition for industrial processes including knowledge about sensor systems is presented. Along with the understanding of the specific process, this data can be refined and used to implement beneficial systems such as, for example, process monitoring or optimization systems. In the following Chapter 3 “Cyber-Physical Systems”, the view is extended towards complex manufacturing environments and their digital representation. This chapter especially aims to convey methods for data clustering and defining efficient subsystems including internal and external communication. Hereafter, one of the most important aspects of Industry 4.0 is addressed in Chapter 4 “Models and Artificial Intelligence”. To be able to generate benefit from available data, a digital representation of the considered system is necessary to determine the correct response to arising problems or challenges. In this chapter, physical and analytical models as well as data-driven modeling methods are presented. In Chapter 5 “Global Connectivity”, the requirements and recommendations regarding a digital infrastructure are addressed considering data availability for various systems, starting at infrastructure concepts like centralized and decentralized production environments, going through industrial machine interfaces, and ending with manufacturing execution (MES) and warehouse systems.

In Chapter 6 “Digital Engineering”, concepts and methods for virtual representations of a system or its behavior are presented. These can range from dedicated simulation-based representations of a specific process to complex interconnected simulations or data-driven representations of processes or production systems using artificial intelligence. Since virtual representations rely on various pieces of information and additional benefit can be generated when including information from multiple stages of the value chain, in Chapter 7 “Complex Value Chain”, concepts of data acquisition and data management from adjacent areas of the shop floor are covered. Additionally, exemplary projects illustrating Industry 4.0 applications for increased efficiency and process flexibility are described.

Finally, in Chapter 8 “Assistance Systems”, I4.0 applications are presented that support humans in various tasks by providing reworked information directly at the work space.

(see Figure 1.3), most of these systems are focused on specialized or separated tasks, while not offering easy integration in existing environments or other systems suitable for collaboration. This is a major drawback, since most benefit can be achieved by considering the whole production or even the entire value chain.

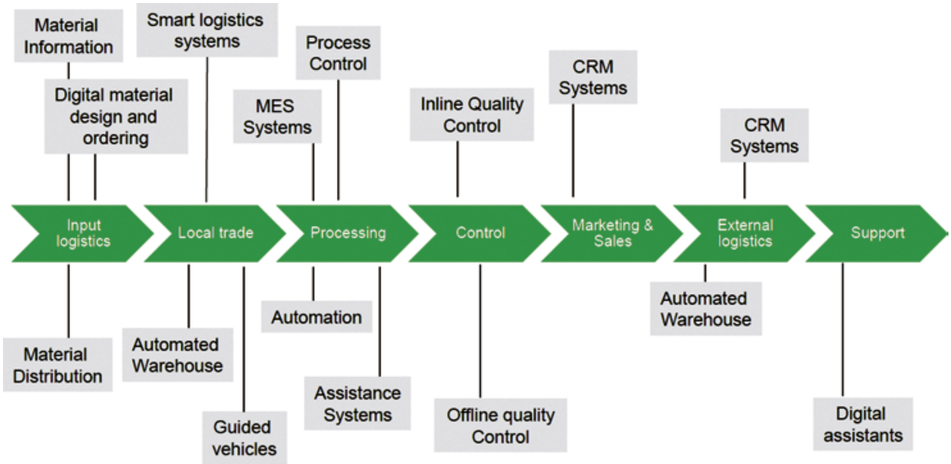

Figure 1.3 Available Industry 4.0 applications along the value chain

There are two major reasons for this. One the one hand, system providers are aiming to establish their platform as a standard, enabling the development and sale of further proprietary products or the offering of additional services in terms of data integration or interfaces. One the other hand, in the field of production systems there are no suitable industry-wide standardized specifications and protocols available that can easily be integrated with a variety of different data sources and database systems. Fortunately, many standards and specifications are currently in development, such that interoperability will improve drastically in the future. This will allow a much easier and faster integration of these systems and therefore reduce the efforts necessary for implementation. Thereby, data-driven systems will also become more interchangeable in the future and, therefore, the system providers will have to compete even more, resulting in lower prices. One of the already established standards for machine communication in the field of Industry 4.0 is OPC-UA. One important aspect of OPC-UA is the separation of the data layer (which is accessible by external systems) and the bus-level of the machine control, allowing a data exchange without the risk of interfering with the machine control. It furthermore implements security and encryption mechanisms allowing a secure data access. The most compelling aspect of OPC-UA is the ability to browse the namespace, allowing the identification of all available information. Therefore, an increased level of data transparency and reliability is given, making it easy and affordable to access the data. Also on the higher level of data structuring and data motion of viscous fluids, and the Carreau model, which describes the relation between shear rate and fluid viscosity. To bypass these complicated and time-consuming inversions, the input of the optimization routine is being produced by simulations controlled by an optimization algorithm. Using proprietary solvers [7] as well as global and local optimization algorithms [8, 9], the updated optimization approach was tested with an L-shaped profile and resulted in a clearly visible improvement of the tool-exiting melt flow speed distribution (see Figure 4.3).

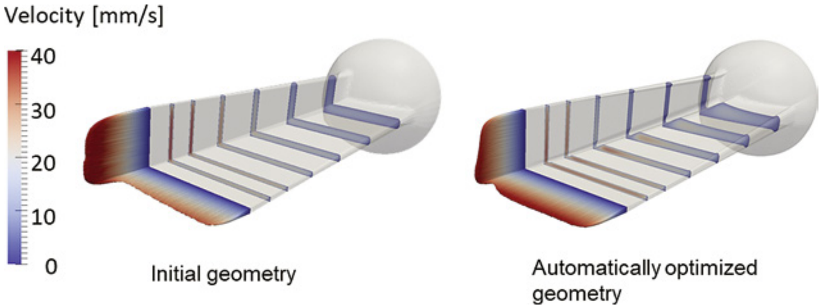

Figure 4.3 Comparison of die-exiting melt speed before (left) and after (right) optimization with the improved optimization routine [6]

The example above uses the simulation data of the real process to make predictions of the resulting quality and subsequently optimize the control variables in the system. In the following, different modeling techniques and corresponding examples from the plastics processing industry are presented to show the variety of approaches. It is first of all necessary to define what a "model" actually is.

■ 4.2 Three Different Categories of Models

In the physical world, models can be seen in various environments with many different people working on them. Architects, for example, build models of the planned structures and houses. Car manufacturers create design models for evaluation of haptics and visuals as well as functional models to test crash behavior. It is even possible to consider structures made out of toy bricks as models, with the goal of having a representation of the real structures which is as similar as possible. All of these models have a physical nature. Theoretical models, however, follow the same idea.

A model can be defined as a specific simplification of reality within boundaries of time and context [10]. As shown in the introduction of the chapter, a model does not aspire to depict reality itself. It rather selects the most significant influences on a process or a state to approximate reality with a tolerated error. This definition corresponds to the characteristics of a model defined by Stachowiak in 1973, who claimed a model has to meet three central aspects [10]:

1. A model needs to be a representation of an existing original or reality.
2. A model needs to neglect certain attributes in favor of those that seem most relevant to the modeler.
3. A model is never limited to its exact original or reality, but is purposeful, temporally confined, and bound to its context.

In the following, three different modeling techniques will be presented and illustrated with different examples in plastics processing.

4.2.1 Physical Models

Physical modeling of a system is the basic approach used by physicists. The models implement known physically quantifiable correlations between parameters and variables to describe the state or behavior of complex systems. The interdependencies are known regarding tendency and amplitude and the resulting value is accurate. Models of this kind belong to the category "white box": the internal logic or more specifically the variables inside the model are identifiable at all times concerning their values and representation [11].

A basic example for physical modeling the system behavior of a manufacturing process is the estimation of the required clamping force in injection molding. The clamping force prevents the opening of the mold during the injection and holding pressure phase of an injection molding cycle. It is necessary as the injected melt applies a defined pressure on the cavity wall. The required clamping force F_C can therefore be estimated with knowledge about the melt pressure $p(x, y, z)$ in each location of the cavity and the projected cavity surface A_{proj} orthogonally to the parting line of the mold (see Equation 4.4).

$$F_C = \int p(x,y,z) * dA_{proj} \tag{4.4}$$

$$F_C = p_{sc} * A_{proj} \tag{4.5}$$

As only selective values of the melt pressure distribution in the mold are measureable by pressure sensors, the equation is simplified by using a constant value for the melt pressure. In most cases, cavity pressure sensors are not available so the pressure of the screw is used for calculation. Equation 4.4 therefore is substituted by Equation 4.5.

Engineers often use these models to determine and calculate the system behavior due to changes of machine setting parameters, the replacement of machines, or design adaptions of the part. In order to even make models of complex processes available, the determined general connections between the system inputs are formulated.

A well-researched example regarding a physical modeling of an entire manufacturing process is the simulation of the system behavior for a high-pressure recirculation reactive injection molding (RIM) machine [12]. In contrast to conventional injection molding, the polymer material is being created by an exothermic chemical reaction of the two reactants, polyol and isocyanate. Detailed information about the RIM process can be obtained in further literature such as [13]. Due to the reaction of plastics material, the process presents specific challenges. One of the most important factors for a good process quality is a reproducible process regarding the mixture from cycle to cycle. For the physical modeling task, relevant influencing parameters for the system need to be identified. The machine influences the mixture quality by temperatures, gas loading, volume flows, injection pressure, and dosing time. The reasons are easily explained: The viscosity of the materials depends e. g. on the temperature of the system. Also, the fluid itself or parts of the pipe system are prone to elastic deformation based on the applied pressure, which can cause dosing variances.

The dependencies in a RIM system concerning static pressure and volume flow are known quite well. A further development described below is the modeling of transient effects in the simulation of the system behavior such as pressure shocks, pressure compensation processes, and pressure pulsations for the viscoelastic polyol component.

The physical modeling is based on a circuit diagram replacing hydraulic elements with equivalent electrical elements (see Table 4.1). This allows the transfer of this modeling procedure to different RIM systems as most systems are unique, e. g. regarding the pipe system, and therefore need an individual model using the same method for simulation.

Table 4.1 Replacement of Hydraulic Elements with Electrical Elements

Hydraulic system	Electrical system
Pressure	Voltage
Volume flow	Current
Dosing pump	Current source
Flow resistance in pipes, nozzles, and throttles	Resistance
Inertia of liquid columns in pipes	Electrical inductivity
Elasticity of pipes and compressibility of fluids	Electrical capacity

4.2.2 Knowledge-Based Systems

Knowledge-based systems leverage implicitly available expert knowledge to approximate systems. Experts are people with experience who deeply understand the original or the reality and know the systems aspects and behavior well. Expert knowledge is never impartial but always biased by the expert. However, it is a relevant modeling technique where physical models cannot be used, e. g. due to lack of knowledge about physical dependencies [24].

A good example concerns the mold design in injection molding. First of all, misdesigned tools can lead to long development times and high manufacturing costs due to several corrections before the production can start. State of the art is a design support software called “feature-technology” to keep the design times to a minimum, reduce corrective interventions into the manufactured tool, and ultimately raise the product quality [25]. The function can be displayed by a snap-fit.

As most design processes start with a CAD file, the software tool automatically creates snap-fits in the designed part. This “feature” snap-fit not only consists of a geometrical CAD element but also contains semantic information about the usage and creation of the element which is machine readable, for example the assembly direction, assembly force, and linking point to another geometrical element (see Figure 4.6).

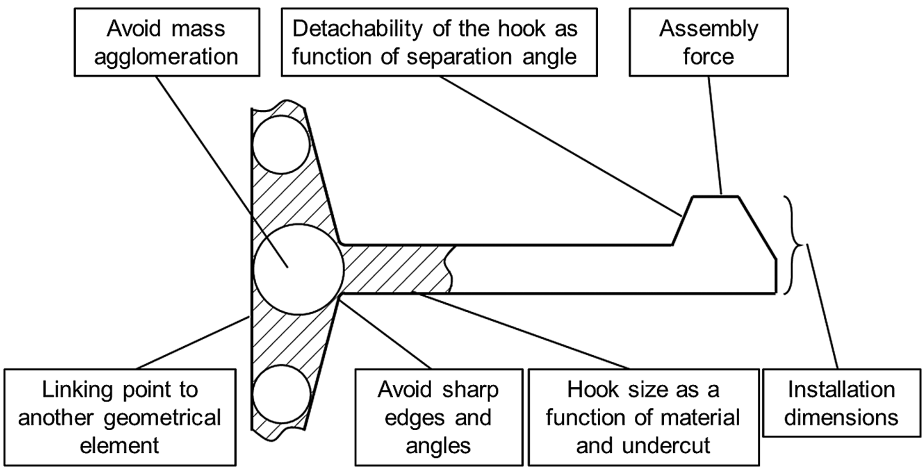

Figure 4.6 Semantic information concerning a snap-fit provided by the feature technology

Overall, the feature technology concept is divided into 4 modules:

- A database containing all semantic information about different types of snap-fits. This database is the core element of this knowledge based support system as it is filled with the expert knowledge about snap-fit design elements. For different parts, a different database would have to be initiated.

- In the design step for snap-fits, the resulting geometry of the element is calculated considering the requirements of the user and several boundary conditions that apply by adjacent elements, for example. In the end, the snap-fit can be added to the CAD file.
- In the following form, the whole design will be checked for constructional issues. An advantage of the feature technology here is that the software automatically notifies the user if the applied snap-fit requires an additional demolding direction.
- An economic evaluation of the design can be performed afterwards based on a rough cost estimation.

The modeling of the feature "snap-fit" was performed in the CAD software Pro/Engineer by PTC Inc., Boston, USA, in the form of a User Defined Feature (UDF) file. Besides the geometrical information about the snap-fit elements, this file format was able to include all semantic feature information. In the same way, different design elements are implemented such as couplings, springs, plastic bearings, or other frequently used elements to reduce the design time and raise the product quality.

As seen in this example, knowledge-based systems completely depend on the expert (group) providing the (initial) stack of information. The system cannot learn by itself but will always provide information about specific elements or known situations. Thus, a KBS might produce excellent approximations of the reality, but it cannot support the user for an unknown situation or more specific request. Every other design requires the involvement of an expert (group).

Expert knowledge is widely used in plastics processing. Another example is an approach to automatically optimize the molded part geometry: Within CAD software, support macros are often implemented which optimize the rough design by removing material where the part experiences low stress levels and adding material where the strain is high, known as topology optimization. However, this "algorithm" does not consider relevant aspects for manufacturing plastic parts such as demoldability, avoidance of mass agglomerations, and undercuts.

In order to consider these aspects, the design may be verified based on the idea of the growth of a crystal [26]. It is assumed that within a finite elements mesh not a single element leads to a design error but an ensemble and an iterative procedure is adopted for optimizing the molded part geometry.

The assembly space is being defined a priori as a finite element mesh with bar-shaped elements. Starting with the initial element, grown elements are defined by assigning the characteristic "dense" in the process. The appearance of undercuts or material agglomeration can therefore be interpreted as a result of each growth step throughout the procedure. Besides that, the evaluation after each growth step can also check if all functional surfaces are completely connected to the rest of the part or if "denseless" volumes still exist that need to be filled. The illustration of a growth step can be seen in Figure 4.7: while the demolding direction has to be specified by the user, the system automatically marks the area that will prevent easy demolding if the elements are marked as dense and inhibits the growth there.

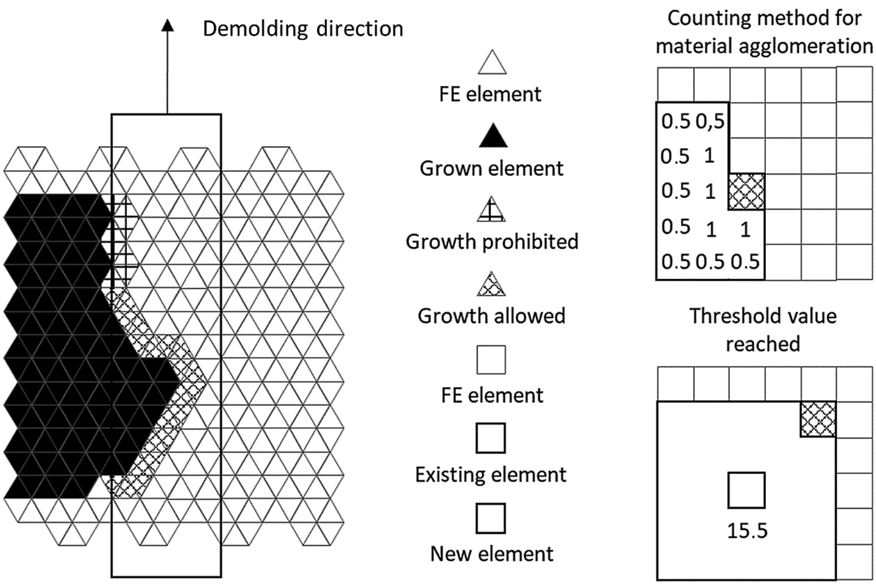

Figure 4.7 Crystalline growth of the molded part to prevent undercuts

Besides the check for undercuts, the system also considers material agglomerations. The implementation can be seen in Figure 4.7 on the right side: Adjacent elements with the characteristic "dense" are assigned the value 1 and elements with no direct contact to the respective element are assigned the value 0.5. If a defined value threshold is exceeded (15.5 in this example), the system generates the error "material agglomeration" to inform the user. The advantage of this determination method for material agglomeration is the omission of distance measurements. However, all FE elements are required to have the same shape to be able to interpret the results. Further development could examine the possibility to automatically determine threshold values depending on the shape of the element's surroundings.

Knowledge-based systems obviously play an important role when it comes to solving problems usually solved by humans. But once again, the creator of a knowledge-based system can usually be considered to be an expert in a very specific field. It is fair to say that the expert has processed a lot of knowledge and experience. All the data, as which the information could also be considered, however, can also be used in a different way: not to train humans, but artificially intelligent systems.

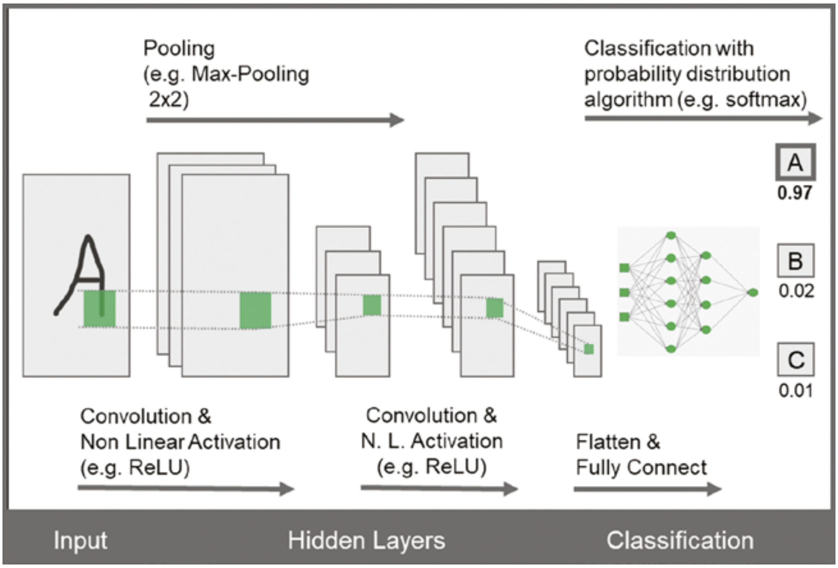

Figure 4.11 Convolutional neural network

Black has the RGB value 0 whereas white ranks the highest with 255. Any value between is a grayscale color between these two. A white pixel surrounded by other white pixel therefore gets, based on the used kernel, a very high or very low value relative to a black pixel surrounded by other black pixels. Any other combination of pixels and surroundings will be within these extreme values.

The pooling layer will pick the maximum value as representation for this part of the processed input data out of an a priori defined coherent area. Significant differences in the activation of areas indicate an edge.

The third widely known type of ANNs is the *recurrent neural network* (RNN). RNNs do not belong to the category of feedforward ANNs but rather contain intra-layer or backwards-orientated connections between neurons (see Figure 4.12). Common use cases are time series prediction, natural language processing, or recognition of handwriting. One exemplary subcategory is *long short-term memory* (LSTM) RNNs that allow the modeler to define the intensity and frequency of recurrent signals in the network.

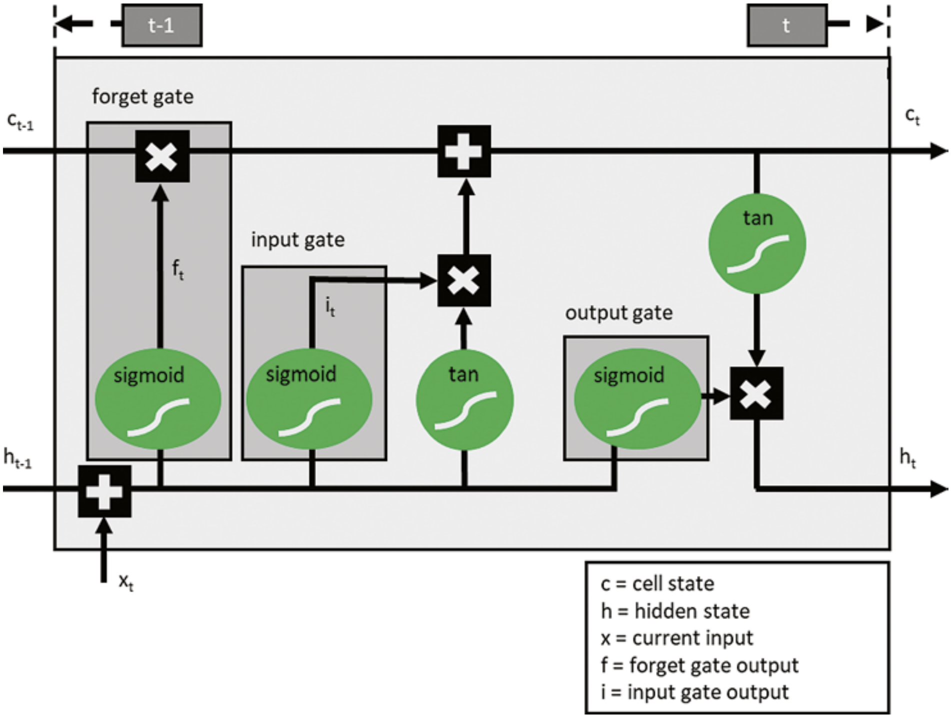

Figure 4.12 Long-Short Term Memory (LSTM) module

4.2.3.2.2 Training of Feedforward ANNs

As the category of feedforward artificial neural networks is the most important subgroup, the training mechanism will be explained for those.

All AI modeling approaches are data-driven, which means that a model can only adapt a posteriori to an already existing data set. Within the scope of artificial intelligence and machine learning, associated data is frequently denoted as a sample M with a number i of labeled data elements (x_i,y_i) of a data domain D (see Equation 4.24). A domain D can be described by a parameter space X (in the following called *"input parameter space"*) and a distribution of the data in the input parameter space $P(X)$ (see Equation 4.25). The purpose of the modeling approach shall be called task T, consisting of the model $f(X)$ itself and the parameter space of the labels Y (in the following called *"output parameter space"*, see Equation 4.26). Data domain D and modeling task T together form the assignment A that can be evaluated (see Equation 4.27).

$$M=\{(x_i,y_i)\mid i=[1,\ldots,m] \text{ and } m\in\mathbb{R}\} \tag{4.24}$$

$$D=\{X,P(X)\} \text{ with } D\subseteq\mathbb{R}^n \text{ and } n\in\mathbb{N} \tag{4.25}$$

6 Digital Engineering

6.1 Introduction

"Digital engineering is the consistent use of digital methods and tools throughout the product development and production process and aims at improved planning quality and process control over the entire product life cycle." [1]. For this purpose, the interoperability of different existing model worlds from the various areas of product development is required. This can be seen as an extension of the five-layer model of virtual engineering, introduced by Bullinger and continued by Ovtcharova, from "data generation, data management, system integration, virtual engineering organization, and application access" [2].

At the beginning of a development process in a virtual environment, there is commonly the (3D) geometry generation, which serves the continuous further processing in all subsequent work steps. This usually takes place in a computer aided design (CAD) environment in which 88% of market participants already assume that digitalization will take place and data exchange between different software solutions via standardized exchange formats is given [3]. An example of an established exchange format is the STEP format standardized in ISO 10303. Based on these models, Digital Mock-Ups (DMU) are generated as a virtual product, e.g. to model production processes in a digital factory. The data management, which includes file storage, management, versioning, distribution, and access control, can be conducted via infrastructure such as Engineering Data Management (EDM), Product Lifecycle Management (PLM), or Product Data Management (PDM). System integration is a compelling prerequisite of digital engineering, since data exchange between facilities, different company divisions, as well as cross-company and cross-system functions must be carried out in order to be able to perform interdisciplinary, interoperable development tasks. Unfortunately, this is not always the case in practice and sometimes leads to considerable manual effort in data maintenance. It can still be seen as a bottleneck with regard to process flow optimization. The organization of virtual engineering aims to coordinate corresponding development processes. That leads to communication-intensive processes which require broad process knowledge. Objectives may vary with project progress, are incomplete or changeable, and contain project and process risks with qualitatively and quantitatively limited resources. Therefore, it is necessary to support process and project documentation throughout, to support the clarification of objectives methodically and IT-wise, to be able to process incomplete and inconsistent process and project information, to combine result-oriented process planning with phase-oriented process planning, to keep all process- and project-relevant information up-to-date, and to integrate and promote informal processes [2]. Finally, the application access is required to guarantee the accessibility of process and project data to all incorporated, geographically distributed teams. In the common development routine of strongly interwoven structures from interdisciplinary industries and company sizes, not all framework conditions necessary for a continuous digital engineering can be represented. Often, the different degree of development with regard to digitization poses a major hurdle for an end-to-end digitized process chain in the sense of Industry 4.0.

In order to bridge from this general and abstract representation of digital engineering to the special circumstances in the field of the plastics processing industry, the engineering area is examined in more detail in the further course of this chapter. Depending on the production process, plastics may have anisotropic mechanical properties. In a continuous virtual integrative process chain, the influence of the manufacturing process must therefore be taken into account when computing mechanical properties of a component. Results of these process simulations can be e.g. fiber orientation distribution, a process-dependent inhomogeneous crystallization, warpage, the location of weld lines, the degree of curing in the field of thermosets, or wrinkle formation in textile products. All these influences must be taken into account as early as the design phase of the product in order to design the manufacturing process and the necessary tools correctly on the one hand, but also to guarantee e.g. dimensional accuracy. For mechanically driven design criteria, it is essential to consider the influences on the product caused by the manufacturing process, since the mechanical material properties can vary significantly locally. In an ideal integrative virtual process chain, the manufacturing process is designed on the basis of the 3D models, the results of the process simulation (e.g. fiber orientation) are transferred to the structure simulation, and the effective material properties are calculated on the basis of the process simulation and micromechanical approaches or even molecular dynamics simulations. Based on the results of the structure simulation, changes can be made to the geometry and process settings. In addition to series production, sensor data are transferred directly to the process and structure simulation in order to evaluate the product on the basis of real process parameters and, if necessary, carry out parameter variations in order to improve the real process and thus the product. This requires a semantic interoperability of the used software systems that is as complete as possible in order to avoid information loss and to enable a further automation of the coupled processes. In industrial practice, this prerequisite represents a considerable hurdle, since there are countless software solutions for a wide variety of questions whose semantic interoperability cannot be regarded as given. Many software packages used in engineering practice often originate from this before digital networking and thus the introduction of generally accepted standards for the lossless transfer of data between different software packages is a major challenge. Therefore, this chapter examines the partial aspects of an integrative simulation chain and shows which technical aspects of plastics should be included in the digital engineering process in the future in order to be able to adequately consider the high degree of production process dependency.

6.1.1 Digital Materials

From the perspective of a highly technical component, Industry 4.0 sees itself as the end-to-end digitization and interlinking of the entire product lifecycle, starting with development, through production, usage, and maintenance, to the recycling of the component. All decisions in product development, production, and application are based on the choice and understanding of the construction material, which in turn result in the need for cross-domain and lifecycle-wide connectivity. The selection of an alternative material, for example, leads to different design requirements, choice of production machinery, and subsequent production processes, as well as maintenance during lifetime and recycling requirements.

The actual properties of technical components made of plastics are defined, usually even more significantly than for other construction materials, by the boundary conditions present during the component production. The influences are very diverse and the mentioned property changes of the component result from effects on different scales. The orientation-dependent elasticity due to the flow behavior of the melt in the injection molding process, or the different shrinkage due to inhomogeneous cooling conditions and thus inhomogeneous crystallization are only a few aspects to be mentioned here. These are examples of macroscopic property changes which are influenced by effects on the microscale. However, effects on the nanoscale can also have an effect here, e. g. stress cracking. For a polymeric material, the mechanical strength is influenced by additives such as a flame retardant or a contacting medium within its usage, which can be explained by the weakening of the intermolecular interactions of the polymers on the nanoscale. The classification of the above-mentioned scales regarding the underlying length is shown in Figure 6.1.

7.2.2 Key Figures for Plastics Processing

Even though key figures need to be determined for a specific process, there are commonalities in different production units, which allow a generalization.

A widely used key figure is the Overall Equipment Effectiveness (OEE), which is described by the following equation (Equation 7.1).

$$OEE = Quality \cdot Performance \cdot Availability \tag{7.1}$$

The OEE indicates the efficiency of a specific production plant. Three factors are included in the equation for this purpose. Each individual factor represents a loss potential. The quality factor represents the loss caused by rejects or rework. The performance factor indicates the actual load on the machine during operation by comparing the actual output quantity with the theoretically possible target output quantity. The performance factor therefore represents short-term/unrecorded standstills or production at reduced speed. The last factor, the availability, indicates those losses in which the machine was not in operation. This is the case with prolonged, unplanned downtimes or setup times. Ultimately, the ratio is a measure of the value added of individual machines. A detailed analysis of the individual loss factors makes it possible to identify which areas cause the losses and where there is potential for improvement. The OEE is suitable for series or mass production and is therefore well suited for the manufacturing areas of the plastics processing industry [8]. In [14], the authors describe some methods to improve the OEE of an injection molding machine. To increase the quality factor, for example, the authors identified six problems, their root cause, and the actions that should prevent them in the future. One problem was the warpage of a specific product that was caused by a blocked cooling channel. To avoid this problem, a checklist about the mold core and cavity temperature was added to guarantee the right temperatures. Additionally, to improve the performance, the authors caught some abnormalities in the injection molding machine that were responsible for unplanned machine downtimes, which turned out to originate in the nozzle heater. By replacing the nozzle heater, these unplanned downtimes were reduced.

Another important key figure is the total cycle time. In contrast to the OEE, which only focuses on one machine or a work center, the total cycle time considers the whole production process including transportation and waiting times. The total cycle time is calculated as follows (Equation 7.2):

$$Total\,Cycle\,Time = Processing\,Time + Transportation\,Time + Waiting\,Time \tag{7.2}$$

The cycle time in general describes the period between the start of the first operation and the end of the last operation. Figure 7.5 shows some different types of the cycle time.

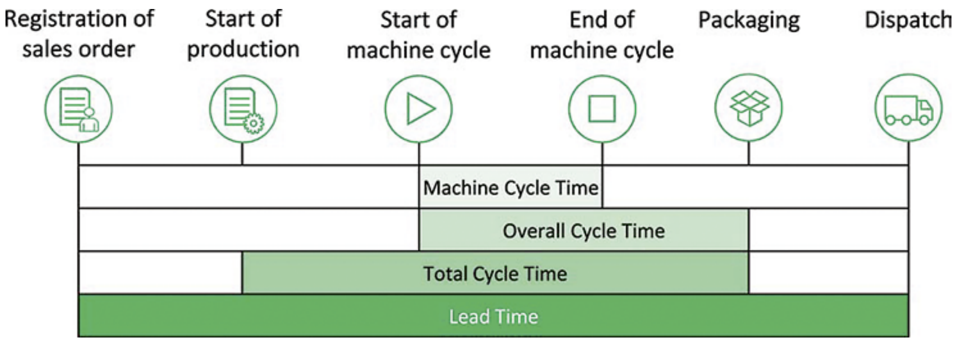

Figure 7.5 Different cycle times

The total cycle time covers the time between the start of production to the delivery for shipping, including all processing, waiting, and transportation times. The overall cycle time only takes into account the time required for the creation and packing of a product; waiting periods (e. g. waiting time in front of the machine) are not considered. The machine cycle time only refers to the period during which the machine is molding or forming a part (e. g. a cycle of an injection molding machine). The lead time covers the time from the receipt of the sales order to the shipment of the finished product. In general, every type of cycle can be recorded as a cycle time KPI. It is only necessary to ensure that the determination of the key figure is significant and gains a benefit for further analyses and reporting. The goal is to minimize the total cycle time to the lowest possible level [8, 15].

The third key figure presented here is the takt time, formulated in Equation 7.3:

$$\mathit{Takt\ Time}\frac{[s]}{[unit]} = \frac{\mathit{Net\ time\ available\ for\ production}[s]}{\mathit{Customers\ daily\ demand}[unit]} \tag{7.3}$$

The takt time describes the time span that is theoretically available for the output of one production unit. The main usage of this key figure is placed in the value stream analysis, another tool in the lean management toolbox. The main goal of the value stream analysis is to point out the actual information and material flow (including processing and storing times) for identifying bottlenecks and non-value-adding process steps. The takt time acts like a pacemaker for the whole production. Because different workstations and machines work with different velocities, the utilization of the production is not smooth. Under consideration of the takt time, it is possible to level the whole production process. This can be achieved by comparing the takt time with the actual cycle time of a machine or workstation. In summary, the takt time can be helpful for designing the production process. If the takt time is shorter than the actual machine cycle time, this machine is classified as a bottleneck because it is not possible to fulfill the customers demand. One possible solution is to increase the net time that is available for production (e. g. an

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