Actionable Artificial Intelligence for the Future of Production

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Abstract

The Internet of Production (IoP) promises to be the answer to major challenges facing the Industrial Internet of Things (IIoT) and Industry 4.0. The lack of inter-company communication channels and standards, the need for heightened

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safety in Human Robot Collaboration (HRC) scenarios, and the opacity of data-driven decision support systems are only a few of the challenges we tackle in this chapter. We outline the communication and data exchange within the World Wide Lab (WWL) and autonomous agents that query the WWL which is built on the Digital Shadows (DS). We categorize our approaches into machine level, process level, and overarching principles. This chapter surveys the interdisciplinary work done in each category, presents different applications of the different approaches, and offers actionable items and guidelines for future work.The machine level handles the robots and machines used for production and their interactions with the human workers. It covers low-level robot control and optimization through gray-box models, task-specific motion planning, and optimization through reinforcement learning. In this level, we also examine quality assurance through nonintrusive real-time quality monitoring, defect recognition, and quality prediction. Work on this level also handles confidence, verification, and validation of re-configurable processes and reactive, modular, transparent process models. The process level handles the product life cycle, interoperability,

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and analysis and optimization of production processes, which is overall attained by analyzing process data and event logs to detect and eliminate bottlenecks and learn new process models. Moreover, this level presents a communication channel between human workers and processes by extracting and formalizing human knowledge into ontology and providing a decision support by reasoning over this information. Overarching principles present a toolbox of omnipresent approaches for data collection, analysis, augmentation, and management, as well as the visualization and explanation of black-box models.

5.1 Introduction

The digital transformation of production fundamentally reshapes the production landscape. The continuous and real-time exchange of data and information across all levels of the production process connects organizations within and across companies. Through this full integration of data across the whole life cycle of design, manufacturing, and use of products and across the whole value chains, production becomes more effective, efficient, and dynamic (Kagermann 2015; Liao et al. 2017; Brauner et al. 2022). Also, the diligent and efficient use of data opens up new business models and workplace opportunities for future generations (Becker et al. 2021b).

The Internet of Production (IoP) transfers the idea of the Internet of Things (IoT) to production and strives for the horizontal and vertical integration of production technology. It is thus related to similar concepts, such as Industry 4.0, the Industrial Internet (Bruner 2013), and the Industrial Internet of Things (IIoT) (Boyes et al. 2018). Yet, many approaches in this direction usually focus on one aspect at a time. They either focus on one layer of industrial environments, tackle challenges of a specific domain, or handle one perspective of the human stakeholders. In contrast, the IoP is a holistic approach to digital production and aims at achieving many of the visions of Industry 4.0 (Brauner et al. 2022; Pennekamp et al. 2019). It thus shares goals with several initiatives around the globe such as the industrial value chain initiative (https://iv-i.org/, last accessed: 2022-08-02), made in China 2025 (http://english.www.gov.cn/2016special/madeinchina2025/, last accessed: 2022-08-02), US advanced manufacturing initiative (https://www.nist.gov/document/molnar091211pdf, last accessed: 2022-08-02), and the high value manufacturing catapult (https://hvm.catapult.org.uk/, last accessed: 2022-08-02). But beyond that, the IoP builds on Digital Shadows (DS) and facilitates the idea of a World Wide Lab (WWL) (Brauner et al. 2022). DSs refer to fast, secure, task- and context-specific, purpose-driven, aggregated, multi-perspective, persistent, and multimodal views on data for production engineering applications (Liebenberg and Jarke 2020). The WWL enables the integration of data from experiments, manufacturing, and usage across lab, company, and country boundaries to generate insights.

The previous (▸ Chaps. 3, “A Digital Shadow Reference Model for Worldwide Production Labs” and ▸ 2, “Evolving the Digital Industrial Infrastructure for Production: Steps Taken and the Road Ahead”) have laid the foundations for a secure, reliable, and trusted physical infrastructure of an IoP and motivated and defined the conceptual foundations of DS as the crucial nexus between the entities of the IoP. This chapter presents the functional perspective of the IoP and demonstrates how to make production data actionable, by linking mathematical models, Artificial Intelligence (AI), and Machine Learning (ML) with model-based analysis and control to provide actionable knowledge to either machines or decision-makers through trusted and bias-free humane interfaces (Calero Valdez et al. 2015; Pause et al. 2019).

The vision is the application of model-integrated AI which combines mathematical models, simulations, and data from different sources to create “data-to-knowledge pipelines.” These pipelines transform massive data into insights and provide actionable knowledge to decision-makers. To this end, we define the following objectives:

1. Develop a systematic approach toward the combination of ML and model-based AI methods in context-adaptive production settings.
2. Develop visualizations, decision support systems, and human-centered interfaces that enable intuitive, adaptive, comprehensible, replicable, interactive assessments of model, simulation, and smart data at different scales and abstraction levels for reporting, diagnosis, prediction, and decision.
3. Definition of a systemic overview on data-to-knowledge pipelines in production and derivation of similarities between pipelines to enable the transfer and cross-learning between different pipelines.

A core idea is creating data-to-knowledge pipelines that transform raw machine data to actionable knowledge usable by either humans or machines. Actions can be taken by shop floor workers, supervisors, or managers. This knowledge can also be integrated into autonomous closed-loop control of the machine as well as other machines on the shop floor or production planning systems to realize self-adaptive production systems (Pause et al. 2019). These data-to-knowledge pipelines are the foundation of human-centered Decision Support Systems (DSSs) providing insights and enabling the human-in-the-loop to make informed, bias-free decisions (Brauner and Ziefle 2019).

Key drivers for the digital transformation in production are the need for process understanding and optimization, management decision support systems, workplace improvement through better ergonomics and safety, cost reduction through defect detection and time reduction, improved horizontal and vertical data integration, and better adoption to customer demands (Liere-Netheler et al. 2018).

Fisher et al. (2018) allow sharing and managing manufacturing capabilities in a micro-service architecture with a focus on inter-company integration (Siderska and Jadaan 2018). Our approach builds on the concepts of the World Wide Web and the

IoT to act as the IIoT. The IIoT promises many improvements in various industries through data exchange and integration, as well as the introduction of digital twins (Pennekamp et al. 2019). According to Xu et al. (2014), the IIoT aims to improve production processes by reducing energy consumption, increasing throughput, as well as safety and security, among other factors.

With the new wave of digitization of production and the increased use of sensors as well as retrofitting old machinery to fit the digitization initiative, Big Data (Manyika et al. 2011) is now omnipresent in production. To support collection, storage, and management of the vast amounts of data collected, the IoP introduced FactStack to manage the full data life cycle while maintaining the FAIR principles: that the data has to be findable, accessible, interoperable, and reusable (Wilkinson et al. 2016; Gleim et al. 2021a). We focus on both inter- and intra-company communication, as well as analysis and optimization of production processes on all levels of production. Our vision is to create, share, and use DSs in different industrial domains in a WWL.

This chapter serves as a toolbox that shows how to apply the concepts and methods of the IoP in different production domains and illustrate their added value. We survey our efforts to achieve the above objectives and demonstrate (1) the application of the concept of DSs in production systems, the creation of data-to-knowledge pipelines, and the realization of validated self-adaptive production systems. (2) Further we shed light on the realization of smart DSSs for human-in-the-loop and shorter, efficient, and agile innovation cycles that build on integrative and interdisciplinary methods. (3) Finally, we show methods for data-driven insights in production processes and back-coupling methods to transform these insights to actions.

This chapter covers the different layers in industrial environments (Fig. 5.1 illustrates its structure). First, we provide an introduction to the WWL and how autonomous agents can make use of DSs and date-to-knowledge pipelines in production (Sect. 5.2). Next, we address the creation and use of DSs at the machine level, where we address the work of individual machines (Sect. 5.3). Then, we address the process level that considers the relation between different production machines on a shop floor (Sect. 5.4). Additionally, we present overarching principles that provide support to the different AI methods as well as aggregate the different aspects toward the vision of the WWL (Sect. 5.5). The chapter concludes with a summary and brief outlook on the future of AI in production (Sect. 5.6).

5.2 Autonomous Agents Beyond Company Boundaries

To make the most out of AI applications in the IoP, particularly with the widespread use of Deep Learning (DL) techniques, we use DSs as an abstract digital representation of the different industrial processes. The digital shadows, inspired from database views (Liebenberg and Jarke 2020; Becker et al. 2021a; Brauner et al.

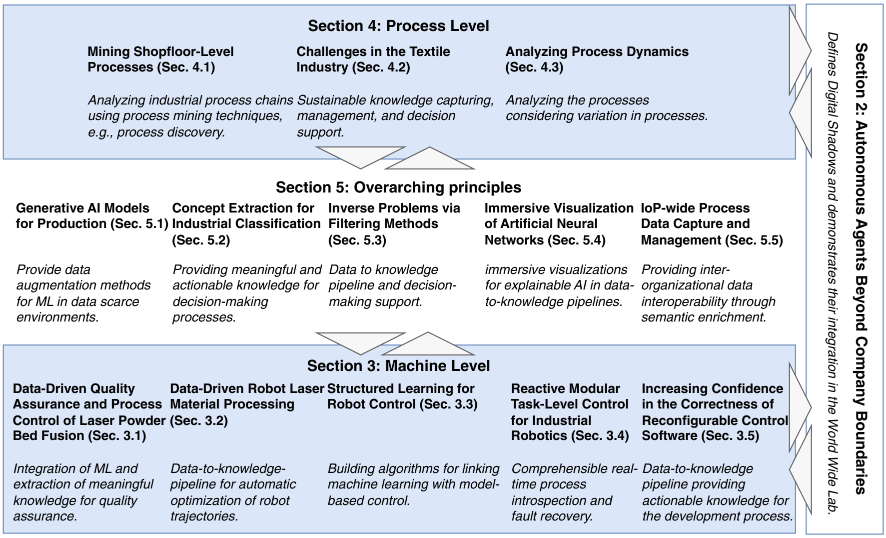


Fig. 5.1 Illustration of this chapter's structure and its individual approaches and contributions

2022), are used as an efficient alternative to digital twins (see previous ▸ Chaps. 3, "A Digital Shadow Reference Model for Worldwide Production Labs" and ▸ 2, "Evolving the Digital Industrial Infrastructure for Production: Steps Taken and the Road Ahead"). Mathematical models can be simplified or can be combined with measurement data or the knowledge created using the data-to-knowledge pipelines. One of the core ideas in the IoP is to share these digital shadows to support production processes with autonomous software agents we call WWL Agents.

The idea of the WWL Agents was introduced in Liebenberg (2021). These autonomous search agents push the boundaries of the IoP beyond control and optimization of production processes within a single company and allow sharing digital shadows across different companies enabling cross-domain data exchange. Additionally, a prototypical implementation of an infrastructure enabling this collaboration as well as two use cases from the IoP where WWL Agents are used to plan the processes of hot rolling and Fiber Reinforced Plastics (FRP) production was presented in Liebenberg (2021). The WWL Agents are able to generate and repair hot rolling schedules using a digital shadow of the process containing data and the fast mathematical models presented in Seuren et al. (2012). They are also able to use traditional planners such as the Temporal Fast Downward (TFD) planner (Eyerich et al. 2009) for the FRP use case.

Figure 5.2 shows the interaction between a production process which can share its digital shadow comprising of data and simplified mathematical models in the WWL. The digital shadow can then be used for automatic control and in DSSs.

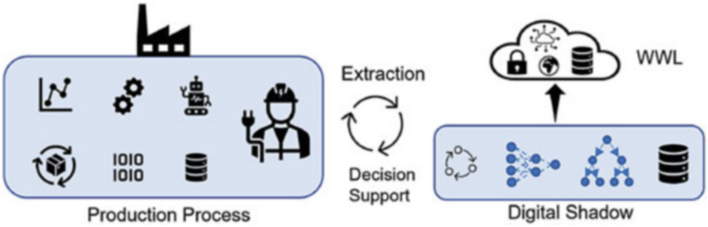


Fig. 5.2 A node in the WWL represents a production process whose models and/or data are continuously shared as a digital shadow in the WWL. These digital shadows are later used as a decision support system causing a feedback loop between the digital shadows and the process itself. (Image adapted from Liebenberg 2021)

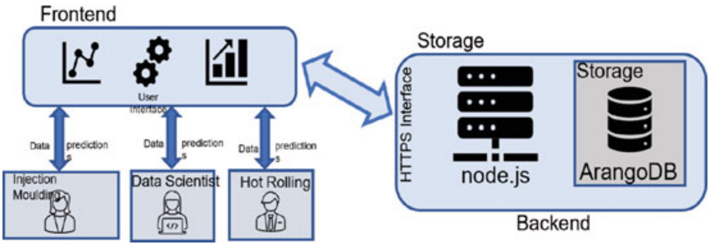


Fig. 5.3 An overview of the framework proposed in Liebenberg (2021) to support the WWL Agents in using the digital shadows provided by different nodes in the WWL. (©Image adapted from Liebenberg 2021)

Figure 5.3 shows an overview of the proposed architecture of the WWL. Users of different roles who provide different use cases have an interface that allows them not only to view process information such as quality prediction but also to upload digital shadows in the form of models and data. The interface acts as an entry point to the WWL as well as a decision support system that can provide insights to the human operators.

In the case of hot rolling, these insights can be in the form of a new rolling schedule or a corrected one in case the quality assessment model predicts an issue with the current one. The underlying models are DL models capable of making different predictions regarding the quality of the product fast enough to allow the operator to get the quality prediction and the suggested corrected schedule and then decide whether to apply the suggested changes in a matter of seconds.

In the case of the FRP manufacturing use case, the insights can be the actions to execute as well as resources and technologies to use in the different steps of the production scenarios. Since the digital shadow for this process contains a classical planner, the process expert would often need to share the problem description, including what resources and tools are available as well as the different steps to be executed for this product. This information is represented using the

Planning Domain Definition Language (PDDL), which is a widely used language for describing planning domains and problems (McDermott et al. 1998).

More use cases still need to be integrated into the framework presented in Liebenberg (2021) to have a truly global interface to the WWL which acts as a search engine with decision support powered by WWL Agents fulfilling the vision of Liebenberg and Jarke (2020). This would showcase the ability of these agents to act as a general cross-domain decision support system for use case experts and machine operators.

To this end, the following sections showcase the creation and usage of DSs for several use cases in the IoP: first for the machine level in Sect. 5.3 and then for the process level in Sect. 5.4. These DSs are extracted from different processes as analytical, DL, or generative models and can be shared across the WWL and later used by the autonomous agents of the WWL for process planning and plan repair, online and offline quality prediction, as well as decision support.

5.3 Machine Level

The aim of modern production is to increase its flexibility to satisfy quickly changing market needs and succeed at the fierce global competition. Therefore, it is crucial to create control systems for machines capable of quickly adapting to new tasks without much engineering effort. This section shows how novel control structures ranging from data-driven, over hybrid, to classical solutions, and their validation methods, can help boost the reconfigurability and flexibility of manufacturing systems on the example of four practical use cases. In the first use case, a monitoring system that enables data-driven control is presented for Laser Powder Bed Fusion (LPBF) machines. The second use case demonstrates the use of data-driven control systems for Laser Material Processing (LMP). The third and fourth use cases present the capabilities of hybrid control systems and hierarchical structures. They combine advantages of classical control methods with data-driven solutions. Finally, we discuss how the safety and robustness of complex control systems can be ensured via a new-generation monitoring architecture.

5.3.1 Data-Driven Quality Assurance and Process Control of Laser Powder Bed Fusion

Additive Manufacturing (AM) offers exciting new opportunities for manufacturing parts with complex geometries or small lot sizes. LPBF is a promising process for metallic components (Spierings et al. 2016). Using AM technique, high flexibility can be achieved when multiple parts with different geometries and sizes can be produced simultaneously. These lead to high freedom with low cost compared to conventional manufacturing. Due to the stochasticity of the manufacturing process, the LPBF process and its production quality are influenced by diverse factors such as laser parameters (Spears and Gold 2016), powder recoating system (Neef et al. 2014), particle gas emissions (Mohr 2019), or powder bed compaction (Ali et al. 2018). Unlike conventional manufacturing processes, the layer-wise production characteristics of LPBF offer the possibility of in situ monitoring and process control layer-wise, which provide insights during the manufacturing process by the monitoring data and adapt the laser scanning strategy for subsequent layers. Thus, it provides the possibility to investigate the correlation between in situ monitoring data and part quality of LPBF process. Based on this, a data-driven method can be used to characterize process performance. Detecting defects needs to be done as early as possible so that a control strategy can prevent the occurrence of the detected defect during the LPBF process. This way we can achieve "first-time-right" and high stability of product quality.

To reach this goal, a closed-loop control strategy to adapt the LPBF process to avoid and compensate defects on the printing parts is required. The whole strategy contains in situ monitoring data acquisition, product quality prediction, and closed-loop control development. The information provided by the in situ monitoring system is an insight into the LPBF process and the basis for a data-driven approach to process control. Existing monitoring systems can be categorized into on-axis and off-axis approaches (Imani et al. 2018). These systems give direct indications if something differs from a predefined "normal" processing condition, which potentially results in material discontinuity. But these anomalies cannot be classified or linked to precise defects yet. In practice, these anomalies are currently detected manually by process knowledge or by simple threshold methods based on monitoring images. According to study of Spears and Gold (2016), the generated amount of data for in-process monitoring or further data processing is a challenge that needs to be handled via careful data preparation. Furthermore, the data analysis approaches are applied for quality assurance. Existing applications are focusing on defect prediction within the product (Imani et al. 2018). These have shown the benefit of machine learning (ML) in a supervised manner. In practice, however, labeling monitoring data needs expensive measurement tools, e.g., computed tomography (CT), which is not applicable for all monitoring data. Thus, a semi-supervised or unsupervised method is required.

The overall approach of data-driven quality assurance can be divided into four steps as follows:

1. Monitoring system that captures layer-wise powder bed and radiation intensity images for LPBF to get insights into the process
2. Algorithms and expert know-how to detect and label anomalies on monitoring data
3. AI-based algorithms to recognize and classify defects
4. Closed-loop control strategy to avoid and compensate defects during manufacturing

In the first step, optical tomography and high-resolution powder bed camera systems are integrated into an EOS M290 LPBF machine. These will capture layer-wise radiation intensity during the manufacturing and layer-wise optical information before and after powder coating. Apart from that, these captured raw data require pre-processing steps such as calibration, noise reduction, and data alignment, to increase the quality for the further usage. Afterward, since these monitoring data cannot be labeled entirely using measurement tools, the labeling step is considered to be done in an unsupervised manner. The dimension of the acquired monitoring data is reduced by a pre-trained Auto Encoder (AE) and clustered by unsupervised learning methods according to the data point distribution. The clustered monitoring data is then evaluated by the process expert to reach the optimized label iteratively. The labeled data is used for process modeling in the third step to recognize and predict potential defects during the process. Finally, the novel control methods are developed and applied to optimize the product quality via parameter adaption during the process or via design optimization before manufacture.

We have integrated an Optical Tomography (OT) camera and a high-resolution powder bed camera on the LPBF machine EOS M290 as in situ monitoring systems for data generation. The monitoring data pipeline, which includes data acquisition, pre-processing (see Fig. 5.4), integration, and transfer, is implemented to generate data automatically during each print job. Based on the monitoring data of the OT and powder bed camera, the images are influenced highly by the environment, such as flare during the laser melting process and the illumination system inside the process chamber. With the original illumination system using LED strips on top, the powder bed image varied significantly depending on the location of the part due to light reflection on the exposed surface. This leads to a complicated situation in determining the typical profile of qualified printed parts. To reduce

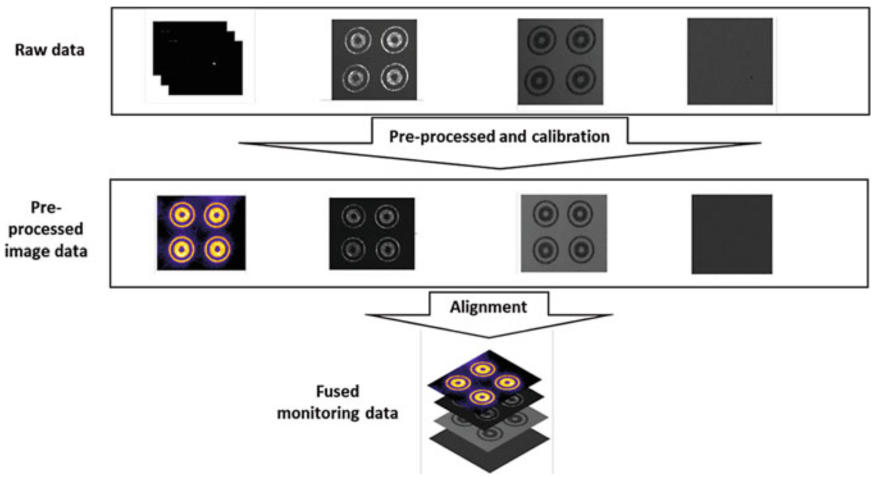


Fig. 5.4 Pre-processing of monitoring data from OT and optical camera for data processing

the environmental factors, an illumination system for powder bed camera using polarized light sources is designed and integrated into the LPBF machine. This shows the improvement of optical monitoring data by avoiding the reflection of ambient light. The printed areas in the optical monitoring images have high contrast to the powder areas, which reserve the morphology on the part surface. Furthermore, a DL-based network is designed to enhance the detailed features on the exposed surface of printed parts on the optical monitoring data (Zhang et al. 2022), which has shown the benefit to provide more information to data labeling.

In the next steps, high-quality monitoring data is required to remove irrelevant features and environmental noise to achieve highly robust data labeling. Data-driven algorithms and expert knowledge should be used to detect anomalies in the LPBF process and classify them as defects. In addition, knowledge of these defects must be discussed individually to determine if it is possible to prevent or to compensate them. At the end, these will represent a control strategy to maintain a high-quality product. This strategy will be integrated into the LPBF machine to evaluate and demonstrate the gains in actual performance. This will enable the use of "data-to-knowledge pipelines" in AM to increase the product quality by extracting process knowledge out of monitoring data to control the manufacturing process.

5.3.2 Data-Driven Robot Laser Material Processing

LMP is characterized by process variety, high accuracy, and geometric flexibility (Helmut Huegel 2009, p. 6). Furthermore, LMP is contact-free which means that no restoring forces act on the kinematic structure of the robot (Helmut Huegel 2009, p. 174). This, in comparison to conventional processes like milling (Cen et al. 2016; Wang et al. 2009), makes it possible to use an Industrial Robot (IR) for LMP. Compared to commonly used machine tools, IRs offer higher geometric flexibility and a bigger workspace at lower costs and hence emphasize LMP's advantages. Nevertheless, low stiffness of the serial kinematic configuration still causes position inaccuracies of the Tool Center Point (TCP) during motion along a given tool path. This leads to lower overall process quality in laser processes, e.g., laser material deposition (Bremer et al. 2021).

Minimization of attained tool path deviations for a steadier motion through laser-specific and model-based trajectory planning can be a promising approach to enable low payload IR for more precise motion and hence higher-quality LMP. Thus, model-based trajectory planning and optimization of motion are investigated using a task-specific digital shadow.

In this context, different optimization criteria such as jerk minimization can be used to generate more suitable robot trajectories and increase trajectory accuracy (Dai et al. 2020). Furthermore, dynamic models of robots are enhanced with measurement data of the robot state to enable better trajectory planning and control and thus enhancing the digital shadow the models are based on. This holds the possibility for further customization and trajectory optimization with a scope of, e.g., minimal energy consumption (Boscariol et al. 2020).

From robotized LMP processes, specimen, process, and robot data can be gathered. The goal is to use specific data from robot and process states to build models of the robotic system and the process induced kinematic degrees of freedom. Based on this data-driven optimization algorithms such as Reinforcement Learning (RL) or graph-based optimization are employed to generate motion trajectories. Afterward, in situ measurements of the robot state during the process are fed back into the models created as described above to further optimize trajectories.

Our approach to LMP-specific trajectory planning is split into two steps. The first step requires an accurate model of robot dynamics. To model the process degrees of freedom, conventional approaches (Sicilliano et al. 2010, p. 247f) are extended with LMP-specific virtual joints – which requires large amounts of expert knowledge. Additionally, Recurrent Neural Network (RNN)-based models making use of data-to-knowledge approaches are evaluated in comparison (Ogunmolu et al. 2016). Novel TCP position estimation concepts are tested regarding their ability to generate a tool for data gathering and dynamic model validation. Model-based inverse kinematics under LMP-specific restrictions are computed for trajectory planning, thereby generating one initial solution of the inverse kinematics problem. The second step makes use of the initial inverse kinematics solution to further minimize trajectory deviation.

Conventional – e.g., graph-based – trajectory optimization approaches are compared to RL-based trajectory optimization approaches. RL-based trajectory optimization approaches are trained both in silico – in a simulation – and in situ, on the real, physical robot. Loss functions of both optimization approaches focus on, e.g., jerk minimization to force smooth trajectories or on end-to-end attained tool path deviation minimization. All approaches make use of LMP-specific restrictions and redundancies, such as required constant TCP velocity and redundancy due to, e.g., a rotational symmetric tool: the laser beam.

Using the described tools, different low payload IRs can be enabled for LMP in production environments with lot size one and highly individualized products by lowering hurdles for task-specific implementations. In combination with suitable sensor concepts for state estimation, IR state data for our approaches is dynamically captured. Based on previous work, the influence of further optimization parameters such as jerk minimization or minimal overall energy consumption of robot motion must be investigated to determine suitable optimization strategies. More research must be conducted on how these principles can be employed for RL-based trajectory planning to assess the overall capabilities.

5.3.3 Structured Learning for Robot Control

Machining of medium- and large-size components (e.g., for the aviation industry) is almost exclusively conducted on machine tools. These machines possess a smaller workspace than their installation space and are more expensive than conventional IR, for instance. IR are less rigid, which negatively impacts the workpiece quality. A model-based feedforward control can compensate the low rigidity of the robot.

For this purpose, an analytical or data-driven model of the robot dynamics is used to calculate a compensation torque from given variables of the robot joints. Analytical dynamics models are based on physics equations such as the Newton-Euler equations, used to describe rigid-body dynamics. These equations depend on inertial parameters, which must be elaborately identified for each robot type. Furthermore, analytical models are error-prone, since it is difficult to embed complex nonlinear effects such as friction. Data-driven models, such as neural networks, on the other hand, try to find relationships between the input and output data of a specific system. They are able to model complex nonlinearities (given sufficient data), but without explicit knowledge about the physical behavior of the system.

Structured learning aims to combine the advantages of these approaches by incorporating available structural knowledge (e.g., in the form of physics priors) into data-driven models (Geist and Trimpe 2020). The resulting model predictions are supposed to comply with critical system constraints under improved generalization (capability to adapt to new, unseen data) and data efficiency. Current approaches of structured models for learning dynamical systems are, for example, deep Lagrangian networks (Lutter et al. 2019) and Lagrangian neural networks (Cranmer et al. 2020). Nevertheless, these models neglect friction effects and show deficits regarding prediction performance and generalizability.

The objective of our work is to extend the Newton-Euler equations with neural networks, therefore creating a structured neural network, to accurately model the dynamics of an industrial robot. Assuming that the major prediction errors of the Newton-Euler equations result from friction and elasticities of the robot joints, it is reasonable to model these specific effects with neural networks (see Fig. 5.5). To avoid overfitting and increase generalization, it is suggested to simultaneously train the inertial and network parameters of the analytical model and the neural network. The training process is accelerated by eventually reaching a local optimum. Therefore, an exact estimation of either set of parameters is averted, which leads to a better prediction for data points outside the training realm.

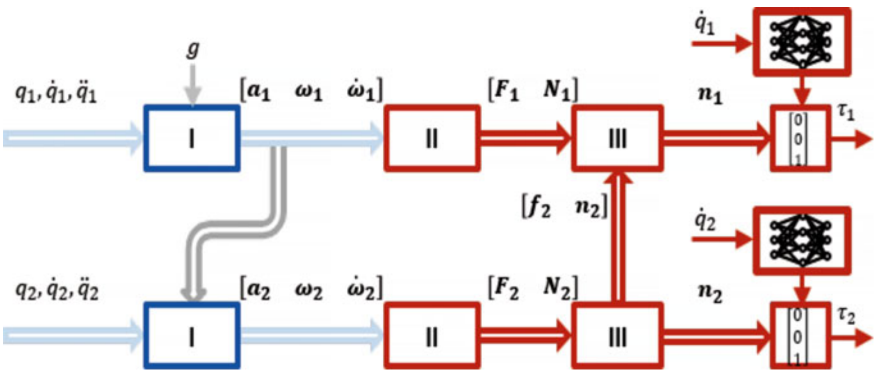


Fig. 5.5 Concept of a structured neural network for dynamics modeling of a robot with two degrees of freedom using the Newton-Euler equations and neural networks

The first findings show an increased interpretability of the structured neural network due to the integrated Newton-Euler equations. Furthermore, the neural network is able to model the characteristic friction behavior during transitioning between negative and positive velocities. Nevertheless, simultaneous training of the inertia and the network parameters is complex without setting individual learning rates and the model accuracy needs to be optimized as well.

Using this new type of structured neural network for model-based feedforward control can prepare industrial robots for highly dynamic processes, like machining. By increasing the interpretability of the network, it may be more suitable for use in a production environment compared to a black-box network because of improved worker acceptance and trust. Further research must be conducted regarding prediction performance and generalizability as well as field studies on real robot applications.

5.3.4 Reactive Modular Task-Level Control for Industrial Robotics

Use cases of robotics go beyond the full automation seen in machining, additive manufacturing, and multi-robot assembly, to Human Robot Interaction (HRI) tasks, which include human-robot teams in collaborative assembly and robot teleoperation in metal forming (Baier et al. 2022). In such tasks, it is important to decrease the reliance on DL for robot control and turn to a new paradigm of robot programming.

To handle the different requirements and cover all use cases in the IoP, we propose extending Behavior Trees (BTs) for the task-level control of these robots. BTs offer a modular alternative to traditional task-level control methods such as Hirarichal Task Networks (HTNs) or Finite State Machines (FSMs) (Colledanchise and Ögren 2018; Iovino et al. 2020).

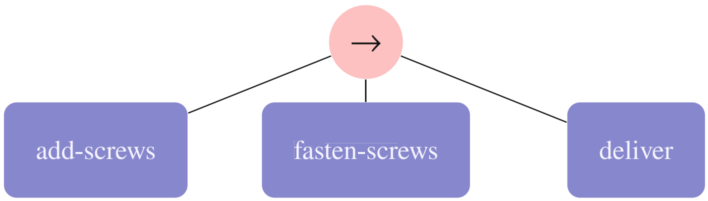
A Behavior Tree (BT) is a model that represents a robot's behavior in a tree structure. The tree is started by ticking the root node. Each tick is a signal that starts at the root to begin the tree execution and then is propagated to the children till it reaches the leaves. When a node is ticked, it returns a status $S \in \{\mathcal{S}, \mathcal{R}, \mathcal{F}\}$ representing Success, Running, or Failure, respectively, to its parent indicating its current state. As defined in Colledanchise and Ögren (2018), each node has one of two types: execution and control flow. Execution nodes are leaf nodes and are responsible for direct interaction with the world. They are either condition nodes, which check certain conditions, or action nodes, which execute actions. Control flow nodes make decisions regarding the propagation of the ticks to their children (Colledanchise and Ögren 2018) as follows:

- Sequence nodes: tick their children in order. Whenever a child fails, they return $\mathcal{F}$, $\mathcal{S}$ if all children succeed, or $\mathcal{R}$ otherwise.
- Selector nodes: tick their children in order whenever a child returns $\mathcal{R}$ or $\mathcal{S}$ they return the same!. If a child returns $\mathcal{F}$, they tick the next. If all of them fail, the selector node returns $\mathcal{F}$.

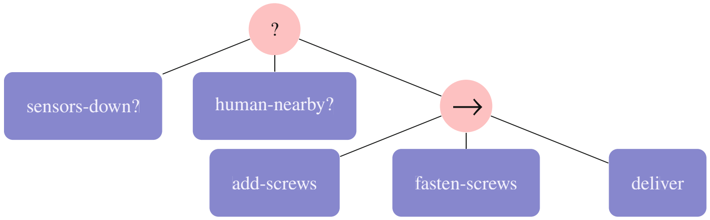
- Parallel nodes: tick the children in parallel. They return $\mathcal{S}$ if at least m children return $\mathcal{S}$, $\mathcal{F}$ if $N - m + 1$ children fail, and $\mathcal{R}$ otherwise, where m is a parameter of the node and N is the number of children.
- Decorator nodes: have only one child and can be used to implement custom policies modifying the returned status of the child.

The tree structure, combined with the returned status, increases the modularity of BTs compared to other robot programming approaches. Additionally, the ticking mechanism increases the reactivity. For example, in the assembly task seen in Fig. 5.6, a safety branch can be added to a tree without modifying the core task. Moreover, if we need to execute the task using a different robot, we only need to reprogram the leaf nodes. We are also able to examine the state of the robot at runtime and find if any problems were faced. This aids in online decision-making to avoid product defects or quality issues. Additionally, some approaches are able to further exploit the reactivity and modularity of the tree by evolving it during runtime to overcome any unforeseen problems (Colledanchise et al. 2019).

We extend the set of BT node classes with new node types that aid in the HRI tasks. We propose $\mathcal{H}$-nodes allowing the robot and human teammates to hand over workpieces seamlessly while minimizing the idle time that may arise when the robot is waiting for the human to finish a sub-task (Behery et al. 2021). This is done by enhancing BTs with an expert system (e.g., CLIPS (Wygant 1989)) that allows the



(a) The main tree for a part of a desk lamp assembly task. This includes adding the screws then fastening them, and finally deliver the lamp.



(b) The tree for assembling a desk lamp after adding sensor and human proximity checks.

Fig. 5.6 An example of a BT used to assemble a desk lamp. (**a**) shows the core of the assembly task, while (**b**) shows the assembly task as the child of a Selector node (root). This tree only executes the assembly if the sensors of the robot are up (first branch fails) and that there is no humans nearby (second branch fails). (**a**) The main tree for a part of a desk lamp assembly task. This includes adding the screws, then fastening them, and finally delivering the lamp. (**b**) The tree for assembling a desk lamp after adding sensor and human proximity checks robot to reason about the human's sub-task and make decisions on when to pause or resume execution of the tree based on the outcome. This extension allows us to form tasks that treat the robot and human teammates as two agents with different capabilities. This way, we can exploit a robot's precision and repeatability while making use of human dexterity and flexibility for handling deformable objects (e.g., cables, cloths, . . .).

To handle teleoperation tasks, Behery et al. (2020) present a method to discretize a robot operator's commands to adapt them for discrete control systems like a BT. This is achieved by applying hysteresis thresholding used in the Canny edge detector (Canny 1986) on the input signals to detect shifts in the operator's commands indicating a change of action. This approach allows us to switch from continuous user input to discrete actions, such that we can learn and encode patterns of operator behavior. These results are a step toward extracting insight from the operator input data. They allow us to use BTs as a representation of the operator patterns despite the traditional use of BTs for discrete behavior modeling.

The future work planned in the IoP regarding task-level action execution and monitoring is to further augment BTs with new node classes that increase their reactivity and guarantee an optimal execution while maintaining modularity, readability, and ease of development.

5.3.5 Increasing Confidence in the Correctness of Reconfigurable Control Software

The IoP severely disrupts the Cyber-Physical Production System (CPPS) life cycles and value chains (Jeschke et al. 2017; Pennekamp et al. 2019). The data-driven approach and the increased reconfigurability and flexibility of the CPPS blur the distinction between development and operational phases along the life cycle, resulting in shorter and more frequent production cycles.

The heterogeneity increases through service-oriented architectures, leading to emergent behavior often unforeseeable during the development phase. Therefore, the verification and testing of logic control software have to go beyond traditional validation of predefined properties to meet intrinsically and extrinsically changing requirements (Grochowski et al. 2019a).

As safety and robustness are vital properties of CPPS, many approaches emerged tackling the diverse and complex field of verification and testing on different levels (Grochowski et al. 2020). Given the intractability of exhaustively verifying distributed, ad hoc CPPSs, configurable runtime monitoring and passive testing are a compromise between feasibility and expressiveness. Runtime monitoring is a lightweight technique that bridges the gap between testing and verification and helps increasing the confidence in the correctness of the digitally networked factory (Grochowski et al. 2019a). Paired with passive testing, a specification-based black-box technique, software quality assurance can be performed during the operational phase of the CPPS to a certain degree (Grochowski et al. 2019b). As reconfigurability and ad hoc networking lead to emergent behavior, passive testing and runtime monitoring are used to safeguard the functionality of the CPPS during the operational phase. Typically, the constraints imposed by safety-critical components in a CPPS contradict the characteristics of most runtime monitoring techniques, which rely on additional source code annotation or instrumentation found in the literature (Cassar et al. 2017). External runtime monitoring is a nonintrusive technique easily embeddable into a system of communicating components. It connects via the underlying machine-to-machine communication protocol of the service-oriented architecture as an additional service, can run on existing or additional hardware, and is scalable. A benefit of the physical separation of the runtime monitor and the monitored component is the guarantee of no delays or restrictions due to the monitoring functionality. Figure 5.7 depicts a high-level overview of an exemplary architecture embedding the monitoring services using an adapter. Because the runtime monitor and passive testing rely on meaningful information exchanged between the services to claim the properties of interest about their internal behavior, the adapter serves as a semiformal interface between the services of the CPPS and the monitoring services. The adapter is responsible for transforming the messages passed between the services into a suitable representation for analysis. The runtime monitor checks the transformed execution trace against a set of formalized requirements and communicates the results back to the adapter, further distributing the results to a database or human experts. Whereas the runtime monitor guarantees that the requirements are not violated, the passive tester monitors the conformance between the implementation and the specification during execution. Due to task-specific digital shadows consisting of temporal data traces or their aggregation and abstraction, it is possible to monitor and test properties beyond the observable behavior, hence partially alleviating the drawback of not annotating or instrumenting the components (Bibow et al. 2020; Jarke et al. 2018).

We implemented a nonintrusive runtime monitoring algorithm as a rudimentary fail-safe. This forces the CPPS to halt in case of a violation of a monitored requirement (Grochowski et al. 2019a). Additional requirements that should be monitored due to intrinsic or extrinsic changes can be added on the fly during the operational phase. The runtime monitor is connected via a semiformal interface to the MQTT's message broker and subscribed to all required topics for the verification task. The runtime monitoring algorithm expects requirements to be expressed formally, e.g., in Metric Temporal Logic (MTL) (Thati and Roşu 2005). A set of requirements templates has been derived from the formal requirements to lower the complexity inherent in generating runtime monitoring objects. Even though the runtime monitor is capable of reasoning about the future time fragment of MTL, we limit ourselves to the past fragment due to inaccuracies caused by asynchronous communication. For

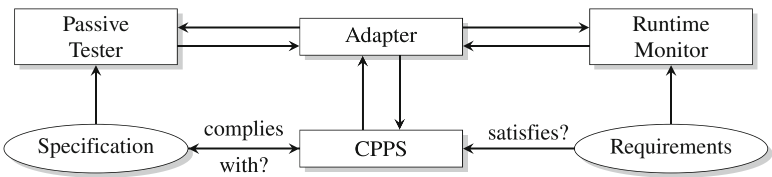


Fig. 5.7 High-level overview of the monitoring architecture

each formalized requirement in MTL, the runtime monitor creates and maintains a monitoring object. Once an observation arrives at the adapter, it notifies each monitoring object subscribed to this particular observation, updating its respective internal state. If enough observations have been considered or a time-bound has expired, the formalized requirement can be evaluated conclusively, and the monitoring object can obtain a verdict. Aside from notifying the runtime monitor, the adapter also notifies the passive tester once a new observation arrives (Grochowski et al. 2019b). As the specification of the CPPS is modeled as a program graph, the passive tester receives either an input action with parameters or an output action with the corresponding digital shadow from the adapter. The simulation starts from the initial state in the transition system described by the program graph of the specification and mimics the observed behavior until an artificial sink state is reached, which indicates deviating behavior. In that case, the passive tester stops and saves the deviating execution fragment for further analysis. It then tries to backtrack to the last location in the graph where the specification and the CPPS were conforming. From that point on, arbitrary behavior is logged until the initial location is reached again. This is justified by the fact that in case a severe violation occurs, it is detected by the accompanying runtime monitor, which would put the CPPS into a safe state or halt. Since the execution of a CPPS usually exhibits cyclical behavior, the passive tester and the CPPS are resynchronized in their initial locations, and the simulation can start over. The prior saved deviating execution fragments can be, on the one hand, used to investigate whether the underlying program graph of the passive tester was underspecified and, on the other hand, aid and guide the developer during the testing and debugging process after reconfiguring the CPPS.

To evaluate the proposed architecture in an industrial setting, the techniques were integrated into an industrial-like use case. We used a service-oriented architecture employing the concepts of digital shadows, edge computing, and their interconnection to realize a completion task of a windshield manufacturer (Brecher et al. 2018, 2019). Here, we were able to monitor the predefined properties during the operational phase, and the passive tester detected deviations from the behavior of the CPPS at runtime. The deviations are limited to implementation inaccuracies with regard to the specification and hence do not reflect any severe errors; the CPPS still produced a feasible outcome, i.e., a completed windshield, but it did not adhere to the expected behavior. While runtime monitoring is a possible solution to monitor requirements in distributed and ad hoc production networks as above, it does not comply with industrial standard communication cycles down to a few milliseconds. Therefore, it is suboptimal for checking requirements regarding the process control, but it can provide insights into the observations in retrospect.

In conclusion, runtime monitoring aids in claiming non-real-time critical propositions over the observable behavior of the CPPS (Grochowski et al. 2019a). Furthermore, it was shown that a specification-based, passive, black-box testing approach paired with runtime monitoring is a suitable technique for increasing the confidence in the correctness of the CPPS during the operational phase. Nevertheless, the application of both approaches is severely limited in the expressiveness with regard to parallelism, asynchronous behavior, and underspecification of the CPPS. Moreover, the derivation of a passive tester from the specification modeled in SysML (Systems Modeling Language) is currently a manual, tedious, and error-prone task that has to be repeated with every change in the component's software. In conclusion, this renders the passive tester far from being a push-button technique (Grochowski et al. 2019b).

We presented a non-collaborative production task in which increasing the confidence in the correctness of the manufacturing process results in limiting the damage or harm being done to the production plant or the manufactured product. Other promising use cases are collaborative production tasks. Here, behavior trees can model human-robot collaboration, because they are suitable for describing and visualizing the potentially complex behavior of autonomous agents (Colledanchise and Ögren 2018). Current approaches for verifying such behavior trees are semi-automatic and require low-level details about the behavior of actions. Therefore, future work should investigate safeguarding for production tasks involving human-robot collaboration by modular verification of reconfigurable behavior trees.

While this chapter focuses on techniques for problem-solving at the machine level, adequate methods for solving emerging problems in a digitally networked factory require contemplation across all levels. The next chapter focuses on issues and insights into potential solutions regarding the process level's perspective.

5.4 Process Level

Implementing data-to-knowledge pipelines that generate insights into entire processes requires expanding the scope from the machine to the shop floor and, eventually, the company level (e.g., including supply chains and multiple factories (Pause et al. 2019)). This, however, raises new challenges regarding data provenance, production planning, or the creation of holistic integrated views on the process. These challenges are further amplified by a constantly increasing complexity of assembly processes. For example, while traditionally special purpose machine manufacturing is characterized by complex and versatile assembly processes, increasing product complexities and customization demands lead to generally more versatile assembly processes. At the same time, companies collect increasing amounts of data on their processes. On the shop floor level, such data are often in the form of discrete event data. Events are, for example, recorded when an assembly step is completed and can contain additional information such as the important machine parameters. Each event is endowed with a timestamp and multiple events are related to (at least) one case (e.g., a product/material id).

Within the IoP, we are following two main tracks to generate insights and improve shop floor-level processes. On the one hand, we apply and conduct research on process mining techniques that leverage the discrete event data. Process mining is a new field of data science that investigates the behavior of processes based on discrete event data (van der Aalst 2016). We investigate how data-driven approaches can be complemented by additional manufacturing-specific structural information to generate comprehensive views onto shop floor processes. Moreover, we develop methods that reveal problems in manufacturing processes (e.g., by monitoring changes). On the other hand, we examine how expert knowledge can be extracted, documented, and exploited in traditional craftsmanship like the textile industry by employing the concepts of the IoP (e.g., AI, ontologies).

5.4.1 Mining Shop Floor-Level Processes

A major challenge when analyzing shop floor-level processes is to create a holistic view on the process. Even though process mining is concerned with the analysis of end-to-end processes, existing techniques are often insufficient to tame the complexity of manufacturing processes. In particular, automatic process model discovery usually fails to return understandable and meaningful results if we have many concurrent processes. However, in contrast to other business processes, additional and reliable structural information is frequently available for manufacturing processes. In this regard, we particularly distinguish between structural information on the shop floor (i.e., how machines or assembly steps are connected) and information on the material composition (e.g., bill of materials).

Assembly Model Information A common approach to organize the shopfloor is to structure the individual assembly activities into assembly lines. This – machine- or assembly activity-centric – production organization can often be directly translated into process models. In particular, for structured but semiautomated production processes for which human resources serve as an essential part of the production processes, process mining can point out the challenges in terms of discovering performance and compliance problems. In such processes, friction may particularly occur at the intersections of different subprocesses (e.g., the assembly cannot proceed due to missing subparts). Therefore, a holistic overview over the production is important to identify problems and eventually improve the process. In the use case of e.GO Mobile AG (Uysal et al. 2020), a young manufacturer of cost-effective and customer-oriented electric vehicles, we modeled the manufacturing process, comprising a general assembly line and several associated subassembly lines, by means of a process model. For the analysis, we applied the PM^2 process mining project methodology (van Eck et al. 2015) and analyzed the process execution in the production line. An interesting finding is presented in Fig. 5.8 which visualizes

Fig. 5.8 Visualization of service time (red color scale) on the general assembly line and subassembly stations. The major bottleneck in the process is formed by the general assembly station GA16

the service times of the stations which are colored in a gray-orange-red color scale. Here, we can easily observe that certain stations expose a bottleneck, such as station *GA 16*, which are associated with sublines, causing some delays in the manufacturing process.

Material Composition Models A different approach to model the production follows a material-centric view by means of material composition models, which describe how different materials (e.g., subparts of a product) are related to each other. For example, the assembly is structured by means of **M**ulti-level **M**anufacturing **B**ills **o**f **M**aterials (M^2BOM). The provided information on the subcomponent composition allows to draw conclusions on the assembly order that are usually reliable due to physical constraints (e.g., supercomponents cannot be finalized without the corresponding subcomponents). Therefore, this information can be exploited to discover well-fitting comprehensive assembly process models.

Within the IoP, we proposed an analysis framework that incorporates additional structural information – particularly M^2BOMs – to analyze manufacturing processes presented in a use case study of Heidelberger Druckmaschinen AG (Brockhoff et al. 2021). In this framework, we discover an M^2BOM-based performance-aware assembly model that, in the first step, is used to discover potential bottlenecks. By incorporating additional manufacturing-specific information, we tame some of the complexity of assembly processes and visualize them beyond small excerpts. In the second step, we apply performance-oriented process mining techniques to further analyze bottleneck candidates to identify root causes.

5.4.2 Challenges in the Textile Industry

In Germany, the textile industry is predominantly formed by Small and Medium sized Enterprises (SME) and is one of the sectors in which large parts of the work steps are still manual (Brillowski et al. 2021b). This includes not only physical work steps but also the planning, design, and layout of processes.

Especially in the field of FRP, the planning of the manufacturing processes is challenging. FRP consist of a limp textile and a liquid plastic matrix. During the multistep process, a highly rigid, solid lightweight composite is created with the help of various technologies (Soutis 2005). Due to the different, changing aggregate states of the material, existing planning and decision support systems cannot be transferred without time-consuming adaptation. In addition, the planning for each novel component must be started anew due to geometric complexity, fiber orientations, and application requirements.

In the course of planning, various decisions have to be made regarding the material (e.g., glass or carbon? $200\,\mathrm{g/m^2}$ or $450\,\mathrm{g/m^2}$ grammage?), the technologies (e.g., CNC cutter or ultrasonic knife for cutting textiles), and the sequence of the process steps (e.g., A before B or A, B, C in parallel). In this context, a labor-intensive and intuitive trial and error procedure based on experience has become established in industry, resulting in promising technology alternatives being overlooked (Brillowski et al. 2020, 2021b).

In this regard, AI approaches promise automated and objective support in decision-making. However, the acceptance and use of these approaches within the textile industry are low, partly because the textile industry is more conservative due to inaccuracies in prediction and fear of substitution (Jacovi et al. 2021). To increase the efficiency and reproducibility of planning FRP process chains, we developed a user-centered planning tool with an integrated decision support system based on human-centered AI (Schemmer et al. 2020). In the form of a wizard, process planners can sequentially define the various steps of a process chain in FRP manufacturing by selecting the required activities (e.g., cutting, fixating, etc.).

When the sequence is finalized, a recommendation system presents suitable technology and parameter suggestions for each process step. The suggestions are based on historical data and provide global and local feedback on the process chain. The decision-making authority remains with the worker and they decide whether to accept or reject suggestions. As global feedback on the recommendation, the estimated costs, quality, and production time for products made in this process chain is presented (see left side of Fig. 5.9). Further, the planning tool displays local feedback by indicating possible complications at individual process steps, which can be fixed by choosing a different activity if necessary (see right side of Fig. 5.9).

In a study, users articulated both advantages and disadvantages of the planning tool: Apart from the criticism of fixed parameters, the application was particularly convincing due to the large number of different and transparent suggestions that a decision-maker can reject or accept (Brillowski et al. 2022a). In a further evaluation with domain experts, we benchmarked the user-centered tool against other tools in terms of planning effectiveness and efficiency, but also subjective measures such as trust, usability, and experience of autonomy. The tool was attested a high usability (91.8 System Usability Scale (SUS) score) and user acceptance (Brillowski et al. 2022a). However, the study also revealed that the comprehensibility of proposed alternatives is one of the critical aspects that significantly influence the subsequent user acceptance. In this context, the research field of eXplainable Artificial Intelli-

Fig. 5.9 Illustration of a recommended process configuration from the FRP process chain planning tool with a global evaluation of the whole chain on the left and local information on possible problems on the right

gence (XAI) offers a variety of possibilities to understand algorithmic decisions and, for example, to obtain reasoning for the exclusion of alternatives (Brillowski et al. 2021a). Besides the need for improved transparency, AI-based decision support systems require large amount of data to make meaningful suggestions. Yet, within and beyond the textile industry data is often only insufficiently or not at all available (Brillowski et al. 2021c). We explore different approaches to address the data scarcity dilemma.

First, the available data sets can be used more efficiently through augmentation or different learning approaches. We are already using Generative Adversarial Networks (GANs) to generate artificial data that cannot be distinguished from real data by experts (Schaaf et al. 2022), which is elaborated in further detail in Sect. 5.5.1. Furthermore, we apply Transfer and Curriculum Learning approaches to achieve better training results of Artificial Neural Networks (ANNs) (Brillowski et al. 2022b).

Second, we collect additional data. Due to the textile industry's long-lasting history and family businesses, machine parks have emerged over time with heterogeneous and often non-networked machines that cannot contribute to the IoP (Jaspert et al. 2021). Therefore, we are researching retrofitting options to enable companies with older machinery to access the advantages of the IoP (Nakakaze et al. 2022).

Third, the data used to generate the planning tools' recommendations can be captured by monitoring planning processes of experienced process planners (knowledge capturing). One challenge is that planning FRP processes in industry was and still is rather intuitive and based on experience and rarely supported by digital tools (Brillowski et al. 2021b). Thus, neither digital models of previous planning processes nor assessments of possible alternative plans are available that can be used as a data source for the recommendation system (cf. data scarcity dilemma). Therefore, one of our goals was to develop a method to systematically capture implicit process knowledge from domain experts and make that available for later integration as a data source for decision support systems.

A typical approach for this is crowdsourcing (Estellés-Arolas and de Guevara 2012), where micro-tasks (such as image classification for text recognition, autonomous driving, etc.) are distributed to many potential contributors. In this case, data generation through crowdsourcing faces two difficulties: First, there are only a small number of domain experts (Hoffmann 1987), and second, instead of independent micro-tasks, we need to capture sequences of related steps that then represent a process chain in FRP manufacturing (e.g., the use of a tool in process step N depends on the previous step $N - 1$).

To compensate for the small number of domain experts, we cannot extract only a few units of knowledge from many, but a few must share their knowledge for longer. We thus developed a serious game-based approach for extracting process knowledge. Serious games harness the motivational potential of games to increase the depth and duration of learning (Breuer and Bente 2010; Brauner and Ziefle 2022). Besides that, the approach can also be mirrored to capture expert knowledge by analyzing the interactions in a game environment. Yet, serious games for

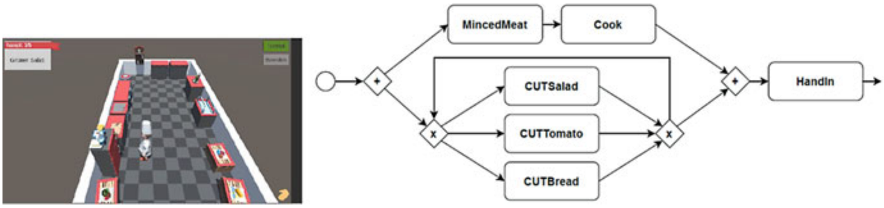


Fig. 5.10 A game-based approach to extract process knowledge from domain experts exemplified through a cooking game. (Images courtesy of the authors from Schemmer et al. 2022). (**a**) Screenshot of the game for extracting process knowledge. (**b**) Extracted process model of a recipe from a user study

capturing process knowledge have not been developed so far. Thus, we developed a proof of concept and investigated whether process knowledge can be captured through this approach, what the quality of the captured data is, and if individual differences influence the quality of the process knowledge extracted through the game-based approach. For the first evaluation, we selected food preparation as a more accessible and familiar scenario. Though it is structurally similar to FRP planning, it does not require the specific domain knowledge and access to participants is easier. Therefore, we developed a web-based serious game recreating a kitchen environment (Fig. 5.10 left), where different ingredients can be processed with different tools and combined to create a dish. All interactions are logged and can be analyzed with process mining tools and metrics.

In an experiment with 60 participants, we could identify process models (Fig. 5.10 right) for all five of the recipes we asked the participants to cook. In this respect, process knowledge could be extracted. However, a drawback was the high variance in the data collected, yielding only satisfactory fitness of the model. Also, our rather laborious approach had little quantifiable advantage over a control condition that queried recipes via an non-gamified drag and drop interface. Yet, clearer task descriptions and less open interactions might yield better results (Schemmer et al. 2022).

In summary, we demonstrated that process knowledge can be extracted with game-based methods, but future work needs to transfer this concept to different and more specific domains and evaluate its applicability. Especially if many different designs for FRP process chains can be captured and then integrated as data sources for providing smarter decision support for FRP process planners.

Other sectors in the textile industry are facing challenges in adopting digital solutions as well. Textile process steps in the Beginning of Life (BOL) and the full Product Life Cycle (PLC) commonly are distributed over poorly orchestrated SMEs with little interoperable data. However, innovation and design in the textile product development require planning and a systems engineering perspective on the process level (Reinsch et al. 2022).

The Digital Capability Center (DCC) is a digital learning factory and acts as a practical demonstrator for digital solutions along the value chain. As a model factory, in the DCC, the reality of textile manufacturing unavoidably is idealized to some degree. Therefore, the data-to-knowledge pipeline in real world requires a powerful component for knowledge acquisition. In the industry, the heterogeneity of process conditions and product variants grow exponentially, digital solutions are hardly standardized, and digital systems often need to be customized for individual use cases (Fromhold-Eisebith et al. 2021). Consequently, the current state of data and model availability in textile production shows open challenges in the IoP. Relevant data and tacit knowledge from interdisciplinary and cross-divisional innovation processes are lacking in order to support model-based and data-driven product development. We investigate the product development of knitted products that require domain knowledge about relations between physical properties, customer requirements, and manufacturing technologies (Beer et al. 2016). In an industrial setting, the development and production of weft and warp knitted fabrics consist of a series of process steps from fiber to end product that includes warping, knitting, and dying. Possible process layouts are diverse and determined by experience-based decisions. Thus, the formalization of domain knowledge and a support system for the full PLC is being envisioned and aimed at Brillowski et al. (2021b).

Semantic web technologies and AI offer potentials for the formalization and the usage of knowledge and data from manufacturing environments. Especially the tasks involved in process analysis as well as data and knowledge acquisition are necessary prerequisites to integrate progress in AI and data science. Therefore, we investigated the current usage of semantic web technologies and especially ontology. We found that many potential application areas of ontology-based solutions remain largely unused in the textile industry. Solutions that allow for integration of interdisciplinary backgrounds, reasoning, and intuitive data access in large and heterogeneous sources of information are rare in the context of textile manufacturing. Most research contributions are directed toward data and service catalogs and the description of textile products either in the design or in the utility phase of the PLC (Reinsch et al. 2022).

We conclude that we need to develop solutions to integrate unused fields of applications of semantic web technologies in the textile manufacturing process. Overcoming this gap and enhancing the accessibility of background information from production is vital for the systematic product development. This applies equally to the integration of AI built on top of tacit domain knowledge and available data from the manufacturing process. However, the textile industry is not only conservative, but also challenges are mentioned repeatedly in the context of textiles and semantics. Unlike established data models and file formats, textile data is barely standardized. Additionally, concepts and entities are very diverse and are regularly only known in the textile domain. Within this diverse field and today's need for interdisciplinary cooperation, information overload is a major problem (Reinsch et al. 2022). We continue our research regarding the development of semantically enriched data models for textile manufacturing and the product development process throughout the PLC.

5.4.3 Analyzing Process Dynamics

Processes in a complex manufacturing environment are rarely in a stable state; instead, they are constantly changing and adapting to new circumstances. Therefore, event data from the same manufacturing line, extracted at two different points in time, can be considered as data from two versions of a process. Process comparison is concerned with the analysis of differences between such process instances. The gained insights can reveal improvement potentials. For example, one subprocess performs better in one process instance than in the other.

Recent approaches in process mining focus on the control-flow perspective (Bolt et al. 2016; Taymouri et al. 2020). However, in manufacturing, the important Key Performance Indicators (KPIs) are time-dependent such as service times. Therefore, comparison approaches that focus on performance are needed. As a first step, based on recent advances in stochastic process mining (Leemans et al. 2021), we developed an approach that detects changes in a process while considering control flow and time simultaneously (Brockhoff et al. 2020). The results can then be used as an entry point for a detailed comparison analysis. One shortcoming of current approach is that it is limited to individual production lines. However, an object-centric view on the production comprehensively considers products, raw materials, orders, etc.

In object-centric view of the process, it is possible to extend the process comparison analysis using an enriched digital shadow of the processes. For example, in described case studies, we have analyzed the process from the car or the printer perspective, although it is possible to analyze the process from other perspectives, e.g., *order*, *customer*, etc. Analyzing the process from multiple perspectives is discussed in a branch of process mining called object-centric process mining (van der Aalst 2019). In Farhang et al. (2021b), we have proposed a standard for Object-Centric Event Logs (OCELs), and several process mining techniques have been developed on top of OCELs (Berti et al. 2022; Cohn and Hull 2009; Fahland et al. 2011). In Farhang et al. (2021a), we proposed a technique to compare the object-centric processes with each other developed a tool on top of that (Farhang and van der Aalst 2022). Using our tool, we have analyzed Heidelberger Druckmaschinen AG data and found the cause of performance problems.

After providing insights and use case studies in process mining and textile industry, we will present the overarching principles serving as a toolbox of omnipresent approaches for data collection and management in the upcoming subsection.

5.5 Overarching Principles

Modern manufacturing and production uses data as a basic resource for improvement. Recent advances have integrated sensor technology, telecommunications, and data-based models to better understand and optimize processes (Brauner et al. 2022; Kagermann 2015). Thus, the concept of data-to-knowledge pipelines has arisen, where data and empirical models serve as a processing engine for generating actionable insights in manufacturing. The IoP tackles challenges emerging from this mix, such as identifying model parameters in complex scenarios, leveraging data-driven models for the generation of insights, or enabling the interoperability of data and ontology. This section first shows techniques for coping with the complexity of industrial data and problems. More specifically, we introduce the usage of generative models to synthesize data leveraging human labels, as well as optimization frameworks for parameter identification. Second, we discuss techniques for understanding of data-driven models, such as concept-based explanations and 3D visualization frameworks. Finally, we detail techniques for increasing the interoperability of data and agents in the industry of the future.

5.5.1 Generative Models for Production

To this day, it is still common to perform quality inspection of manufacturing parts manually through visual inspection. This quality assurance task becomes tedious for the human worker, which results in high error rates and dissatisfaction. Deep learning-based systems that are trained on image data have been increasingly used to automate visual inspection processes, resulting in higher productivity and reduced error rates (Yang et al. 2020).

Using deep learning models for quality control is a popular application of machine learning. Nevertheless, the performance of these models is heavily dependent on the availability of labeled training data. Especially in industrial applications, labeled training data is either associated with high cost or impossible to obtain because of the uncertainty of process measurements. Thus, machine learning methods applicable to data-scarce environments are of interest.

One approach that enables the applicability of deep learning methods is data augmentation. Most commonly, geometric transformations like cropping, flipping, or rotation are applied to artificially increase the amount of training data. In our work, we investigated how well GANs perform as a data augmentation method for synthesizing labeled training data. GANs learn the underlying distribution of the available data and thus are able to generate realistic images from noise. We tested this approach for images of FRP captured during quality control (Schaaf et al. 2022). Our tested generator models were able to synthesize realistic images displayed in Fig. 5.11 and also improve error classification accuracy.

To generate realistic data instances demonstrates that generative models can learn relevant features (i.e., folds and gaps) from data of industrial domains. Although these models do not describe causal relationships, they fit perfectly into the concept of digital shadows. By learning the underlying data distribution from past observations, these models describe a significant aspect of the manufacturing process.

In future work, we investigate the possibility of image synthesis without segmentation maps. Here, we want to train generators of GANs so that the learned features are disentangled from each other. This allows the generation of images

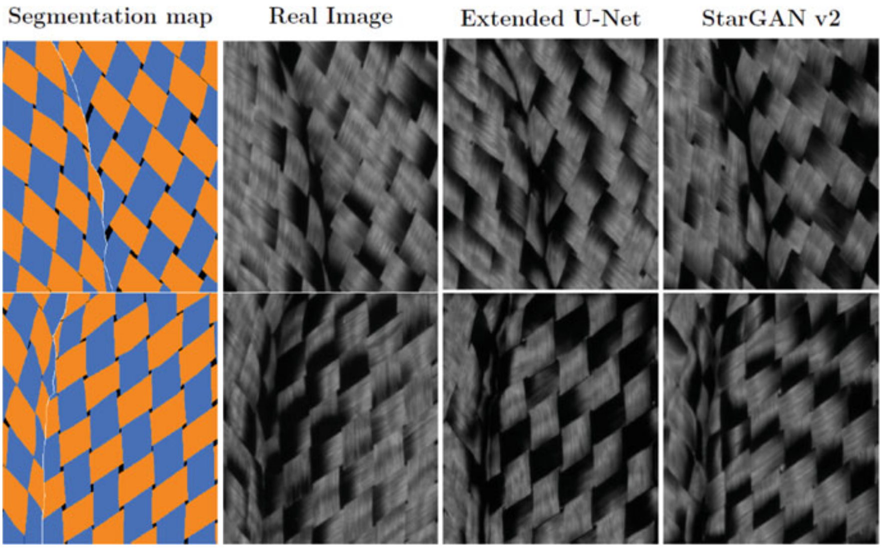


Fig. 5.11 We compared two generator architectures to synthesize realistic images of FRP. Both generators: Extended U-Net (Ronneberger et al. 2015) and the generator from StarGANv2 (Choi et al. 2020) are able to translate the segmentation map to realistic images of fiber-reinforced plastics that preserve material geometry. (Images courtesy of the Institute for Textile Engineering (ITA))

without prior labeling effort. Furthermore, we want to investigate self-supervised learning methods that use training frameworks of GANs for pre-training. The idea is to learn meaningful features unsupervised and fine-tune the model with limited labeled training data afterward. The question of defining and identifying human-understandable features will be presented in the following subsection.

5.5.2 Concept Extraction for Industrial Classification

To apply AI models in critical industrial applications, these must be stable, robust, and trustworthy. However, computer vision-based tasks (e.g., quality control) rely on high-dimensional data and are usually underspecified. This combination makes the used models susceptible to spurious patterns, causing them to be fragile and generating undesired behaviors. In general, this raises the question: Does the AI model do what we want it to do? We tackle this question through the extraction of knowledge from data (or rather from a model trained on these data), and the presentation of this knowledge to a decision-maker. We enable this data-to-knowledge pipeline through the extraction and visualization of abstract patterns (concepts), highlighting them on the input data (here: images) of a model.

As an example, let us consider the quality control of a metal casting process. We can use visual inspection to classify parts into faulty (Fig. 5.13a) or good (Fig. 5.13b), depending on the presence of pinholes or shrinkage defects (Dabhi 2020). This task can be solved using Convolutional Neural Networks (CNNs), but the variety of defects makes a granular (pixel-wise) labeling impractical; thus, it is defined as a classification task between two sets of images. The images contain not only the defects but also other variable factors (e.g., the position of the piece, illumination, or shades in the background), which may pass unnoticed. Ideally, a CNN should distinguish good and bad images, and XAI tells the user how it does it. The XAI should tell the user: I decide good/bad based on the holes. I did not make the decision based on the background.

To extract the knowledge learned by the model, it can be analyzed with global explainability techniques to find which patterns it uses during the prediction process. Then, an expert can validate each pattern (e.g., detection of darker backgrounds, or pinholes) ensuring that they are aligned with the underlying task. For example, users could discard an AI model that makes its predictions based on different background, while they could confirm a model that actually pays attention to the pinholes.

Nonetheless, current explainability methods either are not suited for industrial data or do not reconcile global model explanations with single outcome explanations. On the one hand, feature attribution methods (e.g., Grad-CAM (Selvaraju et al. 2020), IntegratedGradients (Qi et al. 2020)) provide an explanation of which features/pixels are important for a single prediction, but cannot point to which patterns are recurrent, or how one prediction is different from another. On the other hand, global explanation methods, such as concept extraction (e.g., ACE (Ghorbani et al. 2019), VRX (Ge et al. 2021)), perform poorly in industrial use cases. The poor performance is the result of having less data, with less variation, which translates into more rigid and brittle models. Thus, there is a need for global explanation methods which can analyze deep learning models in an industrial context.

By studying state-of-the-art XAI methods for industrial use cases in the IoP, we realized the shortcomings of these methods (scale invariance, lack of traceability, noisy). This motivated the development of a novel concept-based method (Posada-Moreno et al. 2022), which we will present next. Not only is this method able to address the shortcomings of the industrial use case (as we show herein), but it also represents a more general method.

In a general sense, we study the latent spaces of neural networks, finding patterns, and measuring their influence on the model's predictions. The main idea behind our approach is that the structure of the latent space of CNNs reflects what they learn during training. Our approach can be described in four steps, as shown in Fig. 5.12.

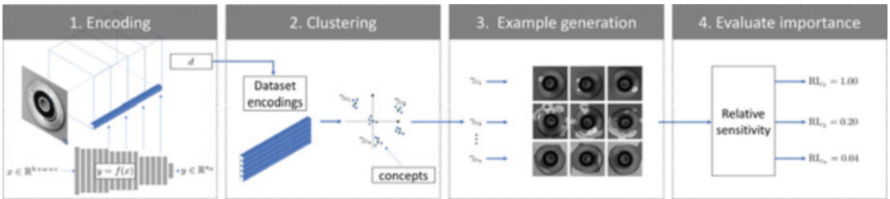
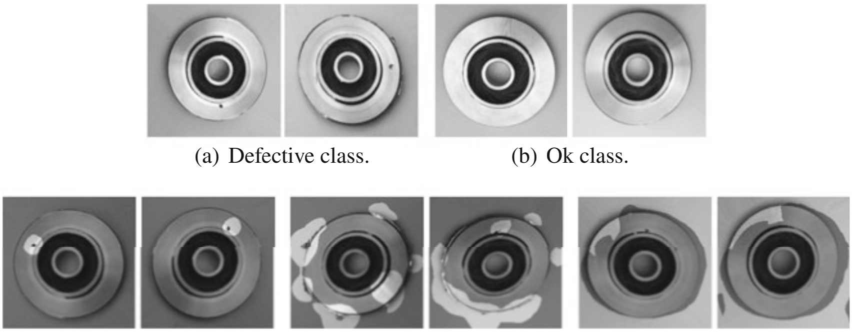


Fig. 5.12 Concept extraction method for CNNs. This method provides a pipeline to extract knowledge from a model, in the form of concepts influencing its prediction process

First, we encode the data set through a representation of the latent space of the CNN. We take the inputs of the model (e.g., images), and encode them in a space, which makes sense in terms of the CNN (activation maps). Second, we cluster the resulting encoded data to mine for patterns. These patterns reflect what has been learned by the network, showing how the CNNs separate the data internally. We call these patterns *concepts*. Third, we extract sets of examples for each concept in the input space of the model. This means we take each mined pattern and find input images which reflect it. These sets of examples provide experts with the means to understand what the pattern is. Fourth, we evaluate the relative importance of each concept based on the sensitivity of the prediction with respect to the pattern.

The core finding of our research is that patterns in the latent space of models are a viable proxy for explaining their global behaviors. Our method outperform state-of-the-art global explainability methods in controlled scenarios and industrial use cases, providing explanations of how a model work, and which types of patterns it has learned to detect (Posada-Moreno et al. 2022). Concept extraction methods can be used to detect undesirable biases learned by a model, explain what features are being detected, and how complete or aligned the prediction process of a model is.

As an example, we present the case mentioned above, where a CNN is trained to perform the quality control of casting pieces. After training a CNN to classify upcoming images as defective or ok, the latent space of the model was analyzed, applying our concept extraction method (Posada-Moreno et al. 2022). The main extracted concepts are shown in Fig. 5.13c, d, or e. The first concept corresponds to pinholes, which is the most important cue for the prediction of defective parts. The second concept corresponds to malformed edges of the part. This concept



(a) Defective class. (b) Ok class.

(c) concept 1, RI=1.0. (d) concept 2, RI=0.2. (e) concept 3, RI=0.04.

Fig. 5.13 Data set of casting parts, where the task is to classify defective (**a**) and ok parts (**b**). After training a DenseNet-121 to perform the said task, our method can analyze what was learned by the model. Figures (**c**), (**d**), and (**e**) show the main extracted concepts, which can be used by experts to ensure compliance with their prior knowledge. The most important concept used by the model are pinholes (**c**) (with relative importance of 1.0), followed by malformed edges (**d**) (RI of 0.2), which the model learned to detect. Concept 3 shows a bias in the background (RI of 0.04), which was detected after a first stage of training, and allowed experts to realize and mitigate this phenomenon by acquiring new sample data also contributes positively to the prediction of defective classes. Similarly, the third concept shows background, with an importance close to zero. These concepts were learned by the model without being explicitly annotated and can be used by experts to ensure that the model decision-making process is aligned with their understanding of the problem.

Our concept extraction method (Posada-Moreno et al. 2022) has been proven as an effective tool for analyzing CNNs, allowing the validation of expert knowledge and the identification of spurious patterns (undesired behaviors). This success has opened several relevant questions for future research. First, we will investigate the application of concept extraction to other use cases in the IoP. Second, we will explore the transferability of our method to other data modalities, such as time series. Finally, the question of how to measure the correctness of a concept extraction method remains.

5.5.3 Inverse Problems via Filtering Methods

Many modern AI methods, such as training of neural networks or clustering, are mathematically high-dimensional and may lead to nonlinear optimization and parameter identification problems, which might be ill posed (Engl et al. 1996). Therefore, in-depth understanding of the underlying methods is relevant to judge the quality and the results of modern AI techniques. Further, many black-box methods may fail at standard tasks, and a deeper understanding of the properties is required to provide suitable solutions and alternatives. Finally, many actual problems, like multi-objective tasks, cannot yet be treated with current AI techniques due to their limited scope. Moreover, most industrial problems are subject to uncertainty, since data and measurements may be affected by noise, the physics of processes could be not completely known, and/or small variations in the production process may occur. This has so far not been treated in classical AI algorithms.

The state-of-the-art methods are not suitable for current applications due to, for example, a lack of possibility to include multi-objective optimization, the requirements of analytical gradients of models that are usually expensive or not available (e.g., in case of models described by neural networks), and the missing knowledge on how to update algorithmic parameters (e.g., hyperparameters for neural networks or weights for multi-objective procedures). Moreover, there is a lack of methodologies to include and quantify the uncertainty existing in the processes.

Our contribution on the IoP vision focuses on the development and the analysis of numerical methods for complex optimization and parameter identification tasks. In this framework, we focus on a numerical method for solving nonlinear optimization and parameter identification problems, namely, the ensemble Kalman filter (EnKF). Furthermore, we provide an efficient numerical method to analyze the propagation of the uncertainty. The EnKF is an iterative filtering method designed for gradient-free optimization, hyperparameter search, and multi-objective optimization (Herty et al. 2021; Yegenoglu et al. 2020). It is a general algorithm with convergence guarantees and stabilization properties which have been proven in Herty and Visconti (2019, 2020). Besides the natural idea of implementing directly the iterative particles scheme, we developed an abstract algorithm with parameter adaptation exploiting the mathematical properties and insights of the EnKF procedure. Both the approaches have been implemented and tested (Herty and Iacomini 2022a). Our algorithm has been applied in the field of automatic control (Schwenzer et al. 2020). Other applications in laser technology and plastic processing are being explored.

Moreover, we investigated the propagation of input uncertainty through a process, e.g., how the uncertainty in the initial data propagates through a model. We provide a method for the expansion of noise in a series. Then, we analyze the equations for the coefficients of the series and develop an efficient numerical treatment of those (Gerster et al. 2021). This allows us to perform a risk estimation, e.g., to detect high probability areas of instabilities, failures, and rare events (Herty and Iacomini 2022b). Although the algorithm and the theoretical framework have to be adapted to the specific process, the methodology is already available, analyzed, and implemented.

Here we provide an example of a developed method for parameter identification. The problem of finding the unknown parameters u in a non-differentiable model $\mathcal{G}$ and given data y is formulated mathematically as:

$$u^* = \text{argmin}_{u \in X} \Phi(u, y), \quad \Phi(u, y) = \frac{1}{2} \|y - \mathcal{G}(u)\|^2 \tag{5.1}$$

For the design of an efficient method, we move to an equivalent description on a mesoscopic level by means of partial differential equation (PDE), which allows us to describe the evolution of the probability distribution of the parameters $f = f(u, t)$, at iteration t. The equation reads as follows:

$$\partial_t f(u, t) - \nabla_u \cdot (\mathcal{C}(f) \nabla_u \Phi(u, y) f(u, t)) = 0, \;\; f(u, 0) = f_0(u) \tag{5.2}$$

for some nonlocal operator $\mathcal{C}(f)$, see Herty and Visconti (2019).

Equation (5.2) can be efficiently discretized by a particles method with $j = 1, \ldots, J$ particles sampled from the initial distribution f_0. This leads to an iterative scheme for candidates such that $\frac{1}{J}\sum_{j=1}^{J} u_j(t) \approx u^*$. The full procedure consists of the following update for $u_j^n = u_j(t^n)$:

$$u_j^{n+1} = u_j^n + C(u^n)\mathcal{G}^T \Gamma^{-1} \left[y_j - \mathcal{G}(u_j^n) \right]$$

$$C(u^n) = \frac{1}{J} \sum_{j=1}^{J} (u_j^n - \overline{u}^n) \otimes (\mathcal{G}(u_j^n) - \overline{\mathcal{G}})$$

$$\overline{u}^n = \frac{1}{J} \sum_{j=1}^{J} u_j^n \quad \overline{\mathcal{G}} = \frac{1}{J} \sum_{j=1}^{J} \mathcal{G}(u_j^n)$$

and the solution u^* is given by the mean of the particles at the end of the evolution at $n = \infty$. This method has been extended in the IoP to a stabilized version, (Armbruster et al. 2022) and a multi-objective framework (Herty and Iacomini 2022a).

We have extended classical AI methods by adaptive algorithms taking into account the particularities of the engineering applications, like nondifferential models (Herty et al. 2022), multi-objective tasks (Herty and Iacomini 2022a), and unknown hyperparameters. Novel methods have been developed and numerically analyzed. Furthermore, they have been implemented and tested. The templates for algorithms have been designed and are available. Those can now be implemented and adapted to the specific programming environment and computer architecture.

We have tested and validated sample problems from different domains and disciplines, e.g., Schwenzer et al. (2020).

Moreover, a methodology for investigating the propagation of uncertainty and performing a risk estimation has been proposed and efficiently implemented.

Future work will focus on developing prototypes of algorithms which might need improvements in computational efficiency, also for dealing with very high-dimensional parameter space, which is still challenging. Moreover, we plan to blend the new methods with existing AI methods to provide a larger toolbox to analyze and solve issues coming from engineering applications.

5.5.4 Immersive Visualization of Artificial Neural Networks

ANNs are the most popular class of machine learning models to date due to their superior performance compared to previous approaches. In many cases, their superiority can be attributed to their complexity, as ANNs can have millions-billions of parameters. While this allows the model to encode a lot of information about the given problem, such as the digital shadow of a production process, this encoding remains opaque to the user. It is currently not possible to fully understand the reasons for the decisions made by ANN, nor is it possible to extract knowledge about higher concepts they might have learned. Nevertheless, without this ability, there is a trust gap between humans and ANN that limits their usefulness in production systems. This is commonly referred to as the black-box problem (Castelvecchi 2016).

To combat this problem, the field of XAI has recently gained traction. It describes a collection of tools that enhance our understanding of AI techniques by means of explanations. One way of generating explanations is through visualizations. When showing abstract data in a visual manner, users can use their own intuition and ability to recognize patterns to gain intuition or find hypotheses. This facilitates an exploratory process that can be further enhanced by interactivity to quickly explore the space of visualization parameters. We want to apply this concept to the entire ANNs.

While visualizations like TensorBoard (the built-in visualization of TensorFlow (Abadi et al. 2016)) exist, which give an overview of the structure of ANN, they do not visualize the learned parameters. Yet, they make use of node-link diagrams, which is a common concept when visualizing ANNs. Likewise, node-link diagrams are often used to explain the basics of ANNs. They show how individual neurons are connected and highlight their similarity to biological neural networks. This brings up the question if this concept can be extended to visualize full-scale ANNs to give insights into their inner working.

The main challenge with this idea is the large size of parameters that would need to be visualized for even relatively small ANNs. Showing them in a 2D visualization becomes infeasible. For this reason, 3D visualization of ANNs has become an active area of research. As an example, Harley (2015) shows a working ANN as a 3D node-link diagram. They show individual values computed by the ANN as boxes and the network's weights as edges between them. For convolutional units, the boxes are arranged in a grid, so that they resemble the filtered image. To avoid clutter, they only show edges that connect to one node, which is selected by the user.

Following this trend, we applied a 3D node-link visualization, similar to Harley (2015), to a real use case in the area of production research (Bellgardt et al. 2020). We visualized a neural network controlling a robotic arm, showing the activation values live during operation. Our expert review revealed that the visualization is useful to understand the scale of the network and find potential problems, such as an incorrect implementation of filter kernels. Nevertheless, the experts commonly requested to see more of the edges at the same time. The visualization of fully connected units, which were simply arranged in a line, was not perceived to be helpful.

From the positive results of the prototypical implementation described above, we conclude that the area of 3D node-link visualization of ANN should be investigated further. It is of particular interest whether different layouts of nodes in the fully connected layers can make them more useful and how the visualization of edges can be improved. Additionally, we conceive further research questions, such as whether visualizing other aspects of the network, than just activation values and weights, is feasible. Unfortunately, pursuing these questions based on our initial prototype would have been difficult, since it was constructed rigidly for its specific use case.

Instead of developing another specialized application from scratch, there seems to be a need for a universal framework that allows rapid prototyping of 3D node-link visualizations for ANN. Such a general framework would need to be integrated into the tools that experts working on ANN are using and allows designing visualizations in a high-level programming language. Since most ANNs are developed using Python frameworks, it is a reasonable choice for the visualization framework to be available as a Python framework as well. This way, the ANN experts could prototype their own visualizations, ideally without the need to be familiar with programming in 3D environments and computer graphics.

Developing the whole framework in Python would not be feasible, as the intense performance requirements of 3D rendering are not met by a high-level language like Python. Hence, the rendering part of the application should be split off and handled by a more optimized rendering engine. This makes it tempting to integrate the Python environment within the engine, since modern game engines

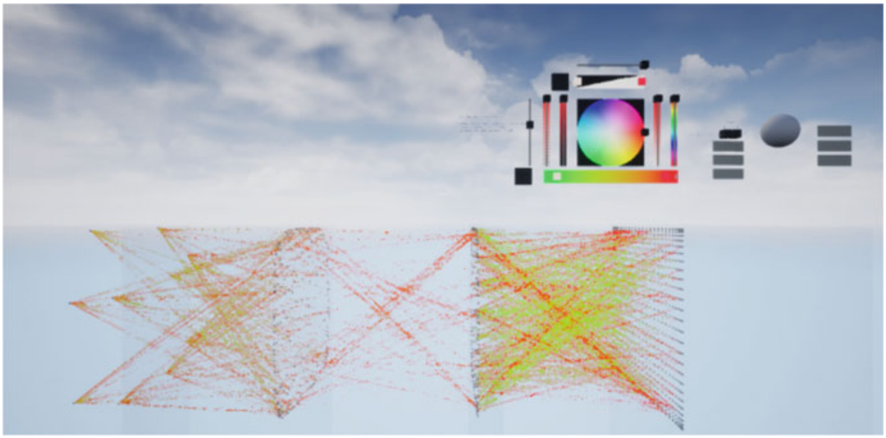


Fig. 5.14 The ANNtoNIA framework enables rapid prototyping of immersive visualization for ANN to facilitate visualization research and improve explainability

often have Python support. This is the solution that was chosen in Aamir et al. (2022). Nevertheless, we argue against this method, since integrating the ANN code this way will still require knowledge of the game engine. Additionally, this would limit the ANN and the visualization to run on the same machine. Since both training/inferring ANN and 3D rendering are performance-intensive tasks, it might be desirable to split them to different machines. For this reason, we argue that it is best to couple the Python part and the rendering part using a network interface.

We develop this visualization framework under the name ANN to Node-link Immersive Analytics (ANNtoNIA) (Fig. 5.14 shows a screenshot) and plan its release under an open-source license.

5.5.5 IoP-Wide Process Data Capture and Management

In agile manufacturing, the seamless integration of processes, data, and information systems throughout the supply chain, even across organizational boundaries, is crucial. Today, data is frequently locked in local data silos and insufficiently linked to products, manufacturing processes, and its own lineage. The lack of standardized and interoperable data management solutions hinders the exchange of data across the IoP, and therefore, meaningful, industrial collaboration.

The FactDAG interoperability model (Gleim et al. 2020a) addresses this issue, by adapting and extending the FAIR data principles (Wilkinson et al. 2016) for industrial data, ensuring data to be findable, accessible, interoperable, and reusable. From a technical perspective, FAIRness requires persistent identification of data, open-access protocols, and rich metadata. The FactDAG itself integrates these three aspects in a directed, acyclic graph (DAG), consisting of immutable data elements called Facts which are linked using standardized provenance relations (Gleim et al.

2020b) based on information from the creating processes, involved systems, and responsible agents. Each Fact has a globally unique, persistent identifier, called FactID. The FactID identifies the responsible authority (e.g., the company owning the data), a data resource, and a specific revision of that resource and allows data to be immutably referenced across the Web (Gleim and Decker 2020). The combined provenance metadata is crucial for the reusability of data and needs to be reliably captured, ideally supported by automated software components.

With the FactStack (Gleim et al. 2021a), an open-source implementation of the FactDAG model, we support an end-to-end data management process based on established open technologies, Web standards, and linked data principles (Bizer et al. 2009). FactStack supports the data management life cycle, ranging from data capture over data preservation to data sharing and finally data reuse. Each data resource is automatically versioned and the persistent identification of data elements enables reliable references to specific revisions of data elements, even across system and organizational boundaries. As such, data and processes can be linked with process provenance throughout the global supply chain in a simple and efficient manner. The automatic collection of provenance and metadata supports data quality and enables interorganizational interoperability and data reuse. Utilizing the FactStack and its underlying linked data principles and technologies, data can be discovered and accessed through the Internet across organizational boundaries using standardized access protocols, such as HTTP and compatible extensions (Gleim et al. 2021b). Nevertheless, data and metadata may still be managed using end-user-friendly graphical user interfaces, e.g., directly in the traditional computer file system (Müller and Gleim 2021).

Capturing and managing process data across agile supply chain enables data- and AI-driven process optimization, e.g., the generation of process models and planning of industrial processes across organizational boundaries by autonomous agents.

5.6 Conclusion

The digital transformation of production enables faster, smarter, and more efficient production and improves value creation (Bruner 2013; Boyes et al. 2018; Brauner et al. 2022). In this chapter, we illustrated how to realize the IoP's vision of integrating data from human experts, machines, and processes across the design, manufacturing, and use cycle to transform data into actionable insights. We introduce the idea of autonomous agents that can query the DSs provided by different users, across different processes, and beyond company and country borders. The applicability of this approach was demonstrated in the two examples of generating pass schedules in hot rolling and injection molding. We surveyed some of the challenges facing the digital transformation on the different abstraction layers of an industrial environment. A central element is bridging the gap between people and machines on the one hand and algorithms and data on the other hand. We introduced "data-to-knowledge pipelines" as a core concept and illustrated the realization of validated self-adaptive production systems.

The work for realizing these pipelines covered various directions. First, we showed that ontology in textile engineering can capture expert knowledge and that it can be integrated in the data lake and the WWL. We further addressed the point of data scarcity in production where data collection can be expensive, time-consuming, and error-prone. This is done by employing GANs to synthesize realistic additional training data for ML applications. By augmenting the training data set with the generated images, the accuracy of a defect classifier for FRP improved significantly.

The industrial usage of ML and especially ANN increases significantly. Nevertheless, the prevalent black-box models are often insufficiently trusted. Hence, we introduced approaches to increase the explainability of the resulting ML models (XAI). On the one hand, by proposing methods to identify high-level explanations (concepts) learned by ANNs and by creating a framework for immersive visualizations that disclose an ANN's structure and functionality. On the other hand, we improved methods for complex optimization and parameter identification to improve the quality of production data. These methods facilitate the validation of models, ensuring that expert knowledge is aligned with their decision-making process.

Further, to improve the explainability, we used gray-box models for robot control and demonstrated this in machining. We proposed a structured neural network for learning the dynamics of an industrial robot. It integrates forces that are difficult to model, such as friction, as ANN and incorporate these into physical models. This combines the advantages of both analytical and data-driven modeling.

For improving robot movement in laser manufacturing, we use RL to generate laser-specific policies for steadier robot trajectories. To realize self-adaptive systems, we further improve these policies by feeding back in situ measurements.

We provided examples of data-to-knowledge pipelines that improve the performance of LPBF-based additive manufacturing processes by detecting defects and adapting the process.

Our data-to-knowledge pipelines have interfaces in the form of smart DSSs that assist operators and managers in making informed production decisions. We integrated AI in DSSs in textile engineering and investigated design requirements for ensuring usability, trust, and acceptance. To demonstrate this, we realized a process planning assistant that builds on historical planning data and experts' knowledge to provide sound and complete process plans based on given optimization criteria.

For enabling safe HRI on the shop floor, we employed BT because they offer higher reactivity, flexibility, and modularity compared to other robot programming approaches. We extended the node types with human-action nodes that allow the robot to anticipate and react to human tasks. To further increase the safety of and confidence in reconfigurable CPPSs, we introduced runtime monitoring to bridge the gap between testing and formal verification.

We model production processes to facilitate process identification, analysis, optimization, comparison, prediction, and conformity checking. In addition, we introduced the OCELs standard and used it for approaches of process visualization and data analysis through object-centric process cubes.

Although the work presented here shows promising steps toward the digital transformation of production, many further milestones need to be passed to achieve the vision of the IoP. First and foremost, the holistic integration of the currently often unconnected applications demonstrated here must be further advanced. Further, the methods and concepts developed must be transferred to the multilayered and very different applications in production, and their suitability must be then verified across the various production domains. Second, the existing methods must be further refined and improved, for example, by using the human digital shadow (Mertens et al. 2021) to provide individually tailored support systems that are context-, task-, and – above all - human-aware. Finally, the data must be integrated into a global WWL that will interconnect research labs and production sites across company and national boundaries (Brauner et al. 2022; Gleim et al. 2020a).

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References

van der Aalst WM (2016) Process mining: data science in action. Springer, Berlin/Heidelberg

van der Aalst WM (2019) Object-centric process mining: dealing with divergence and convergence in event data. In: International conference on software engineering and formal methods. Springer, pp 3–25

Aamir A, Tamosiunaite M, Wörgötter F (2022) Caffe2Unity: immersive visualization and interpretation of deep neural networks. Electronics 11(1):83

Abadi M, Agarwal A, Barham P, Brevdo E, Chen Z, Citro C, Corrado GS, Davis A, Dean J, Devin M et al (2016) Tensorflow: large-scale machine learning on heterogeneous distributed systems. arXiv preprint arXiv:160304467

Ali U, Mahmoodkhani Y, Shahabad SI, Esmaeilizadeh R, Liravi F, Sheydaeian E, Huang KY, Marzbanrad E, Vlasea M, Toyserkani E (2018) On the measurement of relative powder-bed compaction density in powder-bed additive manufacturing processes. Mater Des 155:495–501

Armbruster D, Herty M, Visconti G (2022) A stabilization of a continuous limit of the ensemble Kalman filter. SIAM J Numer Anal 60(3):1494–1515

Baier R, Dammers H, Mertens A, Behery M, Nouduri S, Pelzer L, Shahidi A, Trinh M, Corves B, Gries T, Hopmann C, Hüsing M, Lakemeyer G, Nitsch V (2022) A framework for the classification of human-robot interactions within the internet of production. Lecture notes in computer science, vol 2. Springer, Cham

Becker F, Bibow P, Dalibor M, Gannouni A, Hahn V, Hopmann C, Jarke M, Koren I, Kröger M, Lipp J, Maibaum J, Michael J, Rumpe B, Sapel P, Schäfer N, Schmitz GJ, Schuh G, Wortmann A (2021a) A conceptual model for digital shadows in industry and its application. In: Ghose A, Horkoff J, Silva Souza VE, Parsons J, Evermann J (eds) Conceptual modeling. Springer International Publishing, Cham, pp 271–281

Becker M, Brockmann M, Niemietz P, Trauth D, Bergs T, Brecher C (2021b) Das internet of production als fundament der datenverwertung in der produktion. In: Monetarisierung von technischen Daten. Springer, pp 275–295

Beer MS, Schrank V, Gloy YS, Gries T (2016) Systematic development of technical textiles. In: 48th conference of the international federation of knitting technologists (IFKT), vol 141,1. IOP Publishing, Bristol. https://doi.org/10.1088/1757-899X/141/1/012005

Behery M, Tschesche M, Rudolph F, Hirt G, Lakemeyer G (2020) Action discretization for robot arm teleoperation in open-die forging. In: Proceedings of the SMC 2020 conference

Behery M, Trinh M, Gerhard L (2021) Human action nodes for behavior trees. In: Proceedings of the workshop robotics for people (R4P): perspectives on interaction, learning and safety, pp 13–14

Bellgardt M, Scheiderer C, Kuhlen TW (2020) An immersive node-link visualization of artificial neural networks for machine learning experts. In: Proceedings of IEEE AIVR

Berti A, Farhang A, Park G, van der Aalst WM (2022) A scalable database for the storage of object-centric event logs. arXiv preprint arXiv:220205639

Bibow P, Dalibor M, Hopmann C, Mainz B, Rumpe B, Schmalzing D, Schmitz M, Wortmann A (2020) Model-driven development of a digital twin for injection molding. In: Dustdar S, Yu E, Salinesi C, Rieu D, Pant V (eds) Advanced information systems engineering – 32nd international conference, CAiSE 2020, Grenoble, 8–12 June 2020, Proceedings. Lecture notes in computer science, vol 12127. Springer, pp 85–100. https://doi.org/10.1007/978-3-030-49435-3_6

Bizer C, Heath T, Berners-Lee T (2009) Linked data: the story so far. Int J Semant Web Inf Syst (IJSWIS) 5:1–22. https://doi.org/10.4018/jswis.2009081901

Bolt A, de Leoni M, van der Aalst WMP (2016) A visual approach to spot statistically-significant differences in event logs based on process metrics. In: Nurcan S, Soffer P, Bajec M, Eder J (eds) Advanced information systems engineering. Lecture notes in computer science, vol 9694. Springer, Cham, pp 151–166. https://doi.org/10.1007/978-3-319-39696-5_10

Boscariol P, Caracciolo R, Richiedei D, Trevisani A (2020) Energy optimization of functionally redundant robots through motion design. Appl Sci 10(9). https://doi.org/10.3390/app10093022, https://www.mdpi.com/2076-3417/10/9/3022

Boyes H, Hallaq B, Cunningham J, Watson T (2018) The industrial internet of things (IIoT): an analysis framework. Comput Ind 101:1–12. https://doi.org/10.1016/j.compind.2018.04.015, https://www.sciencedirect.com/science/article/pii/S0166361517307285

Brauner P, Ziefle M (2019) Why consider the human-in-the-loop in automated cyber-physical production systems? Two cases from cross-company cooperation. In: International conference on industrial informatics (INDIN 2019). IEEE, pp 861–866

Brauner P, Ziefle M (2022) Beyond playful learning – serious games for the human-centric digital transformation of production and a design process model. Technol Soc 71:102140. https://doi.org/10.1016/j.techsoc.2022.102140

Brauner P, Dalibor M, Jarke M, Kunze I, Koren I, Lakemeyer G, Liebenberg M, Michael J, Pennekamp J, Quix C, Rumpe B, van der Aalst W, Wehrle K, Wortmann A, Ziefle M (2022) A computer science perspective on digital transformation in production. ACM Trans Internet Things 3(2). https://doi.org/10.1145/3502265

Brecher C, Obdenbusch M, Buchsbaum M, Buchner T, Waltl J (2018) Edge Computing und Digitaler Schatten : Schlüsseltechnologien für die Automatisierung der Zukunft. wt Werkstattstechnik online 108(5):313–318. https://publications.rwth-aachen.de/record/726028

Brecher C, Buchsbaum M, Storms S (2019) Control from the cloud: edge computing, services and digital shadow for automation technologies. In: 2019 international conference on robotics and automation (ICRA), pp 9327–9333. https://doi.org/10.1109/ICRA.2019.8793488

Bremer J, Walderich P, Pirch N, Schleifenbaum JH, Gasser A, Schopphoven T (2021) Effects of path accuracy on additively manufactured specimens by laser material deposition using six-axis robots. J Laser Appl 33(1):012045. https://doi.org/10.2351/7.0000308

Breuer J, Bente G (2010) Why so serious? On the relation of serious games and learning. Eludamos J Comput Game Cult 4(1):7–24. http://www.eludamos.org/index.php/eludamos/article/view/vol4no1-2

Brillowski F, Greb C, Gries T (2020) Increasing the sustainability of composite manufacturing processes by using algorithm-based optimisation and evaluation for process chain design. Int J Sustain Manuf 4(2–4):350–364. https://doi.org/10.1504/IJSM.2020.107128

Brillowski F, Becker M, Vermeulen M, Trauth D, Bergs T, Greb C, Gries T (2021a) Explainable AI for error detection in composites: knowledge discovery in artificial neuronal networks. In: Proceedings of SAMPE Europe conference 2021, Baden/Zürich, 29–30 Sep 2021

Brillowski F, Dammers H, Koch H, Müller K, Reinsch L, Greb C (2021b) Know-how transfer and production support systems to cultivate the internet of production within the textile industry. In: International conference on intelligent human systems integration. Springer, pp 309–315. https://doi.org/10.1007/978-3-030-68017-6_46

Brillowski F, Gries T, Vervier L, Schemmer T, Brauner P, Ziefle M (2022a) User centered design and evaluation of an artificial intelligence based process recommender system in textile engineering. In: Proceedings of 13th international conference on applied human factors and ergonomics (AHFE 2022), New York, 24–28 July 2022, inpress

Brillowski F, Overhage V, Tegetmeyer-Kleine T, Hohnhäuser B (2022b) Overcoming data scarcity in the quality control of safety-critical fibre reinforced composites by means of transfer and curriculum learning. In: Proceedings of conference of production systems and logistics 2022 (CPSL 2022), Vancouver, 17–20 May 2022, in press

Brillowski FS, Gleim LC, Liebenberg MR, Schemmer T, Tirpitz L, Decker SJ, Lakemeyer G, Ziefle M, Greb C, Gries T (2021c) Towards a continuously improving composite manufacturing by employing the internet of production. In: CAMX – the composites and advanced materials expo, Dallas, 19–21 Oct 2021, SAMPE North America

Brockhoff T, Uysal MS, van der Aalst WM (2020) Time-aware concept drift detection using the earth mover's distance. In: 2020 2nd international conference on process mining (ICPM). IEEE, pp 33–40

Brockhoff T, Uysal MS, Terrier I, Göhner H, van der Aalst WM (2021) Analyzing multi-level bom-structured event data. In: Process mining workshops. Lecture notes in business information processing, vol 433

Bruner J (2013) Industrial Internet – the machines are talking. Reilly Media, Inc. O'Reilly Sebastopol, California

Calero Valdez A, Brauner P, Schaar AK, Holzinger A, Ziefle M (2015) Reducing complexity with simplicity – usability methods for industry 4.0. In: 19th triennial congress of the international ergonomics association (IEA 2015), Melbourne. https://doi.org/10.13140/RG.2.1.4253.6809

Canny J (1986) A computational approach to edge detection. IEEE Trans Pattern Anal Mach Intell PAMI-8(6):679–698. https://doi.org/10.1109/TPAMI.1986.4767851

Cassar I, Francalanza A, Aceto L, Ingólfsdóttir A (2017) A survey of runtime monitoring instrumentation techniques. Electron Proc Theor Comput Sci 254(3):15–28. https://doi.org/10.4204/EPTCS.254.2, https://arxiv.org/pdf/1708.07229.pdf

Castelvecchi D (2016) Can we open the black box of AI? Nat News 538(7623):20–23

Cen L, Melkote SN, Castle JB, Appelman H (2016) A wireless force-sensing and model-based approach for enhancement of machining accuracy in robotic milling. IEEE/ASME Trans Mechatron 21:2227–2235

Choi Y, Uh Y, Yoo J, Ha JW (2020) Stargan v2: diverse image synthesis for multiple domains. In: 2020 IEEE/CVF conference on computer vision and pattern recognition (CVPR), pp 8185–8194

Cohn D, Hull R (2009) Business artifacts: a data-centric approach to modeling business operations and processes. IEEE Data Eng Bull 32(3):3–9

Colledanchise M, Ögren P (2018) Behavior trees in robotics and AI: an introduction. arXiv:170900084 [cs]. https://doi.org/10.1201/9780429489105, http://arxiv.org/abs/1709.00084, arXiv: 1709.00084

Colledanchise M, Almeida D, Ögren P (2019) Towards blended reactive planning and acting using behavior trees. In: 2019 international conference on robotics and automation (ICRA), pp 8839–8845. https://doi.org/10.1109/ICRA.2019.8794128

Cranmer M, Greydanus S, Hoyer S, Battaglia P, Spergel D, Ho S (2020) Lagrangian neural networks. 2003.04630

Dabhi R (2020) Casting product image data for quality inspection. Kagglecom https://www.kaggle.com/datasets/ravirajsinh45/real-life-industrial-dataset-of-casting-product

Dai C, Lefebvre S, Yu KM, Geraedts JMP, Wang CCL (2020) Planning jerk-optimized trajectory with discrete time constraints for redundant robots. IEEE Trans Autom Sci Eng 17(4):1711–1724. https://doi.org/10.1109/TASE.2020.2974771

Engl HW, Hanke M, Neubauer A (1996) Regularization of inverse problems, vol 375. Springer Science & Business Media, Dordrecht

Estellés-Arolas E, de Guevara FGL (2012) Towards an integrated crowdsourcing definition. J Inf Sci 38(2):189–200. https://doi.org/10.1177/0165551512437638

Eyerich P, Mattmüller R, Röger G (2009) Using the context-enhanced additive heuristic for temporal and numeric planning. In: Nineteenth international conference on automated planning and scheduling

Fahland D, Leoni Md, Dongen BFv, van der Aalst WM (2011) Behavioral conformance of artifact-centric process models. In: International conference on business information systems. Springer, pp 37–49

Farhang A, van der Aalst WM (2022) A python tool for object-centric process mining comparison. arXiv preprint arXiv:220205709

Farhang A, Berti A, van der Aalst WM (2021a) Process comparison using object-centric process cubes. arXiv preprint arXiv:210307184

Farhang A, Park G, Berti A, van der Aalst WM (2021b) Ocel: a standard for object-centric event logs. In: European conference on advances in databases and information systems. Springer, pp 169–175

Fisher O, Watson N, Porcu L, Bacon D, Rigley M, Gomes RL (2018) Cloud manufacturing as a sustainable process manufacturing route. J Manuf Syst 47:53–68

Fromhold-Eisebith M, Marschall P, Peters R, Thomes P (2021) Torn between digitized future and context dependent past – how implementing 'Industry 4.0' production technologies could transform the German textile industry. Technol Forecast Soc Change 166. https://doi.org/10.1016/j.techfore.2021.120620

Ge Y, Xiao Y, Xu Z, Zheng M, Karanam S, Chen T, Itti L, Wu Z (2021) A peek into the reasoning of neural networks: interpreting with structural visual concepts. In: IEEE conference on computer vision and pattern recognition, CVPR 2021, virtual, 19–25 June 2021. Computer Vision Foundation/IEEE, pp 2195–2204. https://openaccess.thecvf.com/content/CVPR2021/html/Ge_A_Peek_Into_the_Reasoning_of_Neural_Networks_Interpreting_With_CVPR_2021_paper.html

Geist AR, Trimpe S (2020) Structured learning of rigid-body dynamics: a survey and unified view from a robotics perspective. https://doi.org/10.48550/ARXIV.2012.06250, https://arxiv.org/abs/2012.06250

Gerster S, Herty M, Iacomini E (2021) Stability analysis of a hyperbolic stochastic galerkin formulation for the aw-rascle-zhang model with relaxation. Math Biosci Eng MBE 18(4):4372–4389

Ghorbani A, Wexler J, Zou JY, Kim B (2019) Towards automatic concept-based explanations. In: Wallach HM, Larochelle H, Beygelzimer A, d'Alché-Buc F, Fox EB, Garnett R (eds) Advances in neural information processing systems 32: annual conference on neural information processing systems 2019, NeurIPS 2019, Vancouver, 8–14 Dec 2019, pp 9273–9282. https://proceedings.neurips.cc/paper/2019/hash/77d2afcb31f6493e350fca61764efb9a-Abstract.html

Gleim L, Decker S (2020) Timestamped URLs as persistent identifiers. In: Proceedings of the 6th workshop on managing the evolution and preservation of the data web (MEPDaW'20), CEUR Workshop Proceedings

Gleim L, Pennekamp J, Liebenberg M, Buchsbaum M, Niemietz P, Knape S, Epple A, Storms S, Trauth D, Bergs T, Brecher C, Decker S, Lakemeyer G, Wehrle K (2020a) FactDAG: formalizing data interoperability in an internet of production. IEEE Internet Things J 7(4):3243–3253. https://doi.org/10.1109/JIOT.2020.2966402

Gleim L, Tirpitz L, Pennekamp J, Decker S (2020b) Expressing FactDAG provenance with PROV-O. In: Proceedings of the 6th workshop on managing the evolution and preservation of the data web (MEPDaW'20)

Gleim L, Pennekamp J, Tirpitz L, Welten S, Brillowski F, Stefan D (2021a) FactStack: interoperable data management and preservation for the web and industry 4.0. In: 19. Fachtagung für Datenbanksysteme für Business, Technologie und Web (BTW'21), Gesellschaft für Informatik, pp 371–395. https://doi.org/10.18420/btw2021-20

Gleim L, Tirpitz L, Decker S (2021b) HTTP extensions for the management of highly dynamic data resources. In: European semantic web conference (ESWC'21). Springer, pp 212–229. https://doi.org/10.1007/978-3-030-77385-4_13

Grochowski M, Kowalewski S, Buchsbaum M, Brecher C (2019a) Applying runtime monitoring to the industrial internet of things. In: 24th IEEE international conference on emerging technologies and factory automation, ETFA 2019, Zaragoza, 10–13 Sep 2019. IEEE, pp 348–355. https://doi.org/10.1109/ETFA.2019.8869447

Grochowski M, Kowalewski S, Buchsbaum MSK, Brecher C (2019b) Applying passive testing to an industrial internet of things plant. In: VALID 2019: the 11th international conference on advances in system testing and validation lifecycle: 24–28 Nov 2019, Valencia. IARIA, Wilmington, pp 31–37

Grochowski M, Simon H, Bohlender D, Kowalewski S, Löcklin A, Müller T, Jazdi N, Zeller A, Weyrich M (2020) Formale methoden für rekonfigurierbare cyber-physische systeme in der produktion. Autom 68(1):3–14. https://doi.org/10.1515/auto-2019-0115

Harley AW (2015) An interactive node-link visualization of convolutional neural networks. In: International symposium on visual computing, pp 867–877. https://doi.org/10.1007/978-3-319-27857-5

Helmut Huegel TG (2009) Laser in der Fertigung – Strahlquellen – Systeme – Fertigungsverfahren, vol 2. Vieweg+Teubner

Herty M, Iacomini E (2022a) Filtering methods for coupled inverse problems, preprint arXiv:2203.09841

Herty M, Iacomini E (2022b) Uncertainty quantification in hierarchical vehicular flow models. Kinet Relat Models 15(2):239–256. https://doi.org/10.3934/krm.2022006

Herty M, Visconti G (2019) Kinetic methods for inverse problems. Kinet Relat Models 12(5):1109

Herty M, Visconti G (2020) Continuous limits for constrained ensemble Kalman filter. Inverse Probl 36(7):075006

Herty M, Rom M, Visconti G (2021) Einsparung kostenintensiver experimente und simulationen durch maschinelles lernen. In: Monetarisierung von technischen Daten. Springer, pp 691–709

Herty M, Iacomini E, Visconti G (2022) Recent trends on nonlinear filtering for inverse problems. Commun Appl Ind Math 13(1):10–20

Hoffmann RR (1987) The problem of extracting the knowledge of experts from the perspective of experimental psychology. AI Mag 8(2):53. https://doi.org/10.1609/aimag.v8i2.583

Imani F, Gaikwad A, Montazeri M, Rao P, Yang H, Reutzel E (2018) Process mapping and in-process monitoring of porosity in laser powder bed fusion using layerwise optical imaging. J Manuf Sci Eng 140(10):101009

Iovino M, Scukins E, Styrud J, Ögren P, Smith C (2020) A survey of behavior trees in robotics and AI. arXiv:200505842 [cs] http://arxiv.org/abs/2005.05842, arXiv: 2005.05842

Jacovi A, Marasović A, Miller T, Goldberg Y (2021) Formalizing trust in artificial intelligence: prerequisites, causes and goals of human trust in AI. In: Proceedings of the 2021 ACM conference on fairness, accountability, and transparency, pp 624–635

Jarke M, Schuh G, Brecher C, Brockmann M, Prote JP (2018) Digital shadows in the internet of production. ERCIM News 115:26–28. https://ercim-news.ercim.eu/en115/special/2104-digital-shadows-in-the-internet-of-production

Jaspert D, Ebel M, Eckhardt A, Poeppelbuss J (2021) Smart retrofitting in manufacturing: a systematic review. J Clean Prod 312:127555. https://doi.org/10.1016/j.jclepro.2021.127555

Jeschke S, Brecher C, Song H, Rawat DB (2017) Industrial internet of things – cybermanufacturing systems. Springer series in wireless technology. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-319-42559-7, https://publications.rwth-aachen.de/record/672764

Kagermann H (2015) Change through digitization – value creation in the age of Industry 4.0. In: Management of permanent change. Springer, Berlin, Germany. pp 23–45

Leemans SJ, van der Aalst WM, Brockhoff T, Polyvyanyy A (2021) Stochastic process mining: Earth movers' stochastic conformance. Inf Syst 102:101724

Liao Y, Deschamps F, Loures EdFR, Ramos LFP (2017) Past, present and future of Industry 4.0 – a systematic literature review and research agenda proposal. Int J Prod Res 55(12):3609–3629. https://doi.org/10.1080/00207543.2017.1308576

Liebenberg M (2021) Autonomous agents for the world wide lab: artificial intelligence in the manufacturing industry. PhD thesis, RWTH Aachen University

Liebenberg M, Jarke M (2020) Information systems engineering with digital shadows: concept and case studies. In: International conference on advanced information systems engineering. Springer, pp 70–84

Liere-Netheler K, Packmohr S, Vogelsang K (2018) Drivers of digital transformation in manufacturing

Lutter M, Ritter C, Peters J (2019) Deep lagrangian networks: using physics as model prior for deep learning. 1907.04490

Manyika J, Chui M, Brown B, Bughin J, Dobbs R, Roxburgh C, Hung Byers A et al (2011) Big data: the next frontier for innovation, competition, and productivity. McKinsey Global Institute, Washington, DC

McDermott D, Ghallab M, Howe A, Knoblock C, Ram A, Veloso M, Weld D, Wilkins D (1998) Pddl–the planning domain definition language–version 1.2. Yale Center for Computational Vision and Control, Technical Report, CVC TR-98-003/DCS TR-1165

Mertens A, Putz S, Brauner P, Brillowski F, Buczak N, Dammers H, Van Dyck M, Kong I, Konigs P, Kordtomeikel F, Rodemann N, Schaar AK, Steuer-Dankert L, Wlecke S, Gries T, Leicht-Scholten C, Nagel SK, Piller FT, Schuh G, Ziefle M, Nitsch V (2021) Human digital shadow: data-based modeling of users and usage in the internet of production. In: 14th international conference on human system interaction (HSI). IEEE, pp 1–8. https://doi.org/10.1109/HSI52170.2021.9538729

ML van Eck et al (2015) PM^2: a process mining project methodology. In: CAISE 2015. LNCS, vol 9097. Springer, pp 297–313

Mohr G (2019) Measurement of particle emissions in laser powder bed fusion (L-PBF) processes and its potential for in-situ process monitoring

Müller L, Gleim L (2021) Managing versioned web resources in the file system. In: International conference on web engineering (ICWE'21). Springer, pp 513–516. https://doi.org/10.1007/978-3-030-74296-6_41

Nakakaze O, Koren I, Brillowski F, Klamma R (2022) Retrofitting industrial machines with webassembly on the edge. WISE22 (to be published)

Neef A, Seyda V, Herzog D, Emmelmann C, Schönleber M, Kogel-Hollacher M (2014) Low coherence interferometry in selective laser melting. Phys Proc 56:82–89

Ogunmolu OP, Gu X, Jiang SB, Gans NR (2016) Nonlinear systems identification using deep dynamic neural networks. ArXiv abs/1610.01439

Pause D, Brauner P, Faber M, Fischer M, Hunnekes P, Petruck H, Mertens A, Nitsch V, Schuh G, Stich V, Ziefle M (2019) Task-specific decision support systems in multi-level production systems based on the digital shadow. In: Proceedings – 2019 IEEE international conference on industrial cyber physical systems, ICPS 2019. https://doi.org/10.1109/ICPHYS.2019.8780186

Pennekamp J, Glebke R, Henze M, Meisen T, Quix C, Hai R, Gleim L, Niemietz P, Rudack M, Knape S, Epple A, Trauth D, Vroomen U, Bergs T, Brecher C, Bührig-Polaczek A, Jarke M, Wehrle K (2019) Towards an infrastructure enabling the internet of production. In: 2019 IEEE international conference on industrial cyber physical systems (ICPS), pp 31–37. https://doi.org/10.1109/ICPHYS.2019.8780276

Posada-Moreno AF, Surya N, Trimpe S (2022) Eclad: extracting concepts with local aggregated descriptors. ArXiv abs/2206.04531

Qi Z, Khorram S, Li F (2020) Visualizing deep networks by optimizing with integrated gradients. In: The 44. AAAI conference on artificial intelligence, AAAI 2020, The 32. Innovative applications of artificial intelligence conference, IAAI 2020, The 10. AAAI symposium on educational advances in artificial intelligence, EAAI 2020, New York, 7–12 Feb 2020. AAAI Press, pp 11890–11898. https://ojs.aaai.org/index.php/AAAI/article/view/6863

Reinsch L, Greb C, Gries T (2022) Ontologies – introduction and practical approach to textile engineering. In: Intelligent human systems integration (IHSI 2022): integrating people and intelligent systems. Taylor and Francis. https://doi.org/10.54941/ahfe1001061

Ronneberger O, Fischer P, Brox T (2015) U-net: convolutional networks for biomedical image segmentation. In: Navab N, Hornegger J, Wells WM, Frangi AF (eds) Medical image computing and computer-assisted intervention – MICCAI 2015. Springer International Publishing, Cham, pp 234–241

Schaaf N, Zhou H, Enslin C, Brillowski F, Lütticke D (2022) Controlled synthesis of fibre-reinforced plastics images from segmentation maps using generative adversarial neural networks. In: Proceedings of the 14th international conference on agents and artificial intelligence – Volume 3: ICAART, INSTICC. SciTePress, pp 801–809. https://doi.org/10.5220/0010913700003116

Schemmer T, Brauner P, Schaar AK, Ziefle M, Brillowski F (2020) User-centred design of a process-recommender system for fibre-reinforced polymer production. In: Human interface and the management of information, HCII 2020. Springer, Cham, pp 111–127. https://doi.org/10.1007/978-3-030-50017-7_8

Schemmer T, Reinhard J, Brauner P, Ziefle M (2022) Advantages and challenges of extracting process knowledge through serious games. In: GamiFIN conference 2022, pp 11–21

Schwenzer M, Visconti G, Ay M, Bergs T, Herty M, Abel D (2020) Identifying trending model coefficients with an ensemble Kalman filter–a demonstration on a force model for milling. IFAC-PapersOnLine 53(2):2292–2298

Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D (2020) Grad-CAM: visual explanations from deep networks via gradient-based localization. Int J Comput Vis 128(2):336–359. https://doi.org/10.1007/s11263-019-01228-7

Seuren S, Willkomm J, Bücker H, Bambach M, Hirt G (2012) Sensitivity analysis of a force and microstructure model for plate rolling. In: Metal Forming 2012, proceedings of the 14th international conference on metal forming, 16–19 Sep 2012, Krakow. Wiley-VCH, pp 91–94

Sicilliano B, Sciavicco L, Villani L, Oriolo G (2010) Robotics – modelling, planning and control, vol 1. Springer, London

Siderska J, Jadaan KS (2018) Cloud manufacturing: a service-oriented manufacturing paradigm. a review paper. Eng Manag Prod Serv 10(1):22–31

Soutis C (2005) Fibre reinforced composites in aircraft construction. Progress Aerosp Sci 41(2):143–151. https://doi.org/10.1016/j.paerosci.2005.02.004

Spears TG, Gold SA (2016) In-process sensing in selective laser melting (SLM) additive manufacturing. Integr Mater Manuf Innov 5(1):16–40

Spierings AB, Dawson K, Voegtlin M, Palm F, Uggowitzer PJ (2016) Microstructure and mechanical properties of as-processed scandium-modified aluminium using selective laser melting. Cirp Ann 65(1):213–216

Taymouri F, La Rosa M, Carmona J (2020) Business process variant analysis based on mutual fingerprints of event logs. In: Dustdar S, Yu E, Salinesi C, Rieu D, Pant V (eds) Advanced information systems engineering. Springer International Publishing, Cham, pp 299–318

Thati P, Roşu G (2005) Monitoring algorithms for metric temporal logic specifications. Electron Notes Theor Comput Sci 113:145–162. https://doi.org/10.1016/j.entcs.2004.01.029, http://www.sciencedirect.com/science/article/pii/S1571066104052570, Proceedings of the Fourth Workshop on Runtime Verification (RV 2004)

Uysal MS, van Zelst SJ, Brockhoff T, Farhang A, Pourbafrani M, Schumacher R, Junglas S, Schuh G, van der Aalst WM (2020) Process mining for production processes in the automotive industry. In: Industry forum at BPM 2020 co-located with 18th international conference on business process management (BPM 2020), Sevilla
Wang J, Zhang H, Fuhlbrigge T (2009) Improving machining accuracy with robot deformation compensation. In: 2009 IEEE/RSJ international conference on intelligent robots and systems, pp 3826–3831. https://doi.org/10.1109/IROS.2009.5353988
Wilkinson M, Dumontier M, Aalbersberg IJ, Appleton G, Axton M, Baak A, Blomberg N, Boiten JW, Bonino da Silva Santos LO et al (2016) The FAIR guiding principles for scientific data management and stewardship. Sci Data 3. https://doi.org/10.1038/sdata.2016.18
Wygant RM (1989) Clips a powerful development and delivery expert system tool. Comput Ind Eng 17(1–4):546–549
Xu LD, He W, Li S (2014) Internet of things in industries: a survey. IEEE Trans Ind Inform 10(4):2233–2243. https://doi.org/10.1109/TII.2014.2300753
Yang J, Li S, Wang Z, Dong H, Wang J, Tang S (2020) Using deep learning to detect defects in manufacturing: a comprehensive survey and current challenges. Materials (Basel, Switzerland) 13(24). https://doi.org/10.3390/ma13245755
Yegenoglu A, Krajsek K, Pier SD, Herty M (2020) Ensemble Kalman filter optimizing deep neural networks: an alternative approach to non-performing gradient descent. In: International conference on machine learning, optimization, and data science. Springer, pp 78–92
Zhang S, Fu T, Jahn A, Collet A, Schleifenbaum JH (2022) Towards deep-learning-based image enhancement for optical camera-based monitoring system of laser powder bed fusion process. Int J Comput Integr Manuf 1–14. https://doi.org/10.1080/0951192X.2022.2104461