

Interdisciplinary Excellence Accelerator Series

Christian Brecher · Günther Schuh
Wil van der Aalst · Matthias Jarke
Frank T. Piller · Melanie Padberg *Editors*

Internet of Production

Fundamentals,
Methods and Applications

INTERNET OF
PRODUCTION | RWTH AACHEN
UNIVERSITY

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Interdisciplinary Excellence Accelerator Series

Series Editors

Christian Brecher, Werkzeugmaschinenlabor WZL, RWTH Aachen University,
Aachen, Germany

Melanie Padberg, Werkzeugmaschinenlabor WZL, RWTH Aachen University,
Aachen, Germany

The Interdisciplinary Excellence Accelerator Series (IDEAS) is an innovative book series highlighting interdisciplinary and excellent research conducted at universities, such as the 'Cluster of Excellence' at RWTH Aachen University, Germany, and their collaborating partners across the world. The series enables a new form of fast publication anchored in the spirit of interdisciplinary collaboration from authorship to review to dissemination.

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Christian Brecher • Günther Schuh •
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Frank T. Piller • Melanie Padberg
Editors

Internet of Production

Fundamentals, Methods and
Applications

With 160 Figures and 4 Tables

 Springer

Editors

Christian Brecher
Cluster of Excellence Internet of Production
RWTH Aachen University
Aachen, Germany

Wil van der Aalst
Process and Data Science (PADS)
RWTH Aachen University
Aachen, Germany

Frank T. Piller 
Technology and Innovation Management
RWTH Aachen University
Aachen, Germany

Günther Schuh
Laboratory for Machine Tools and
Production Engineering
RWTH Aachen University
Aachen, Germany

Matthias Jarke
Information Systems and Databases (DBIS)
RWTH Aachen University
Aachen, Germany

Melanie Padberg
Cluster of Excellence Internet of Production
RWTH Aachen University
Aachen, Germany



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Preface

Crossing Disciplinary Boundaries: RWTH Aachen and Springer Start a New Publishing Partnership

This first volume of the new Interdisciplinary Excellence Accelerator Series (IDEAS) is the first major outcome of more than a year of joint work with its inception in a 2-day publishing lab workshop with researchers from the Excellence Cluster “Internet of Production” at RWTH Aachen (Germany) and editors from Springer held in March 2021. The aim of the online event was to understand current researcher needs and pain points, as well as exploring ideas for potential solutions.

The event was well prepared – including a survey which RWTH Aachen addressed to students and researchers at their Cluster of Excellence – and eventually centered around two main themes in research and publishing:

- How to accelerate the journey from research to publication and scholarly knowledge transfer?
- How to facilitate truly interdisciplinary research and publishing?

In what follows, we put forward the three tenets which the participants of this workshop have agreed upon as the way to encourage, enhance, and propagate accelerated interdisciplinary work.

Tenet 1: Reduce the Time Between Research, Publication, and Scholarly Knowledge Transfer

Scientific research has accelerated dramatically over the last decades. This is not only a consequence of the rise of digital technologies and the Internet. Emergencies such as the Covid pandemic and the climate crisis have also increased the political and public demand for faster research outcomes. The development of effective Covid-19 vaccines in less than one year after the pandemic hit can be considered as an impact of such demand.

On the academic side, researchers with good reason would say: *If you want us to produce research results faster, then you have to provide us with the appropriate tools, resources, and dissemination infrastructure.*

Academic publishers have not always fully understood current researchers' needs in their actual lab and scholarly environments. Particularly, it takes too much time for research results to become available in the scholarly knowledge transfer and teaching. One can highlight this by pointing to textbooks which, in many cases, take between 3 and 5 years from conception to their release. By that time, the presented research results and data are often outdated already. This might have been fine in former decades with a much slower pace of the research progress. In a time of accelerated research, this is not fast enough anymore which is a severe problem.

At the publishing lab, we clearly addressed that research publishers need to find solutions to bring current research outcomes into the scholarly knowledge transfer and academic teaching with a much faster turnaround. And there are a number of ways to do so:

- An “Online First” publication may be one part of the mix.
- Solutions to provide researchers, teachers, and students with the ability to compile and recompile their material themselves according to current status and requirements may be another part.
- Keeping content up to date in a more continuous way instead of publishing new editions every 3 to 5 years is yet another component.

Many of such partial solutions already exist, yet the challenge is to combine them in a smart and convenient way – also balancing the classical triangle of time, quality, and value – so they have a positive impact on scholars.

Tenet 2: Make Interdisciplinary Review Mandatory

The second major theme of the publishing lab was the interdisciplinary aspect of research. It is a matter of fact that the global challenges of our days require researchers to overcome the boundaries of the discipline silos. In consequence, the Cluster of Excellence “Internet of Production” at RWTH Aachen puts a particular focus on interdisciplinary research: “With the Internet of Production, our vision is to enable a new level of cross-domain collaboration” (<https://www.nature.com/articles/d42473-019-00089-5>).

Yet, the reality in research and publishing does not always fit with such demand for interdisciplinary research as we discussed at the publishing lab:

- Although it is often quite clear which academic disciplines are required to collaborate on a given field of problems, it is a common experience that putting researchers from different disciplines at one table is not sufficient as they might not understand each other due to the languages, jargons, and even the academic approach specific to their disciplines.

- While interdisciplinary research is the order of the day, research communities tend to prioritize and reward the outcomes and publications within their own disciplines rather than interdisciplinary work.
- Research methods and data frequently stay within their discipline boundaries instead of being mutually shared between the disciplines, where applicable.
- Existing publishing formats do not intrinsically encourage researchers to cross the bridge to other disciplines.

The discipline silos also become apparent when it comes to peer-review. Peer-reviewers, by the nature of their remit, may not bridge the gap between the disciplines and at the same time, cross-discipline¹ reviewer recommendation is not a common feature in peer-reviewer finder tools either.

In the ideal world of the Excellence Cluster “Internet of Production,” the reality would look as in this simplified example:

1. A researcher in Mechanical Engineering shares research data from the lab.
2. A Computer Scientist reviews the data and writes an analysis.
3. A Social Scientist reviews the analysis and writes a reflection.
4. Every single step is published and adds to researchers’ credits.
5. All three pieces together (points 1, 2, and 3) make up for the final research publication.

We also thought about where exactly do people from different domain backgrounds come together and actually talk to each other as well as jointly experiment on their ideas. In the IT and tech domain, this is common practice and is termed “hackathons.” So why not establish dedicated peer-review events that follow a cross-domain approach such as hackathons do. Such events would also accelerate the reviewing itself. And more than that, events like this might over time help cultivate a language that different disciplines understand and which would also help building interdisciplinary communities and allow cross-discipline application of methods hitherto used in siloed disciplines only.

Tenet 3: Use books as calls to action and solution vehicles

This first book of the Interdisciplinary Excellence Accelerator Series (IDEAS) is a starting point. It is composed of chapters each of which has been prepared by an interdisciplinary research team. In the spirit of agile development, we want to iterate over the course of the next 2 to 3 years in order to introduce a new way of collaboration (including dedicated review events) together with a new research

¹ In this introduction, the terms “cross-discipline” and “interdisciplinary” are being used interchangeably.

publishing format which we call *Crosstracts*. It is this new concept of *Crosstracts* which will allow researchers to:

- Find potential collaborators at an early research stage
- Publish research and research data early and faster
- Recognize the various stages of the knowledge and manuscript creation
- Make interdisciplinary review and feedback mandatory, collaborative, and transparent in a novel and constructive manner
- Facilitate interdisciplinary research with a positive impact on global challenges and societal recognition
- Boost the creation of cross-discipline communities with a language and knowledge configuration that all participants understand
- Resulting in a cross-discipline book series that is engineered in such a way that it crosses the boundaries of single disciplines with a much earlier re-usability in the scholarly knowledge transfer (in German: “*akademische Lehre*”)

There is a reason why we decided to begin with a book series. First of all, books are a great opportunity to experiment, iterate, and adjust on the way forward. But there is more to it. Books have an impact both on the consumption side – i.e., for their readers – as well as on the side of their creators. The various existing book categories – such as monographs, handbooks, textbooks, encyclopedias – all require their authors to create them in a specific way. In consequence, books are not only helping their readers to achieve certain goals, e.g., passing exams. Books are increasingly also specific calls to action toward their authors themselves.

This is exactly what a *Crosstracts* book series wants to achieve: Make it obligatory to interdisciplinary research teams to not only collaborate but also mutually review each other’s research and hence truly understand and influence each other, so *the whole of their interdisciplinary research becomes greater than the sum of their discipline-specific parts*. In that very sense, books are not only representing research outcomes to an audience. They are also an excellent solution vehicle for research teams in general.

It is a beginning of the change which academia has always been seeking, and it is an ongoing process. We call upon readers of this publication to come forward and suggest further improvements, ideas, or initiatives to contribute to a new reality of truly interdisciplinary, fast, and impactful scholarly knowledge transfer.

VP Content innovation. Springer Nature,
Tiergartenstr. 17, 69121 – Heidelberg, Germany.
henning.schoenenberger@springer.com

Henning Schoenenberger

Editorial

With the Cluster of Excellence Internet of Production (IoP), more than 200 scientists from the fields of production engineering, computer science, materials engineering, social science, and business administration are simultaneously facing up to the task, but also the obligation, of addressing future challenges and goals for production technologies with all their facets to generate innovative solutions and practical concepts to shape the production of tomorrow.

The vision of the IoP is to identify relevant data from production, development and use in real time, select, and reduce it in a form that it can be used adequately by solving interdisciplinary tasks and thereby provide the decisive research impetus for shaping the future of digitalization in production engineering. This involves industrial artificial intelligence, advanced manufacturing and materials, intelligent data infrastructures, and a holistic view of the future of work. This means the main task is to derive and create real added value from the gigantic amounts of data that already exist in all areas of production – for the entire production itself, the individual machine, and all the people involved – described by transferring the IoT to the world of production.

Interdisciplinary publishing presents us with major challenges. What is already “state of the art” for some is applied in another discipline new research for others. By linking topics that have already been researched in different disciplines, new fields of research emerge as limitations are re-challenged. Each discipline has its own language, styles, and requirements for scientific publishing. Whereas in one discipline the description of applications and use cases is mandatory, in others they are considered to be delicate or even frowned upon. And even the internal review process, with different disciplines looking at each other, cannot always be fully transferred to the topics. Often, no direct feedback on the work can be given, but rather a new perspective can be shown, an outlook on upcoming topics can be considered, and a dialog is created that requires and enables a view beyond one’s own focus.

Fortunately, together with Springer, we were given a unique opportunity to understand and approach publishing in a new way. We developed a new series called Interdisciplinary Excellence Accelerator Series (IDEAS). The series enables a new form of fast publication anchored in the spirit of interdisciplinary collaboration from authorship to review to publication. The resulting high-quality books can be used

both by academics and practitioners for different purposes ranging from teaching to research and knowledge transfer. This book is the first of this series.

To provide a fast publication process and taking in account that most readers only read certain chapters of their interest, the individual chapters of the book are intended to stand on their own. The book is intended to provide an overview of the challenges of tomorrow's production technology and describe initial approaches to solutions along the way.

This book presents and summarizes the interim results of the Cluster of Excellence during the first half of the funding phase under the Excellence Strategy. For more detailed results, reference is made to corresponding scientific publications. An update with further research results will follow.

We would like to thank all scientists for their extraordinary commitment and excellent results, as well as the German Research Foundation (DFG) for funding the Cluster of Excellence "Internet of Production" in the funding period of the Excellence Strategy.

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Aachen
May 2023

Prof. Christian Brecher
Prof. Günther Schuh
Prof. Dr. Wil van der Aalst
Prof. Matthias Jarke
Prof. Frank T. Piller
Melanie Padberg

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and Frank T. Piller

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About the Editors

Prof. Dr.-Ing. Christian Brecher has held the Chair of Machine Tools at RWTH Aachen University since January 2004. His research areas include machine technology, machine data analysis and NC technology, control technology and automation, gear technology, precision machines, fiber composite technology, and integrative lightweight construction. At the same time, he became a member of the Board of Directors of the Laboratory for Machine Tool and Production Engineering (WZL) and of the Fraunhofer Institute for Production Technology IPT in Aachen.

From 2006 to 2018, Prof. Brecher was spokesperson for the Cluster of Excellence “Integrative Production Technology for High-Wage Countries” at RWTH Aachen University. In 2012, he founded the Aachen Centre for Integrative Lightweight Production (AZL) together with Prof. Hopmann. In 2018, Prof. Brecher was appointed Director of the Fraunhofer Institute for Production Technology IPT. Currently, Prof. Brecher is also, among other positions, spokesperson for the Cluster of Excellence EXC2023 “Internet of Production” (IoP) at RWTH Aachen University, spokesperson for the SFB/Transregio 96, Fellow of the International Academy of Production Engineering (CIRP), and member of the German Academy of Science and Engineering (acatech). In 2020 and 2021, he was President of the Scientific Society for Production Engineering (WGP).

Prof. Dr.-Ing. Dipl.-Wirt. Ing. Günther Schuh has held the Chair of Production Engineering at RWTH Aachen University and is a member of the Board of Directors of the Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University and the Fraunhofer-Institute for Production Technology (IPT) in Aachen. He is also Director of the Research Institute for Industrial Management at RWTH Aachen University (FIR e. V.). Additionally, he is one of the deputy spokesperson of the Cluster of Excellence “Internet of Production” at RWTH Aachen University. In 2005, Prof. Schuh initiated the RWTH Aachen Campus, a network of science and business with currently more than 420 technology companies.

As a scientist and entrepreneur, Prof. Schuh is concerned with disruptive innovations, information and production management, as well as sustainable mobility

solutions. He supports the approach that complex interrelationships and systemic innovations require scientific and entrepreneurial collaboration. For more than 30 years, he has been working on issues of innovation and technology management, industrial production, and complexity management in industrial systems. With researchers and developers in the industry, he has repeatedly proven to develop cost-effective industrially manufactured products, especially electric vehicles, with Industry 4.0-based highly iterative development processes as well as new product and production architectures. In order to implement new mobility concepts into practice, he is still the founder of various companies that develop and produce mobility solutions. The focus is on holistic solutions to drive the transformation to new individual transport.

Prof. Dr. Ir. Wil van der Aalst is Full Professor at RWTH Aachen University, leading the Process and Data Science (PADS) group and deputy spokesperson of the Cluster of Excellence “Internet of Production” at RWTH Aachen University. He is also the Chief Scientist at Celonis, part-time affiliated with the Fraunhofer FIT, and a member of the Board of Governors of Tilburg University. His research interests include process mining, Petri nets, business process management, workflow management, process modeling, and process analysis. Wil van der Aalst has published over 900 articles and books and is considered to be in the top-15 of most cited computer scientists with an H-index of 170 and more than 130,000 citations.

Van der Aalst is an IFIP Fellow, IEEE Fellow, ACM Fellow, and received honorary degrees from the Moscow Higher School of Economics (Prof. h.c.), Tsinghua University, and Hasselt University (Dr. h.c.). He is also an elected member of the Royal Netherlands Academy of Arts and Sciences, the Royal Holland Society of Sciences and Humanities, the Academy of Europe, and the North Rhine-Westphalian Academy of Sciences, Humanities and the Arts. In 2018, he was awarded an Alexander-von-Humboldt Professorship.

Prof. em. Dr. Matthias Jarke is Professor em. of Databases and Information Systems at RWTH Aachen University. After his Doctorate from Hamburg University in 1980, he held professorships at the Stern School of Business at New York University and the University of Passau before joining RWTH in 1991. Key teaching contributions focus on RWTH internationalization, founding the Bonn-Aachen International Center for IT (b-it) and as Inaugural Dean at the GUTech German University of Technology in Oman. After 8 years as Chairman of Aachen’s CS Department, he became Executive Director of the Fraunhofer Institute for Applied Information Technology FIT. As ICT representative in the Fraunhofer Presidency 2010–2015, he co-initiated the International Data Space concept for European data sovereignty.

Jarke’s research addresses database query processing, metadata management, requirements, and information systems engineering. Large interdisciplinary projects studied Chemical Engineering processes, Media and Cultural Communication, and Highspeed Mobile Information and Communication. Currently, he serves as deputy spokesperson of the Cluster of Excellence “Internet of Production” at RWTH

Aachen University. As President of the GI German Informatics society, Jarke coordinated the BMBF Science Year 2006, which started the German Chancellor's Digitalization Summits. He was elected to the German Academy of Technology and Sciences acatech and received prestigious awards including ACM Fellow and GI Fellow.

Prof. Dr. rer. pol. Frank T. Piller is Professor of Management and Head of the Institute for Technology and Innovation Management at RWTH Aachen University. Prior to that, he had positions at MIT and TU Munich. He is also the Academic Director of the Institute for Management Cybernetics (ifu e.V.), an independent research institute associated with RWTH Aachen with a focus on applied machine intelligence, systemic change, and institutional transformations. Prof. Piller's current research focuses on the need of established corporations to deal with disruptive business model innovation and supporting organizational structures and cultures. Leadership for Industry 4.0 and Managing a Digital Transformation are core topics in this field. He also is currently building a research program on the role of AI&ML in the innovation process and managing hybrid innovation teams, where human experts and algorithms/machines collaborate ("hybrid intelligence"). Prof. Piller is a Principal Investigator in the Cluster of Excellence "Internet of Production" at RWTH Aachen and serves as a scientific advisor to Germany's national Industry 4.0 policy. Prof. Piller has consulted with many Dax30 or Fortune500 companies and serves as an advisor for several deep-tech startups.

Melanie Padberg, M.Sc., received the B.Sc. degree in Mechanical Engineering and the M.Sc. degree in Automation Engineering from RWTH Aachen University, Aachen, Germany. After her graduation, she started as a researcher within the Chair of Machine Tools at the Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University. Her research focused on automation and safety in the Industrial Internet of Things, and cloud and edge computing as enabler for the digital shadow.

Since January 2022, she is Managing Director of the Cluster of Excellence "Internet of Production." In her position, she is responsible for the comprehensive scientific coordination of the Cluster of Excellence and its sustainable personnel, scientific, and structural development.

Section Editors

Christian Brecher Cluster of Excellence Internet of Production, RWTH Aachen University, Aachen, Germany

Günther Schuh Laboratory for Machine Tools and Production Engineering, RWTH Aachen University, Aachen, Germany

Wil van der Aalst Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Matthias Jarke Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Frank T. Piller Technology and Innovation Management, RWTH Aachen University, Aachen, Germany

Melanie Padberg Cluster of Excellence Internet of Production, RWTH Aachen University, Aachen, Germany

Contributors

Dirk Abel Institute of Automatic Control (IRT), RWTH Aachen University, Aachen, Germany

Mustapha Abouridouane Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Marc Ackermann Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Frank Adjei-Kyeremeh Foundry Institute, RWTH Aachen University, Aachen, Germany

André Amft Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Aachen, Germany

Sebastian Apelt Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Muzaffer Ay Institute of Automatic Control (IRT), RWTH Aachen University, Aachen, Germany

Ralph Baier Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany

David Bailly Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Annika Becker Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Marco Becker Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Mohamed Behery Knowledge-Based Systems Group (KBSG), RWTH Aachen University, Aachen, Germany

Martin Bellgardt Visual Computing Institute (VCI), RWTH Aachen University, Aachen, Germany

Anastasiia Belova Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Thomas Bergs Manufacturing Technology, Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Fraunhofer Institute for Production Technology (IPT), Aachen, Germany

Benedikt Biernat Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Charline Blankart Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Kirsten Bobzin Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Matthias Bodenbenner Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Marie-Noemi Bold Institute for Digital Additive Production (DAP), RWTH Aachen University, Aachen, Germany

Carsten Boßmann Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Frederike Brasche Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Philipp Brauner Human-Computer Interaction Center (HCIC), RWTH Aachen University, Aachen, Germany

Christian Brecher Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Thomas Bremen Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Malte Brettel Innovation und Entrepreneurship Group (WIN), RWTH Aachen University, Aachen, Germany

Kristof Briele Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Florian Brillowski Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany

Tobias Brockhoff Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Christoph Broeckmann Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Andreas Bührig-Polaczek Foundry Institute, RWTH Aachen University, Aachen, Germany

Daniel Buschmann Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Paul Buske Technology of Optical Systems (TOS), Aachen, Germany

Marco Carlet Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Sayan Chatterjee Foundry Institute, RWTH Aachen University, Aachen, Germany

Ester Christou Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Aachen, Germany

Burkhard Corves Institute of Mechanism Theory, Machine Dynamics and Robotics, RWTH Aachen University, Aachen, Germany

Simon Cramer Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Rainer Dahlmann Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Markus Dahlmanns Communication and Distributed Systems, RWTH Aachen University, Aachen, Germany

Hannah Dammers Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany

Stefan Decker Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany

Yuanbin Deng Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Patricia de Oliveira Löhner Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Iraklis Dimitriadis Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany

Seyed Ruhollah Dokhanchi Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Thomas Eberius Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Morten Endrikat Research Unit International Economics, RWTH Aachen University, Aachen, Germany

Chrismarie Enslin Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Mauricio Fernández ACCESS e.V, Aachen, Germany

Markus Fischer Institute for Industrial Management (FIR), RWTH Aachen University, Aachen, Germany

Roman Flaig Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Frank Flemisch Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany

Cailing Fu Technology of Optical Systems (TOS), RWTH Aachen University, Aachen, Germany

Judith Fulterer Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Aymen Gannouni Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Sandra Geisler Data Stream Management and Analysis (DSMA), RWTH Aachen University, Aachen, Germany

Anahita Farhang Ghahfarokhi Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Arnold Gillner Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Lars Gleim Institute for Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Leon Gorißen Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Thomas Gries Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany

Marco Grochowski Institute for Embedded Software (ES), RWTH Aachen University, Aachen, Germany

Andreas Gützlaff Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Christian Haase Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Constantin Leon Häfner Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Bengt Hallstedt Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Hendrik Heinemann Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Christian Heinigk Nonlinear Dynamics of Laser Manufacturing Processes (NLD), RWTH Aachen University, Aachen, Germany

Malte Heithoff Software Engineering, RWTH Aachen University, Aachen, Germany

Thomas Henn Institute for Embedded Software (ES), RWTH Aachen University, Aachen, Germany

Martin Henze Security and Privacy in Industrial Cooperation, RWTH Aachen University, Aachen, Germany

Annkristin Hermann Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Michael Herty Institute of Geometry and Applied Mathematics (IGPM), RWTH Aachen University, Aachen, Germany

Daniel Hilger Computational Analysis of Technical Systems, RWTH Aachen University, Aachen, Germany

Christian Hinke Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Gerhard Hirt Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Carlo Holly Technology of Optical Systems (TOS), RWTH Aachen University, Aachen, Germany

Christian Hopmann Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Katharina Hornberg Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Norbert Hosters Computational Analysis of Technical Systems, RWTH Aachen University, Aachen, Germany

Louis Huebser Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Mathias Hüsing Institute of Mechanism Theory, Machine Dynamics and Robotics, RWTH Aachen University, Aachen, Germany

Elisa Iacomini Institute of Geometry and Applied Mathematics (IGPM), RWTH Aachen University, Aachen, Germany

Christian Idzik Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Georg Jacobs Institute for Machine Elements and Systems Engineering, RWTH Aachen University, Aachen, Germany

Patrick Jagla Institute for Machine Elements and Systems Engineering, RWTH Aachen University, Aachen, Germany

Tim Janke Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Julia Janowitz Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Nico Jansen Software Engineering, RWTH Aachen University, Aachen, Germany

Matthias Jarke Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany

Christian Kalscheuer Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Thomas Kaster Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Hannah Kelbel Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany

Marco Kemmerling Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Zahra Kheirandish Nonlinear Dynamics of Laser Manufacturing Processes (NLD), RWTH Aachen University, Aachen, Germany

Raphael Kiesel Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Soo-Yon Kim Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Aline Kluge-Wilkes Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Moritz Kolter Institute for Digital Additive Production (DAP), RWTH Aachen University, Aachen, Germany

István Koren Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Stefan Kowalewski Institute for Embedded Software (ES), RWTH Aachen University, Aachen, Germany

Moritz Kröger Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Ulrich Krupp Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Torsten W. Kuhlen Visual Computing Institute (VCI), RWTH Aachen University, Aachen, Germany

Maximilian Kuhn Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Ike Kunze Communication and Distributed Systems, RWTH Aachen University, Aachen, Germany

Gerhard Lakemeyer Knowledge-Based Systems Group (KBSG), RWTH Aachen University, Aachen, Germany

Markus Landwehr Fraunhofer IPT, Aachen, Germany

Carmen Leicht-Scholten Gender and Diversity in Engineering, RWTH Aachen University, Aachen, Germany

Martin Liebenberg Knowledge-Based Systems Group (KBSG), RWTH Aachen University, Aachen, Germany

Luca Liehner Human-Computer Interaction Center (HCIC), RWTH Aachen University, Aachen, Germany

Maria Linnartz Institute for Industrial Management (FIR), RWTH Aachen University, Aachen, Germany

Yannik Lockner Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Vincent Lohrmann Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Dirk Lüttgens Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Aachen, Germany

Daniel Lütticke Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Samuel Mann Welding and Joining Institute (ISF), RWTH Aachen University, Aachen, Germany

Maximilian Meißner Institute for Machine Elements and Systems Engineering, RWTH Aachen University, Aachen, Germany

Felix Melzer Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Alexander Mertens Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany

Matthias Mertens Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Judith Michael Software Engineering, RWTH Aachen University, Aachen, Germany

Michael Millan Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Aachen, Germany

Benjamin Montavon Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Aleksandra Müller Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Kai Müller Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany

Sebastian Münstermann Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Saskia K. Nagel Human Technology Center/Applied Ethics, RWTH Aachen University, Aachen, Germany

Philipp Niemiets Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Verena Nitsch Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany

Lucia Ortjohann Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Melanie Padberg Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Alexander Peitz Aachen Center for Integrative Lightweight Production, Aachen, Germany

Lukas Pelzer Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Jan Pennekamp Communication and Distributed Systems, RWTH Aachen University, Aachen, Germany

Martin Perau Institute for Industrial Management (FIR), RWTH Aachen University, Aachen, Germany

Stefan Perau Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Frank T. Piller Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Aachen, Germany

Tobias Plum Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Andres Felipe Posada-Moreno Institute for Data Science in Mechanical Engineering (DSME), RWTH Aachen University, Aachen, Germany

Mahsa Pourbafrani Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Michael Preutenborbeck Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany

Felix Pütz Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Sebastian Pütz Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany

Siyuan Qin Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Christoph Quix Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany

Pascal Rabe Welding and Joining Institute (ISF), RWTH Aachen University, Aachen, Germany

Iris Raffeis Foundry Institute, RWTH Aachen University, Aachen, Germany

Ali Rajaei Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Niklas Reinisch Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Leon Reinsch Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany

Uwe Reisgen Welding and Joining Institute (ISF), RWTH Aachen University, Aachen, Germany

Lisa-Marie Reitmaier Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Markus Rey Innovation und Entrepreneurship Group (WIN), RWTH Aachen University, Aachen, Germany

Niklas Rodemann Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Michael Rom Institute for Geometry and Applied Mathematics (IGPM), RWTH Aachen University, Aachen, Germany

Soheil Rooein Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Maximilian Rudack Foundry Institute, RWTH Aachen University, Aachen, Germany

Fridtjof Rudolph Institute of Metal Forming (IBF), RWTH Aachen University, Aachen, Germany

Bernhard Rumpe Software Engineering, RWTH Aachen University, Aachen, Germany

Adrian Karl Rppel Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Vladimir Samsonov Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Mark P. Sanders Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Patrick Sapel Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Jana Sasse Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Niklas Schfer Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Thomas Schemmer Human-Computer Interaction Center (HCIC), RWTH Aachen University, Aachen, Germany

Oliver Schenk Institute for Materials Applications in Mechanical Engineering (IWM), RWTH Aachen University, Aachen, Germany

Dominik Scheurenberg Institute of Automatic Control (IRT), RWTH Aachen University, Aachen, Germany

Sven Schiller Fraunhofer IPT, Aachen, Germany

Peter Schlegel Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Johannes Henrich Schleifenbaum Institute for Digital Additive Production (DAP), RWTH Aachen University, Aachen, Germany

Tino X. Schlosser Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Robert H. Schmitt Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Production Metrology and Quality Management, Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Fraunhofer IPT, Aachen, Germany

Georg J. Schmitz ACCESS e.V, Aachen, Germany

Mauritius Schmitz Institute for Plastics Processing (IKV), RWTH Aachen University, Aachen, Germany

Sebastian Schneider Gender and Diversity in Engineering, RWTH Aachen University, Aachen, Germany

Alexander Scholleman Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Marco Schopen Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Günther Schuh Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Wolfgang Schulz Nonlinear Dynamics of Laser Manufacturing Processes (NLD), RWTH Aachen University, Aachen, Germany

Tobias Schulze Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Steffen Schupp Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Alexandros Serafeim Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Amir Shahidi Institute of Mechanism Theory, Machine Dynamics and Robotics, RWTH Aachen University, Aachen, Germany

Linda Steuer-Dankert Gender and Diversity in Engineering, RWTH Aachen University, Aachen, Germany

Volker Stich Institute for Industrial Management (FIR), RWTH Aachen University, Aachen, Germany

Lena Stöcker Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Stoyan Stoyanov Fraunhofer Institute for Laser Technology (ILT), Aachen, Germany

Johannes Theissen-Lipp Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany

Liam Tirpitz Institute for Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Jonas Tittel Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Sebastian Trimpe Institute for Data Science in Mechanical Engineering (DSME), RWTH Aachen University, Aachen, Germany

Minh Trinh Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Merih Seran Uysal Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Wil van der Aalst Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany

Luisa Vervier Human-Computer Interaction Center (HCIC), RWTH Aachen University, Aachen, Germany

Tarik Viehmann Knowledge-Based Systems Group (KBSG), RWTH Aachen University, Aachen, Germany

Sönke Vogel Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Carsten Vogels Surface Engineering Institute (IOT), RWTH Aachen University, Aachen, Germany

Marcus Völker Institute for Embedded Software (ES), RWTH Aachen University, Aachen, Germany

Uwe Vroomen Foundry Institute, RWTH Aachen University, Aachen, Germany

Philipp Walderich Laser Technology (LLT), RWTH Aachen University, Aachen, Germany

Jing Wang Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Klaus Wehrle Communication and Distributed Systems, RWTH Aachen University, Aachen, Germany

Martin Welsing Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Sebastian Wesselmecking Steel Institute (IEHK), RWTH Aachen University, Aachen, Germany

Marian Wiesch Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Daniel Wolff Computational Analysis of Technical Systems, RWTH Aachen University, Aachen, Germany

Dominik Wolfschläger Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Tiandong Xi Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Omid Zarei Institute for Digital Additive Production (DAP), RWTH Aachen University, Aachen, Germany

Michael Zeng Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Song Zhang Institute for Digital Additive Production (DAP), RWTH Aachen University, Aachen, Germany

Hans Aoyang Zhou Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Martina Ziefle Human-Computer Interaction Center (HCIC), RWTH Aachen University, Aachen, Germany



Actionable Artificial Intelligence for the Future of Production

5

Mohamed Behery, Philipp Brauner, Hans Aoyang Zhou, Merih Seran Uysal, Vladimir Samsonov, Martin Bellgardt, Florian Brillowski, Tobias Brockhoff, Anahita Farhang Ghahfarokhi, Lars Gleim, Leon Gorißen, Marco Grochowski, Thomas Henn, Elisa Iacomini, Thomas Kaster, István Koren, Martin Liebenberg, Leon Reinsch, Liam Tirpitz, Minh Trinh, Andres Felipe Posada-Moreno, Luca Liehner, Thomas Schemmer, Luisa Vervier, Marcus Völker, Philipp Walderich, Song Zhang, Christian Brecher, Robert H. Schmitt, Stefan Decker, Thomas Gries, Constantin Leon Häfner, Michael Herty, Matthias Jarke, Stefan Kowalewski, Torsten W. Kuhlen, Johannes Henrich Schleifenbaum, Sebastian Trimpe, Wil van der Aalst, Martina Ziefle, and Gerhard Lakemeyer

M. Behery (✉) · M. Liebenberg · G. Lakemeyer
Knowledge-Based Systems Group (KBSG), RWTH Aachen University, Aachen, Germany
e-mail: behery@kbsg.rwth-aachen.de; marin.liebenberg@rwth-aachen.de;
gerhard@kbsg.rwth-aachen.de

P. Brauner (✉) · L. Liehner · T. Schemmer · L. Vervier · M. Ziefle
Human-Computer Interaction Center (HCIC), RWTH Aachen University, Aachen, Germany
e-mail: brauner@comm.rwth-aachen.de; liehner@comm.rwth-aachen.de;
schemmer@comm.rwth-aachen.de; vervier@comm.rwth-aachen.de;
ziefle@comm.rwth-aachen.de

H. A. Zhou · V. Samsonov
Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen
University, Aachen, Germany
e-mail: hans.zhou@ima.rwth-aachen.de; vladimir.samsonov@ima.rwth-aachen.de

M. S. Uysal · T. Brockhoff · A. F. Ghahfarokhi · I. Koren · W. van der Aalst
Process and Data Science (PADS), RWTH Aachen University, Aachen, Germany
e-mail: uysal@pads.rwth-aachen.de; brockhoff@pads.rwth-aachen.de;
farhang@pads.rwth-aachen.de; koren@pads.rwth-aachen.de; vdaalst@pads.rwth-aachen.de

M. Bellgardt · T. W. Kuhlen
Visual Computing Institute (VCI), RWTH Aachen University, Aachen, Germany
e-mail: bellgardt@vr.rwth-aachen.de; kuhlen@vr.rwth-aachen.de

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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

F. Brillowski · L. Reinsch · T. Gries
 Institute of Textile Technology (ITA), RWTH Aachen University, Aachen, Germany
 e-mail: florian.brillowski@ita.rwth-aachen.de; leon.reinsch@ita.rwth-aachen.de;
thomas.gries@ita.rwth-aachen.de

L. Gleim · L. Tirpitz
 Institute for Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany
 e-mail: gleim@dbis.rwth-aachen.de; tirpitz@dbis.rwth-aachen.de

L. Gorißen · T. Kaster · P. Walderich · C. L. Häfner
 Laser Technology (LLT), RWTH Aachen University, Aachen, Germany
 e-mail: leon.gorissen@llt.rwth-aachen.de; thomas.kaster@llt.rwth-aachen.de;
philipp.walderich@llt.rwth-aachen.de; constantin.haefner@llt.rwth-aachen.de

M. Grochowski · T. Henn · M. Völker · S. Kowalewski
 Institute for Embedded Software (ES), RWTH Aachen University, Aachen, Germany
 e-mail: grochowski@embedded.rwth-aachen.de; henn@embedded.rwth-aachen.de;
voelker@embedded.rwth-aachen.de; kowalewski@embedded.rwth-aachen.de

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,

E. Iacomini · M. Herty

Institute of Geometry and Applied Mathematics (IGPM), RWTH Aachen University, Aachen, Germany

e-mail: iacomini@igpm.rwth-aachen.de; herty@igpm.rwth-aachen.de

M. Trinh · C. Brecher

Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

e-mail: m.trinh@wzl.rwth-aachen.de; c.brecher@wzl.rwth-aachen.de

A. F. Posada-Moreno · S. Trimpe

Institute for Data Science in Mechanical Engineering (DSME), RWTH Aachen University, Aachen, Germany

e-mail: andres.posada@dsme.rwth-aachen.de; trimpe@dsme.rwth-aachen.de

S. Zhang · J. H. Schleifenbaum

Institute for Digital Additive Production (DAP), RWTH Aachen University, Aachen, Germany

e-mail: song.zhang@dap.rwth-aachen.de; johannes.henrich.schleifenbaum@dap.rwth-aachen.de

R. H. Schmitt

Information Management in Mechanical Engineering (WZL-MQ/IMA), RWTH Aachen University, Aachen, Germany

Production Metrology and Quality Management, Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany

Fraunhofer IPT, Aachen, Germany

e-mail: r.schmitt@wzl.rwth-aachen.de

S. Decker · M. Jarke

Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany

e-mail: decker@informatik.rwth-aachen.de; jarke@informatik.rwth-aachen.de

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 data-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.

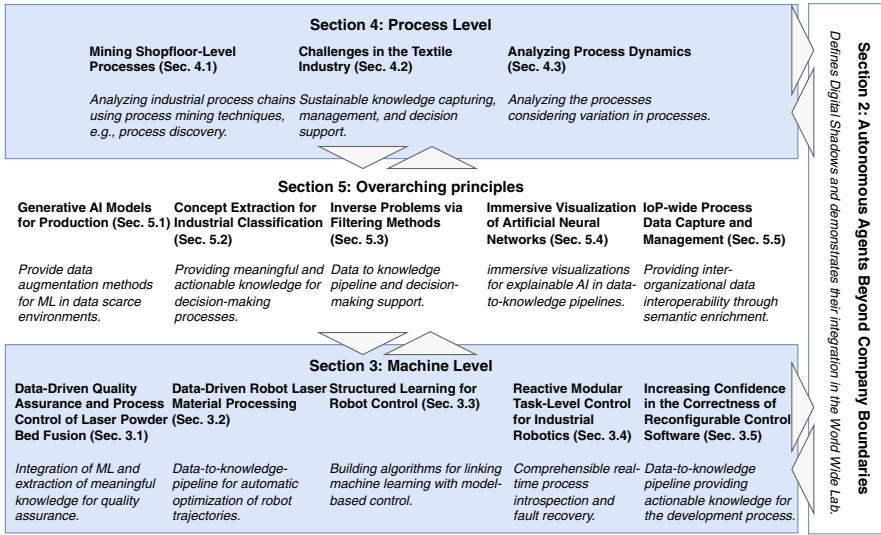


Fig. 5.1 Illustration of this chapter’s structure and its individual approaches and contributions

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.

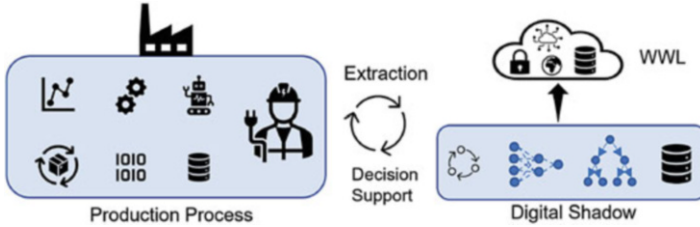


Fig. 5.2 A node in the WWL represents a production process whose models and/or data are continuously shared as a digital shadow in the WWL. These digital shadows are later used as a decision support system causing a feedback loop between the digital shadows and the process itself. (Image adapted from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

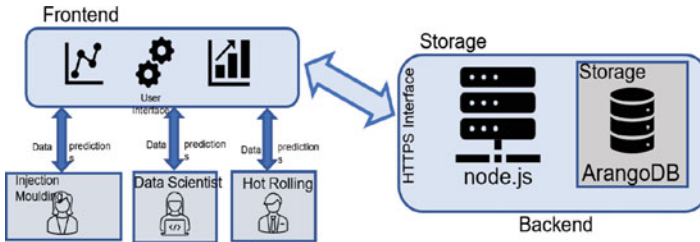


Fig. 5.3 An overview of the framework proposed in Liebenberg (2021) to support the WWL Agents in using the digital shadows provided by different nodes in the WWL. (©Image adapted from Liebenberg 2021)

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

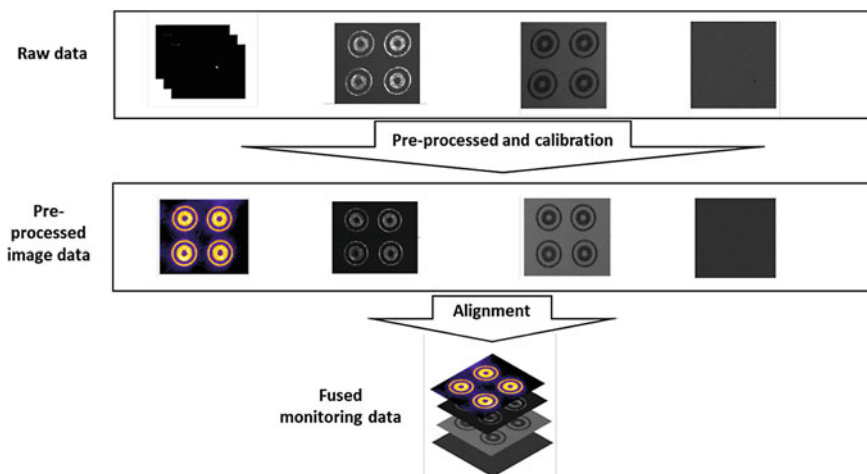


Fig. 5.4 Pre-processing of monitoring data from OT and optical camera for data processing

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.

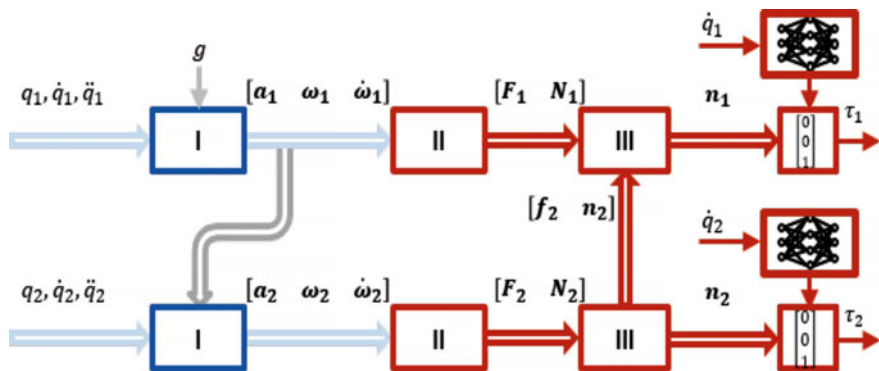


Fig. 5.5 Concept of a structured neural network for dynamics modeling of a robot with two degrees of freedom using the Newton-Euler equations and neural networks

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 Hierarchical 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

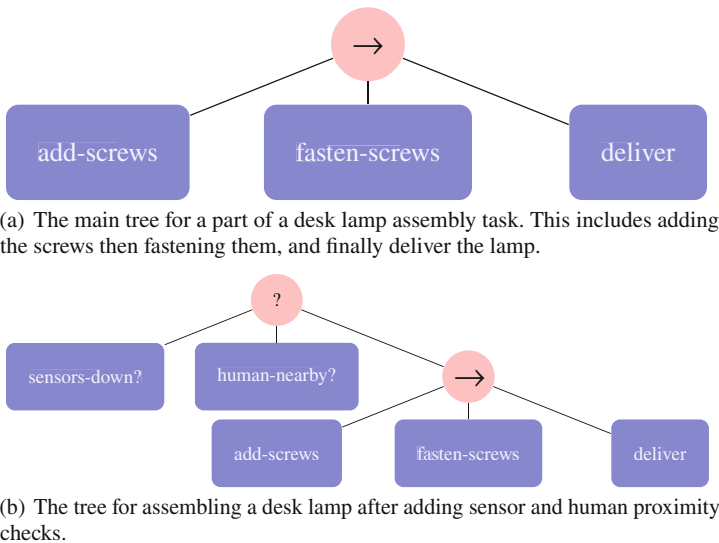


Fig. 5.6 An example of a BT used to assemble a desk lamp. (a) shows the core of the assembly task, while (b) shows the assembly task as the child of a Selector node (root). This tree only executes the assembly if the sensors of the robot are up (first branch fails) and that there is no humans nearby (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

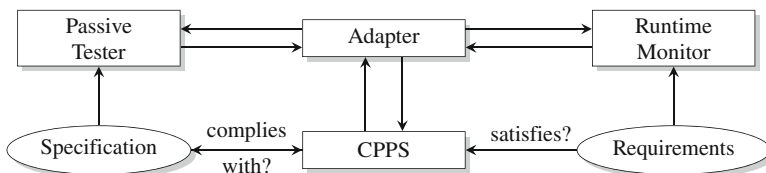


Fig. 5.7 High-level overview of the monitoring architecture

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 PM² 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

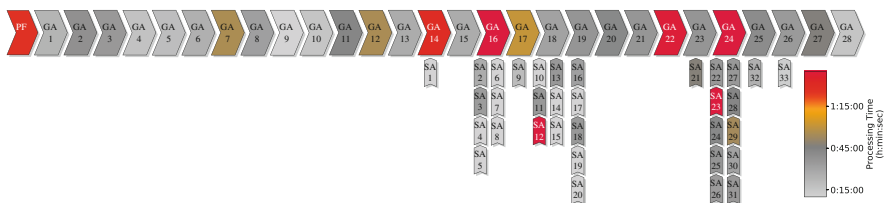


Fig. 5.8 Visualization of service time (red color scale) on the general assembly line and subassembly stations. The major bottleneck in the process is formed by the general assembly station GA16

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 **Multi-level Manufacturing Bills of Materials (M²BOM)**. 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 M²BOMs – to analyze manufacturing processes presented in a use case study of Heidelberg Druckmaschinen AG (Brockhoff et al. 2021). In this framework, we discover an M²BOM-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 g/m² or 450 g/m² 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

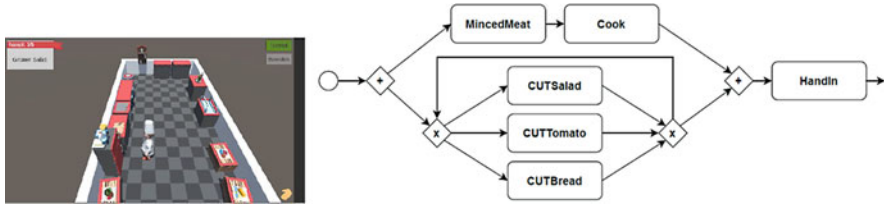


Fig. 5.10 A game-based approach to extract process knowledge from domain experts exemplified through a cooking game. (Images courtesy of the authors from Schemmer et al. 2022). (a) Screenshot of the game for extracting process knowledge. (b) Extracted process model of a recipe from a user study

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 dyeing. 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

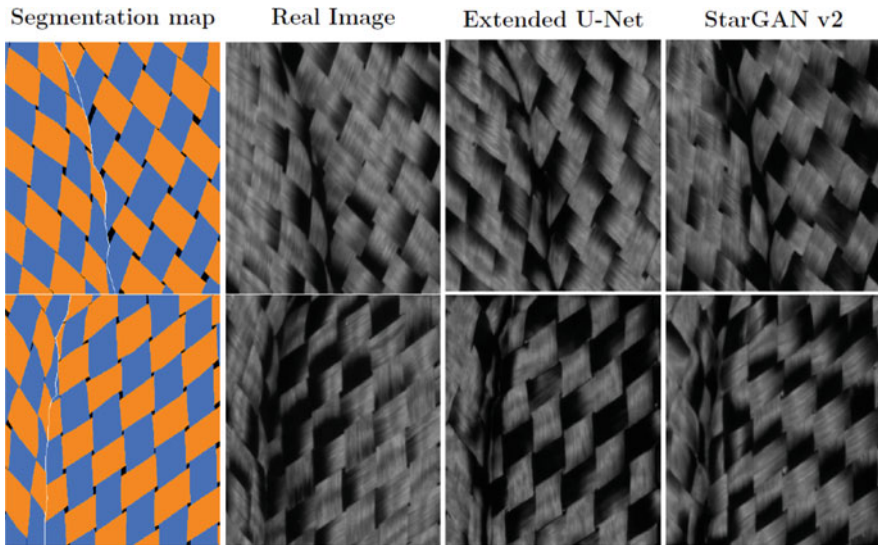


Fig. 5.11 We compared two generator architectures to synthesize realistic images of FRP. Both generators: Extended U-Net (Ronneberger et al. 2015) and the generator from StarGANv2 (Choi et al. 2020) are able to translate the segmentation map to realistic images of fiber-reinforced plastics that preserve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

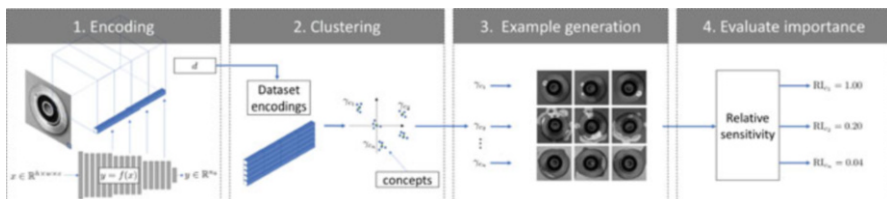


Fig. 5.12 Concept extraction method for CNNs. This method provides a pipeline to extract knowledge from a model, in the form of concepts influencing its prediction process

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 outperforms state-of-the-art global explainability methods in controlled scenarios and industrial use cases, providing explanations of how a model works, 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

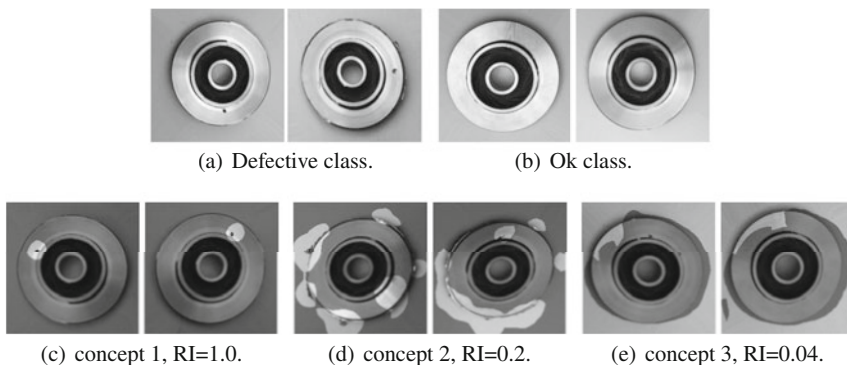


Fig. 5.13 Data set of casting parts, where the task is to classify defective (a) and ok parts (b). After training a DenseNet-121 to perform the said task, our method can analyze what was learned by the model. Figures (c), (d), and (e) show the main extracted concepts, which can be used by experts to 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:

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

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:

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

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

Equation (5.2) can be efficiently discretized by a particles method with $j = 1, \dots, J$ 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 $u_j^n = u_j(t^n)$:

$$\begin{aligned} u_j^{n+1} &= u_j^n + C(u^n) \mathcal{G}^T \Gamma^{-1} \left[y_j - \mathcal{G}(u_j^n) \right] \\ C(u^n) &= \frac{1}{J} \sum_{j=1}^J (u_j^n - \bar{u}^n) \otimes (\mathcal{G}(u_j^n) - \bar{\mathcal{G}}) \\ \bar{u}^n &= \frac{1}{J} \sum_{j=1}^J u_j^n \quad \bar{\mathcal{G}} = \frac{1}{J} \sum_{j=1}^J \mathcal{G}(u_j^n) \end{aligned}$$

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

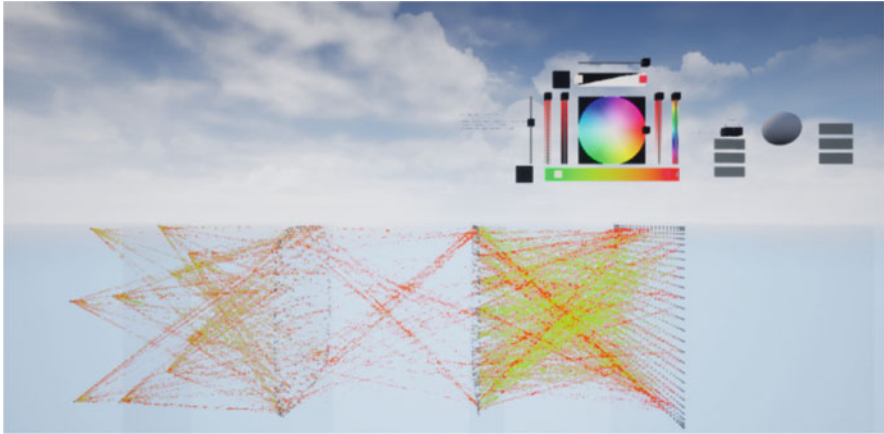


Fig. 5.14 The ANNtoNIA framework enables rapid prototyping of immersive visualization for ANN to facilitate visualization research and improve explainability

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/infering 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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