Integrative Production Technology

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Editors

Integrative Production Technology

Theory and Applications

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Foreword

More than ten years ago the *Federal and State Excellence Initiative* created important new development impulses for the German research landscape. Universities were given the unique opportunity to expand their fundamental and application-oriented, top-level research by improving framework conditions as well as to promote their research at an international level—an opportunity and challenge that the RWTH Aachen University was keen on accepting.

Since its foundation in 1870, the RWTH Aachen University has grown from a local polytechnic school to one of Europe's leading technical universities with an outstanding international reputation. With the future concept "2020: Meeting Global Challenges" the RWTH succeeded in redefining its strategic approach and realigning itself towards the future—while moving ahead vigorously. We want to make an essential contribution to top-level university research in Germany, compete globally and become one of the best technical universities in the world, under the motto "Excellence through integration, interdisciplinarity and innovative strength".

The Cluster of Excellence "Integrative Production Technology for High-Wage Countries" represents the successful, high-quality bundling of Aachen's competencies in the field of production technology. With the involvement of approximately 30 professors in the disciplines mechanical engineering, material science, computer science, mathematics, economics and psychology—as well as cooperation between 25 institutes, affiliated institutes and research facilities who conduct research together—the core feature of interdisciplinary, scientific research was impressively implemented. The focus is on sustainable approaches for the introduction of new technologies, products and theories—especially in the field of individualization, virtualization, hybridization and self-optimization. The aim is to strengthen and expand production in high-wage countries with regard to their competitiveness—and sustainability.

I am pleased that this book gives an overview of the developments and results of the Cluster of Excellence, making them also visible to the public while providing an outlook on key topics in production technology. I would like to thank all those who are dedicated to the Cluster of Excellence's research and have made contributions to this book.

Finally, let us look forward towards to continuing an excellent future together. The achieved results emphasize that the mutually pursued path in this extraordinary successful network has changed—and is still changing—the Aachen research environment and institutions. This can be seen via the creation of issue-specific, cross-institutional collaborations within the RWTH Aachen University campus that, in fact, is one of the biggest evolving production technology research landscapes in Europe.

Therefore, I wish you—and all of us—continued success going forward.

Aachen, Germany
August 2016

Univ.-Prof.Dr.-Ing. Ernst Schmachtenberg
Rector of RWTH Aachen University

Preface

In this book, the results of the second phase of the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" are summarized, addressing the question how to compete in high-wage countries successfully and sustainably in a changing economic, ecological and social environment. These changes underlie high dynamics that, for instance, result from varying customer needs, growing scarcity of raw materials and from demographic changes.

The integrative and interdisciplinary research approach of the Cluster of Excellence enables controlling and reacting to the related effects on production systems. The integration of production, material, natural and social scientists as well as of business economists allows combining expert knowledge for a holistic view of the interdependencies in complex socio-technical production systems across all production levels and value chain stages.

The defined research fields of the Cluster of Excellence—individualization, virtualization, integrated technologies and self-optimization—set the framework for integrative research and collaboration. The aims of the four technology-driven research fields are to be able to produce individualized products at mass production costs, virtually model methodologies and tools for assessing and predicting product properties and production systems, evaluate multi-technology platforms and products and to develop socio-technical production systems that are able to autonomously define and reach as well as maintain optimal operating points. The goal of the cross-sectional processes is to consolidate the technological research results towards sustainability in terms of scientific, personnel and structural development.

This book presents and summarizes the findings of the Cluster of Excellence during the second phase of funding in the Excellence Initiative framework. For more detailed results please refer to the corresponding scientific publications.

I would like to thank all contributing scientists for their extraordinary commitment and excellent results, as well as the German Research Foundation (DFG) for financing the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" during the second funding period of the Excellence Initiative. Furthermore, I would like to thank Anja Weber, Olga Blank and Robert Kinsella for their very helpful revision and editing work in this book.

Aachen, Germany
August 2016

Prof.Dr.-Ing. Christian Brecher
CEO of the Cluster of Excellence
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Overview

Chapter 1: Integrative Production Technology—Theory of Production at Application
Christian Brecher, Denis Özdemir, Anja Weber

Manufacturing is a key factor in a country's economic success. In manufacturing-oriented high-wage countries of Europe, Japan or South Korea it contributes to the largest share of exports and innovation. Skill shortages, volatility of markets and the urge to compete through innovation are major challenges for these countries. To cope with these challenges, ICT integration promises to increase productivity and shorten time-to-market.

This chapter first gives an overview on the economic background of manufacturing, and subsequently outlines opportunities and challenges for high-wage countries. The third section outlines the vision of integrative production technology in the scope of the economic background and thus provides a framework for the subsequent chapters.

Chapter 2: Direct, Mould-Less Production Systems
Wolfgang Bleck, Reinhart Poprawe, Frank Piller, Günther Schuh, Sebastian Barg, Arne Bohl, Sebastian Bremen, Jan Bültmann, Christian Hinke, Ruth Jiang, Robin Kleer, Simon Merkt, Ulrich Prahl, Michael Riesener, Johannes Schrage, Christian Weller, Stephan Ziegler

Additive Manufacturing (AM) technologies in general—and in particular, Selective Laser Melting (SLM)—are characterized by a fundamentally different relationship with respect to costs, lot size, and product complexity compared to conventional manufacturing processes. There is no increase of costs for small lot sizes (in contrast to mould-based technologies) and none for shape complexity either (in contrast to subtractive technologies). Thus, only the holistic development of a direct, mould-less production system that takes all relevant interdependencies along the product creation chain into account provides the full economic, ecologic and social benefits of AM technologies in future production. The following six subjects of the product creation chain were examined:

(i) New business models and customer willingness to pay for AM parts are revealed. (ii) The Product Production System (PPS) was totally revised regarding the adoption of SLM technology into conventional manufacturing environment. (iii) The SLM manufacturing costs were examined regarding different machine configurations. (iv) A high-power SLM process was developed for enhancing the process productivity. (v) High manganese steel was qualified for the SLM process. (vi) Finally, two lattice structure types and a design methodology for customer parts were developed.

Chapter 3: Mould-Based Production Systems
Andreas Bührig-Polaczek, Marek Behr, Christian Hopmann, Günther Schuh, Abassin Aryobsei, Stefanie Elgeti, Markus Frings, Jan Kantelberg, Michael Riesener, Frank Schmidt, Roland Siegbert, Uwe Vroomen, Christian Windeck and Nafi Yesildaq

Mould-based production systems are vastly common in mass production processes, due to the high investment costs of production equipment. In order to address the challenge of a strong tendency towards individualized customer demands, companies in high-wage countries are forced to react towards these changes. This chapter describes recent advances in the field of individualized production for mould-based production systems regarding plastics profile extrusion and high-pressure die casting. A holistic methodology for an integrated product and mould design is presented based on the principles of simultaneous engineering. In addition, recent advances in the field of numerical optimization are shown. The advances in numerical optimization will be carried out based on the processes mentioned above. The monitoring and simulation of the viscoelastic swell will be shown for plastics profile extrusion. For the field of high-pressure die casting the strategy to optimize the entire process will be outlined and current experimental results shown. For both application cases, the potential benefit of additive manufacturing technologies—such as Selective Laser Melting (SLM)—will be evaluated and validated inasmuch as possible.

Chapter 4: Virtual Production Intelligence
Sabina Jeschke, Achim Kampker, Torsten W. Kuhlen, Günther Schuh, Wolfgang Schulz, Toufik Al Khawli, Christian Büscher, Urs Eppelt, Sascha Gebhardt, Kai Kreisköther, Sebastian Pick, Rudolf Reinhard, Hasan Tercan, Julian Utsch, and Hanno Voet

The research area Virtual Production Intelligence (VPI) focuses on the integrated support of collaborative planning processes for production systems and products. The focus of the research is on processes for information processing in the design domains *Factory* and *Machine*. These processes provide the integration and interactive analysis of emerging, mostly heterogeneous planning information. The demonstrators (flapAssist, memoSlice und VPI platform) that are information systems serve for the validation of the scientific approaches and aim to realize a continuous and consistent information management in terms of the Digital Factory. Central challenges are the semantic information integration (e.g., by means of metamodelling), the subsequent evaluation as well as the visualization of planning information (e.g., by means of Visual Analytics and Virtual Reality). All scientific and technical work is done within an interdisciplinary team composed of engineers, computer scientists and physicists.

Chapter 5: Integrated Computational Materials and Production Engineering
Wolfgang Bleck, Christian Brecher, Michael Herty, Gerhard Hirt, Christian Hopmann, Fritz Klocke, Nikolai Borchmann, Jens Dierdorf, Hamidreza Farivar, Patrick Fayek, Axel Häck, Viktor Kripak, Markus Krömer, Gottfried Laschet, Ulrich Prahl, Markus Rüngeler, Georg J. Schmitz, Marcel Spekowius, Phillip Springer, Andre M. Teixeira

The research area "Integrative Computational Materials and Production Engineering" is based on the partial integration of individual models areas within separated simulation platforms with the objective of further development and integration into a single comprehensive ICMPE (Integrative Computational Materials and Production Engineering) platform that combines materials and machining simulation with factory and production planning. In order to realize an operational platform concept, the AixViPMaP has been implemented. AixViPMaP serves as a technology platform for the knowledge-driven design, implementation and improvement of complicated process chains for materials in high-value components. This allows manufacturing related influences to be considered during production in order to optimize process performance and materials properties.

The extension and application of the AixViPMaP platform towards production modelling in the sense of an ICMPE based on one holistic system integrates production related models with all material-related models into a single, unified concept. Advanced test cases are under examination to validate and assess this new integrated approach (e.g., new alloys for large gears for the wind industry).

Chapter 6: Multi-technology Platforms
Christian Brecher, Wolfgang Bleck, Jörg Feldhusen, Gerhard Hirt, Fritz Klocke, Uwe Reisgen, Robert Schmitt, David Bailly, Markus Bambach, Laura Conrads, Frédéric du Bois-Reymond, Alexander Göttmann, Stefan Gräfe, Mohammed Harraz, Jan Erik Heller, Werner Herfs, Krishna Komerla, Marvin Laugwitz, Manuel Löwer, Chris Mertin, Andreas Naumov, Johannes Nittinger, Martin Peterek, Ulrich Prahl, Jan Rey, Alexander Schiebahn, Alexander Schmid, Roman Schmitz, Stefan Tönissen, Holger Voswinckel, Maximilian Wegener, Frederik Wellmann

The growing demand for individualized commodities requires new solutions for a highly flexible yet cost-efficient production. Hence, the research results described in this chapter address the question of how different manufacturing technologies could be combined and employed efficiently in industrial practice.

Reaching across the whole field of Multi-Technology Platforms (MTPs) a generalized design methodology was examined. The resulting template-based procedure, combining function structure and technology chains, is introduced in the first section. Consecutively, the next section advances this approach by illustrating the incorporation of metrology into machine tools and MTPs. For technological validation, all newly developed scientific approaches were successfully integrated into four demonstrator test beds located at the RWTH Aachen University:

a Multi-Technology Machining Center, a Hybrid Sheet Metal Processing Center, a Conductive Friction Stir Welding Center and a laser-enhanced hybrid lathe. The economic efficiency of manufacturing technology integration is reviewed before a profitability assessment based on the aforementioned demonstrator test beds is performed. The chapter concludes with an outlook on future research topics.

Chapter 7: Multi-technology Products
Kirsten Bobzin, Andreas Bührig-Polaczek, Christian Hopmann, Peter Loosen, Reinhart Poprawe, Uwe Reisgen, Tobias Brögelmann, Arnold Gillner, Thomas F. Linke, Mehmet Öte, Uwe Vroomen, Christian Windeck, Michael Berens, Claudia A. Hartmann, Jan Klein, Nathan C. Kruppe, Xifang Liao, Patrick Messer, Mona Naderi, Philipp Ochotta, Magnus Orth, Florian Petzinka, Malte Röbig, Alexander Schiebahn, Johannes Schönberger, Michael Steger

Development of technical solutions that lead to widening the use of multi-technological products as well as in assessing ecological and economic potentials of multi-technological products have not yet been studied intensively. The activities conducted in the context of this research area focus on these aspects. The aforementioned aspects have been examined, evaluated and quantified on the basis of three example products resulting from the first funding period. The research activities conducted on the example components deliver the basis for the layout of different integrated multi-technology production systems.

Technical solutions that enable coupling of different process steps with each other as well as the integration of different functionalities and different materials in final multi-technology products have been proposed. The complex interdependencies of the products themselves and their associated production processes have been researched and evaluated intensively. Finally, a profitability assessment of the proposed solutions was conducted and future research topics identified.

Chapter 8: Cognition-Enhanced, Self-optimizing Production Networks
Christopher M. Schlick, Volker Stich, Robert Schmitt, Günther Schuh, Martina Ziefle, Christian Brecher, Matthias Blum, Alexander Mertens, Marco Faber, Sinem Kuz, Henning Petruck, Marco Fuhrmann, Melanie Luckert, Felix Brambring, Christina Reuter, Niklas Hering, Marcel Groten, Simone Korall, Daniel Pause, Philipp Brauner, Werner Herfs, Markus Odenbusch, Stephan Wein, Sebastian Stiller, Marvin Berthold

This research area focuses on the management systems and principles of a production system. It aims at controlling the complex interplay of heterogeneous processes in a highly dynamic environment, with special focus on individualized products in high-wage countries. The project addresses the comprehensive application of self-optimizing principles on all levels of the value chain. This implies the integration of self-optimizing control loops on cell level, with those addressing the production planning and control as well as supply chain and quality management aspects. A specific focus is on the consideration of human decisions during the production process. To establish socio-technical control loops, it is necessary to understand how human decisions are made in diffuse working processes as well as how cognitive and affective abilities form the human factor within production processes.

Chapter 9: Self-optimizing Production Technologies

Fritz Klocke, Dirk Abel, Thomas Gries, Christian Hopmann, Peter Loosen, Reinhard Poprawe, Uwe Reisgen, Robert Schmitt, Wolfgang Schulz, Peter Abels, Oliver Adams, Thomas Auerbach, Thomas Bobek, Guido Buchholz, Benjamin Döbbeler, Daniel Frank, Julian Heinisch, Torsten Hermanns, Yves-Simon Gloy, Gunnar Keitzel, Maximilian Kemper, Diana Suarez Martel, Viktor Reimer, Matthias Reiter, Marco Saggiomo, Max Schwenzer, Sebastian Stemmler, Stoyan Stoyanov, Ulrich Thombansen, Drazen Veselovac and Konrad Willms

Customer demands have become more individual and complex, requiring a highly flexible production. In high-wage countries, efficient and robust manufacturing processes are vital to ensure global competitiveness. One approach to solve the conflict between individualized products and high automation is Model-based Self-optimization (MBSO). It uses surrogate models to combine process measures and expert knowledge, enabling the technical system to determine its current operating point and thus optimize it accordingly. The objective is an autonomous and reliable process at its productivity limit.

The MBSO concept is implemented in eight demonstrators of different production technologies such as metal cutting, plastics processing, textile processing and inspection. They all have a different focus according to their specific production process, but share in common the use of models for optimization. Different approaches to generate suitable models are developed. With respect to implementation of MBSO, the challenge is the broad range of technologies, materials, scales and optimization variables. The results encourage further examination regarding industry applications.

Chapter 10: Cognition-Enhanced, Self-optimizing Assembly Systems

Robert Schmitt, Burkhard Corves, Peter Loosen, Christian Brecher, Sabina Jeschke, Walter Kimmelmann, Mathias Hüsing, Jochen Stollenwerk, Felix Bertelsmeier, Tim Detert, Sebastian Haag, Max Hoffmann, Martin Holters, Stefan Kurtenbach, Eike Permin, Marcel Prochnau, Christoph Storm, Markus Janßen

Due to shorter product life cycles and a rising demand for customization, flexibility and adaptability of assembly processes will become key elements in achieving sustainable success of industrial production in high-wage countries. Cognition-enhanced self-optimization as presented in this chapter has been identified as one major contributor to the enhancement of this flexibility and adaptability. The proposed approach to realize cognition-enhanced self-optimization for assembly systems in a broad range of application domains is to integrate dynamic behaviour allowing reactions on disturbances and unforeseen events by dynamically adapting the target objectives of internal control loops. Unlike the approach of traditional closed control loops in which target objectives of an optimization process are determined in advance, this approach defines goal functions as dynamically adaptable throughout the process.

The chapter concludes with two application examples—one dealing with the assembly of large-scale components (airplane structures) and the other with small component assembly (micro-optical elements)—presented to illustrate the industrial deployment of self-optimization for assembly tasks.

Chapter 11: Scientific Cooperation Engineering
Sabina Jeschke, Wolfgang Bleck, Anja Richert, Günther Schuh, Wolfgang Schulz, Martina Ziefle, André Bräkling, André Calero Valdez, Kirsten Dahmen, Ulrich Jansen, Claudia Jooß, Sarah L. Müller, Ulrich Prahl, Anne Kathrin Schaar, Mamta Sharma, Thomas Thiele

Scientific Cooperation Engineering researches, fosters and supports scientific cooperation on all hierarchical levels and beyond scientific disciplines as a key resource for innovation in the Cluster of Excellence. State-of-the-art research methods—such as structural equation models, success models or studies on success factors—that are frequently used in IS research are applied to create profound knowledge and insights in the contribution and optimal realization of scientific inter and trans-disciplinary communication and cooperation. A continuous formative evaluation is used to derive and explore insights into interdisciplinary collaboration and innovation processes from a management perspective. In addition, actor-based empirical studies are carried out to explore critical factors for interdisciplinary cooperation and intercultural diversity management. Based on these results, workflows, physical networking events and tailor-made training programs are created and iteratively optimized towards the cluster's needs. As Scientific Cooperation Engineering aims to gain empirical and data-driven knowledge, a Scientific Cooperation Portal and a prototypic flowchart application are under development to support workflows and project management. Furthermore, data science methods are currently implemented to recognize synergetic patterns based on bibliometric information and topical proximity, which is analyzed via project terminologies.

Chapter 12: Towards a Technology-Oriented Theory of Production
Günther Schuh, Malte Brettel, Christina Reuter, David Bendig, Christian Dölle, Niklas Friederichsen, Annika Hauptvogel, Thomas Kießling, Till Potente, Jan-Philipp Prote, Anja Ruth Weber, Bartholomäus Wolff

Manufacturing companies in high-wage countries—one of the pillars of the European national economies—are particularly exposed to changes in global markets and rising market volatility. It is therefore necessary that manufacturers in these countries not only focus on reducing costs, but instead address the entire set of commonly defined operational capabilities: cost, quality, flexibility and delivery performance. Although the optimization of these factors has been viewed since long as being largely mutually exclusive, we argue that advances in modern production technology might enable the resolution of the involved dichotomous relationships. In this chapter, we hence aim at presenting a technology-oriented theory of production that operationalizes the link between technological advances and possibilities to strengthen the four competitive priorities of manufacturing companies. For this purpose, existing production theories are first reviewed to ground and classify our theory. We subsequently formalize the technology-oriented theory by adopting a profitability assessment perspective derived from the insights of all projects within the Cluster of Excellence Integrative Production for High-Wage Countries.

Chapter 13**: Technology Platforms**
Christian Brecher, Günther Schuh, André Bräkling, Denis Özdemir, Anja Wassong, Anja Weber

The Cluster of Excellence (CoE) focuses on foundational research within production engineering as the basis for future innovation in high-wage countries. Turning the results of basic research into subsequent future innovation requires bidirectional knowledge transfer between universities and industry. Therefore, the CoE pushed the idea of so-called technology platforms. This includes new cooperation and communication structures, such as virtual platforms as well as new education and training concepts. This chapter provides an overview of the communication means and technology platforms that were established during the duration of the CoE. However, motivation, research questions, and the state-of-the-art of technology platforms are outlined beforehand.

Chapter 4
Virtual Production Intelligence (VPI)

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4.1 Summary

The Research Area (RA) *Virtual Production Intelligence* (VPI) is based on integration, analysis, and visualization methods to manage information in the area of virtual production continuously and semantically. By providing different information systems, the objective is to support production planning processes via the analysis of planning data in different design domains. Consequently, this chapter

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presents information processing research comprising the tasks identification, integration, extraction, analysis, and visualization of planning and simulation data generated along planning processes. Our approach, (VPI), draws on the successful concepts of Business Intelligence (BI) in the fields of data aggregation/condensation as well as their interpretation and exploitation.

Aggregation and propagation of heterogeneous data generated in virtual production environments is one of the main challenges in this area to facilitate the use of such information for interactive planning processes. The VPI approach opens up new opportunities of computer-based analysis and exploration for users from a broad range of different target groups, reaching from business administration over research and development (R&D) up to production engineers. It leads to better understanding of the underlying system's behavior, as well as new possibilities for knowledge transfer.

In order to implement this approach, it is necessary to integrate and validate methods and concepts of various disciplines like Computer Science, Mathematics, and Mechanical Engineering including data integration and visualization, knowledge engineering, modeling, and numerical simulation. Here, the main objective is a continuous and consistent information management for a batter decision support in production planning processes. This is reached by means of consolidation of planning data in the involved design domains and their harmonization using knowledge-based technologies, the development of domain-specific data exploration and data mining techniques, and their implementation into an interactive visualization and presentation. It accelerates and simplifies the process of finding cause–effect relations within modeled processes. Knowledge obtained this way enables, in our opinion, deriving formal correlations.

The VPI comprises methods to analyze and explore problems that arise in the field of Production Engineering, like the comparison of different simulated manufacturing processes considering domain-specific quality criteria. This facilitates deeper understanding of the socio-technical system *production* by providing, for example, ontology-based methods for robust tolerance prediction, comprehensive correlation analysis, and sensitivity analysis. Consequently, understanding the system's behavior helps to improve the underlying system models by model reduction or model refinement. This provides a sound basis for further optimization of the production system's outcome.

Furthermore, the vision of the VPI is to provide and analyze different design alternatives of production processes, which enables engineers to estimate and balance resource needs before they arise in the real production process. This contributes to the idea of green production leading to energy efficient and low-emission production. In addition, the application of a platform for the education and training of engineers provides the opportunity to consider production processes and their simulations from a hands-on viewpoint. VPI supports the reduction of skills shortages by enabling and encouraging a knowledge transfer between scientists and skilled engineering workers. Hence, VPI contributes to the economical, ecological, and social aspects of sustainable, competitive production in high-wage countries.

The comprehensive view of consolidated simulation and historical data developed in the previous funding period of the cluster of excellence leads to new and adopted analysis and evaluation methods. These are required by business administration, researchers, engineers, and students regarding current research fields, like green production and social phenomena, such as demographic change. The methods, for example robust tolerance prediction or sensitivity analysis, support a better understanding of the system's behavior and thus the possibility of optimizing underlying models. This includes scientific as well as information visualization aspects providing a seamless explorative space, wherever possible, through the available data and its interrelations.

To apply the concept of VPI to different areas of production planning, we regard the two main design domains *Factory* and *Machine* and research information systems that support planners to plan factories, production processes or products more efficiently and with a better understanding of the ongoing processes are taken into account. Within the domain of factory planning, the focus is on reaching interoperability of planning tools by means of ontologies and on new interaction concepts to visualize planning results, especially in the context of Virtual Reality (VR) applications. Regarding the machine level, we emphasize the process of laser cutting. We have developed a metamodel that generates a process map from simulation data of a multi-dimensional production process in order to analyze the laser cutting process again with interactive visualization techniques.

Although the requirements within the two domains are quite different, the VPI approach allows the use of similar methods and tools by following the same development process. Within the outlook, we present an integrative application scenario to combine both design domains. We implemented the results in an interactive analysis platform and in VR applications. Following this approach, we realized a continuous validation with the users in order to achieve improvement in the obtained results.

4.2 Motivation and Research Question

4.2.1 Virtual Production Intelligence (VPI)

Today, one of the most challenging tasks for manufacturers in high-wage countries consists in attaining high-quality products despite the complexity of production processes and the large number of production parameters. The objective is to achieve a better understanding of the underlying processes and to determine the dependencies of process parameters on quality and productivity criteria to be able to optimize production processes continuously. Furthermore, the planning of production processes is complicated by the fact that the required knowledge is dispersed among experts from different fields working on various aspects of the planning process, often at the same time. Hence, existing processes and technical support solutions support neither a quantitative evaluation of the planning itself nor a holistic and systematic decision support during the planning process, since adequate information systems currently do not exist. An effective approach to the realization of such a support tool is based on BI concepts. To enable the transformation of large amounts of data in a structured information model, solutions of simulations of factory or production processes have to be linked together in such a way that interdependencies in the planning process can be identified and analyzed flexibly. Therefore, the use of simulation applications in the field of production technology has gained importance in recent years.

VPI designates our concept that enables product, factory, and machine planners to plan products and their production collaboratively and holistically (Reinhard et al. 2012). The concept comprises methods to consolidate and propagate data generated in the domain of virtual production. Furthermore, it includes visualization and interaction techniques to analyze and to explore the retrieved information. We chose the term following the original idea of BI Systems with regard to virtual production. VPI refers to the mentioned concept of an integrated handling and analysis of information generated in the context of virtual production as defined in the VDI Guideline 4499 *Digital Factory* (VDI 2008).

We follow the principle of an adopted information management cycle to implement a new domain or to extend an existing one (see Fig. 4.1). Starting with the identification of the *information user*, information needs that are not satisfied with the current information infrastructure are identified and gathered. Afterward, we identify possible *information sources* and integrate them into the information structure. We realize this step by providing access as *information resources*. Furthermore, domain-specific analysis methods such as descriptive analysis or data mining are used to enrich existing information. The user triggers and controls the analysis via the *information products*, here our demonstrators. The VPI comprises

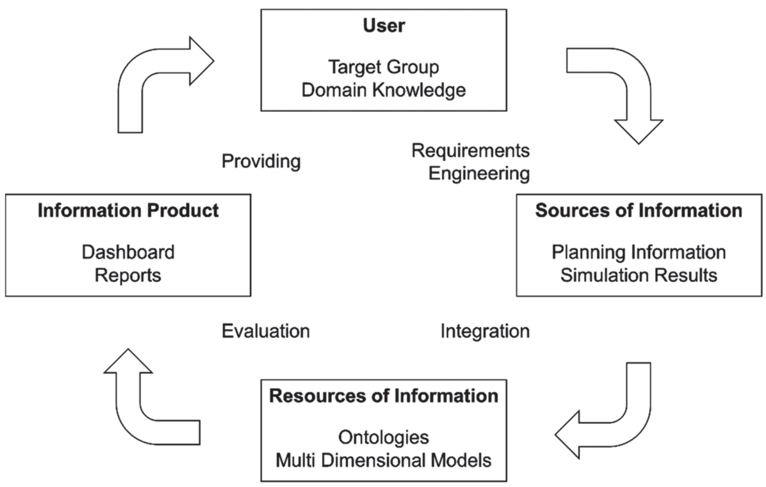

Fig. 4.1 Information management cycle. Adapted from Krcmar (2011)

the reduction of planning efforts and the increase of planning efficiency by providing an integrative analysis and its presentation through process maps, interactive planning cockpits and VR applications.

Thus, a central component in the information management cycle toward the information system is the definition of the underlying model with respect to the logic of the regarded domain and not just considering the data. Based on such consistent models, such as domain ontologies or metamodels of manufacturing processes, different applications, and services are used to integrate, process, and analyze the data in the backend of the information system and to present them in a user-driven way.

4.2.2 Research Questions and Solution Hypothesis

The overall research question concerning VPI is as follows:

> How can a continuous and consistent information management for virtual production starting from information integration up to analysis and visualization be realized by closing the gap between deterministic and cybernetic models to provide IT-based decision support in terms of optimizing production systems and improving the process knowledge?

This research question is specified in the two domains *Factory* and *Machine*. Concerning the information modeling of factory planning, research questions are:

(i) "How can the relevant concepts of the domain of factory planning and their interrelations be formalized in an explicit way?"
(ii) "What are the necessary steps of modeling and integration to provide semantic interoperability of planning and simulation applications used in factory planning?"
(iii) "How can VR techniques support the interactive factory planning (especially factory layout planning), and how can such tools semantically interact with the whole information system?"

Concerning the modeling of manufacturing processes that is considered in the domain *Machine*, in particular laser cutting, research questions are:

(i) "How can the choice of optimal machine working points be facilitated for a specific manufacturing task (e.g., in laser cutting) using the latest (theoretical) understanding/model of the specific manufacturing process?"
(ii) "How can a basic understanding of a complex model be improved by replacing the simulation model by a metamodel; and how can such metamodels be efficiently generated and validated within the pre-specified requirements by the domain expert or engineer?"
(iii) "How can metamodels be analyzed with the goal to first, foster the overall process understanding and second, perform optimizations for dedicated manufacturing tasks?"

The solution presented is to provide methods and methodologies from Computer Science for a collaborative analysis over different planning levels. First, the approach focuses on interoperability between all information sources that are used within a precise application scenario. This ensures that users can maintain their existing and approved information sources. Therefore, all concepts of the considered domain are explicitly formalized so that domain logic can be represented in the technical system. Finally, flexible and targeted analyses are realized based on a semantic annotation of planning information with the objective to optimize production systems and improve the process knowledge.

In factory planning, the solution hypothesis is to enrich planning data semantically by a comprehensive information model and by smart human–machine interaction, especially in VR. The so-gained information is analyzed and visualized using 2D/3D KPI cockpits. Concerning the modeling of manufacturing processes, in particular laser cutting, the solution hypothesis comprises the use of numerically operative process maps to apply the current (theoretical) understanding, which sets the base for any decision making in manufacturing management processes. Additionally, we investigate metamodeling methods and techniques to decrease the number of required simulation runs intelligently.

Within the RA VPI, the following four institutes work closely together: The Institute of Information Management in Mechanical Engineering from the Cybernetic-Cluster IMA/ZLW & IfU (*IMA*), the Visual Computing Institute (*VCI*), the Department of Factory Planning from the Laboratory for Machine Tools and Production Engineering (*WZL*), and the Nonlinear Dynamics of Laser Manufacturing Processes Instruction and Research Department (*NLD*). These partners fully cover the information management cycle in the regarded design domains (see Fig. 4.2). The WZL and the NLD are the domain experts in factory planning and laser cutting, respectively. They represent the information users, specify the requirements, and provide the information sources. The IMA is responsible for the

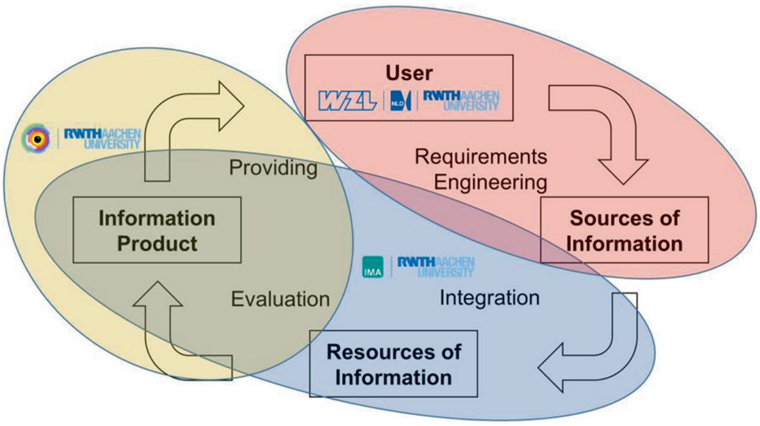

Fig. 4.2 Interaction of involved institutes

semantic information integration and modeling. The evaluation of information and the implementation of the information products are done by the IMA and the VCI, while the VCI additionally focuses on the interaction with the users.

4.3 State of the Art

In this section, the state of the art is presented concerning the relevant fields starting with the overarching aspect of information management with special focus on information modeling. This is followed by the two design domains—*Factory* and *Machine*—presenting the domain-specific state of the art as well as information integration and evaluation methods. Special focus is on the visualization of multi-dimensional data as well as on VR.

4.3.1 Information Management

4.3.1.1 Information Systems

An information system is a socio-technical system which has the objective of satisfying a specific demand of information for a certain task and user (Heinrich et al. 2011). In the context of production management, BI Systems play a decisive role. The term, coined by Luhn (1958), describes a fully automated system that facilitates the processing and propagation of data to the responsible departments. Nowadays, decision support systems (DSS), or more concrete BI Systems like data-driven DSS or Enterprise Information Systems (EIS), approach Luhn’s vision closest (Arnott and Pervan 2005). Nevertheless, due to the broad addressed targets of BI Systems, it is not surprising that several authors have criticized the term; and so new terms for a strict separation like Decision Intelligence System have emerged (Baars et al. 2010).

Recently, in factory and production planning the aim of information systems is to intelligently combine historical data from former planning processes or the real production and Virtual Factory (VF) models to optimize production and planning processes before the implementation of real factories (Hibino et al. 2006; Zhou 1999). Therefore, the use of simulation applications in the field of production technology has gained importance in recent years. However, numerous software solutions exist that provide IT support within the planning phase. Most of the existing systems are stand-alone solutions that focus on one aspect of the planning task. Especially EIS—which improve the functions of enterprise business processes by providing data, for instance, from Enterprise Resource Planning (ERP) or Computer-aided technologies (CAx) systems—serve as information sources to support planning decisions. Each system has its own focus and mostly its own information model that does not allow easy and autonomous data exchange between the systems. EIS thus provide a process model for the interchange, but do not solve the heterogeneity on the data level. Therefore, these heterogeneous systems are insufficient for evaluating the overall planning process due to the lack of interoperability (Brecher et al. 2012; Büscher et al. 2015).

4.3.1.2 Information Modeling

Information systems that provide interoperability of information sources are based on integrative information modeling of a whole (planning) process. As stated by Siau (1999), “Information modeling is the cornerstone of information systems analysis and design. Information models, the products of information modeling, [...] provide a formal basis for developing tools and techniques used in information system development.” Instead of focusing on the communication aspects, the technical point of information modeling deals with the formalization of a domain and the data gathered and observed within it. Halpin and Morgan (2008) elaborate that databases, in-memory object models, and user interfaces of typical software applications “deal with information and are best derived from an information model that clearly reveals the underlying semantics of the domain.”

In the domain of production and factory planning, heterogeneity still represents one of the main challenges as several different applications and standards exist. One tempting solution to solve the problems of heterogeneity is standardization—but its broad realization often fails (Doan et al. 2012). Again, systems that provide semantic interoperability of information sources are a valid alternative. This requires a suitable information model and corresponding integration processes. Basically, the concepts of information integration and application integration are distinguished. The consolidation of information from different data sources with normally diverse data structures is referred to as information integration, the consolidation of whole IT solutions along business processes as application integration (Ruh et al. 2001; Giachetti 2004). This research concentrates on the information integration and especially on the materialized integration—in contrast to the virtual integration—where data from sources are loaded, cleansed, and stored in a central database (Alexiev 2005; Meisen 2012).

4.3.2 Design Domain Factory

4.3.2.1 Factory Planning

Most existing factory planning approaches are based on an analytical view. They define factory planning as a linear process and divide it into discrete, sequential phases (Aggteleky 1987; Grundig 2009; Tompkins et al. 2010; Schenk et al. 2014). The phase model published in the German guideline VDI 5200 (VDI 2011), for instance, describes factory planning as a linear, isolated process composed of seven planning phases (see Fig. 4.3). A phase does not start until the preceding phase has been completed and predefined milestone criteria are met.

Several other factory planning approaches aim for a high configurability of planning projects. Factory planning is divided into many general sub-processes forming a modular system with modules that can be changed, specified, or omitted based on the project at hand (Bergholz 2005). Further approaches focus on project management solutions for the synchronization of concurrently executed sub-tasks and the coordination of multiple disciplines (Nyhuis et al. 2004). In addition to above-mentioned chronological or modular division for planning purposes, the functional elements (e.g., buildings, production resources, logistics resources) of the factory have to be addressed within the planning process.

Resources such as workers, material, and machinery form the smallest, distinguishable participants in value creation. Their behavior and influence on the produced good is governed by several parameters and properties. One exemplary resource might be a laser cutting process. This widely used technology is characterized by the parameters cutting speed, beam radius, beam focus, and shielding gas stream. The required knowledge for the design and configuration of all factory levels (whole factories, resources, processes; see Fig. 4.4) is hence highly fragmented and spread over a wide range of specialized disciplines. Factory planning is therefore performed by experts of different specializations and disciplines (such as factory planners, logisticians, technology experts) (Kampker et al. 2012; Barth

Fig. 4.3 Phase model of the factory planning process (VDI 2011)

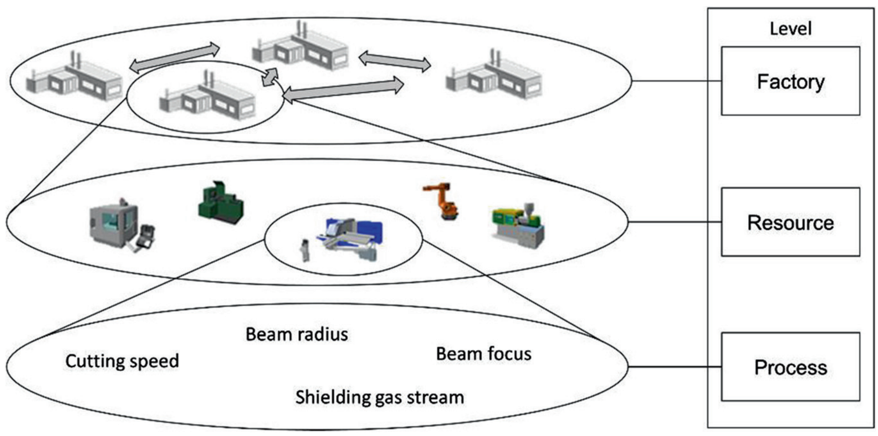

Fig. 4.4 Levels of production creation. Adapted from Bergholz (2005)

2011), whereas the selection and configuration of production resources is done by industrial engineers and technology experts. In practice, the approaches of discrete, sequential phases show several limitations, and the described fragmented execution of specific planning tasks by experts of many different disciplines leads to problems that require solutions.

First of all, current factory planning approaches do not provide guidelines for the type of information that must be exchanged among the planning participants or for when this exchange must take place (Kampker et al. 2012; Schenk et al. 2014). This lack of transparency leads to inefficiencies within the planning process (e.g., idling, relaying of false, insufficient or over-engineered information).

Furthermore, it is not possible to address changes during the planning process—such as those due to varying production forecasts or an updated product—in an efficient manner. Within a sequential proceeding, every change results in a second execution of already finished planning tasks. In fact, the high connectivity of planning tasks calls for an information-focused approach for the planning process. A clustering of tasks with strong interdependencies would allow for a faster and more efficient reaction to changes.

In terms of planning fragmentation among experts, the problem of local optimization at the cost of missing the global planning optimum arises (Kampker et al. 2012). Experts do not know exactly whether or how results influence other planning tasks, as they work more or less independently from other experts in isolated knowledge clouds. These knowledge clouds exist on all factory levels (e.g., factory planners, technology experts; see Fig. 4.5) and the identification and establishment of necessary information flow between them is a major challenge for factory planning projects.

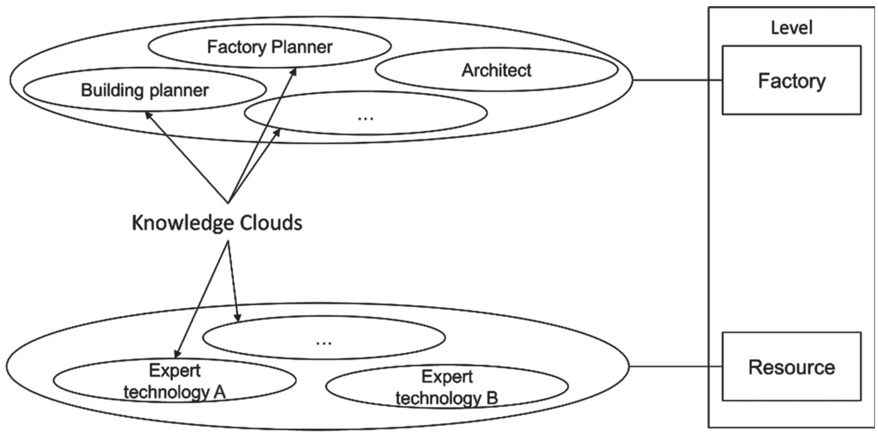

Fig. 4.5 Knowledge clouds on different factory levels. Adapted from Bergholz (2005)

4.3.2.2 Information Management in Factory Planning

In recent years, efforts have emerged which consider the factory as a whole. The objectives are a comprehensive network of digital models, methods and tools (within Digital Factory), or even an integrated simulation model of major subsystems in a factory (within VF) (VDI 2008; Bracht et al. 2011). The common challenge consists in the integration of methodologies and applications within an adequate platform, which has not been reached yet (Tolio et al. 2013). In addition to the idea of standardization and complete software suites that cover various functionalities of VF in different tools by means of an implicit overall model, promising technologies appear from Computer Science, such as the definition of ontologies and the semantic enrichment of data for an interoperability of EIS. Thus, information systems that provide such a semantic interoperability of heterogeneous information sources gain importance toward realizing the vision of VF (Zdravković et al. 2011; Lin et al. 2004).

Based on the described information processing techniques, one aim of the current research in factory planning consists in systematizing the knowledge of experts. Again, information modeling is the fundamental approach. Terkaj et al. (2012) presented with their VF Data Model a framework which provides a common definition of the data that is shared among the considered software tools. Within the underlying EU project *VF Framework* an information model is set up by means of several ontologies to realize a functional virtual model of a real factory. Furthermore, several information models have been developed over the past few years focusing on different aspects of factory planning and in varying levels of detail. For instance, Chen (2012) developed an information model for factory layout planning to structure and represent information and knowledge. Weimer (2010) and Ackermann et al. (2013) concentrated on the integration of factory planning and factory operation. All approaches provide advanced concepts using mostly classical modeling languages. Nonetheless, instead of using the information model only to define a common language between engineers and business users or to derive the logical data model, the information model should be integrated as a central component into the technical system. Hence, the presented approaches are not practicable for the desired support of factory planning projects by means of semantic modeling.

4.3.2.3 Factory Layout Planning Using Virtual Reality

In recent past, VR technology and visualization techniques have been repeatedly applied to virtual production. Here, their main purpose is to help in reducing the time and costs that is necessary to bring a product from conceptualization to its manufacturing. In the context of factory layout planning, VR and visualization techniques are used to support planners in evaluating and reviewing their layouts before implementing them in the real factory. However, while many essential support tools have already been realized, we argue that factory layout planning will benefit from additional VR tools.

In a user study, Korves and Loftus (2000) determined the added-value of an immersive HMD-based approach over a non-immersive monitor-based one in the context of factory planning. To this end, study participants were asked to virtually examine a workplace using both systems and detect certain design flaws that had been put in. Results indicated that users were more likely to detect flaws using the HMD approach. They concluded that immersive VR is advantageous for design reviews in factory planning. Korves and Loftus (1999) also described a CAVE-like virtual environment (VE) to support the layout planning process of individual manufacturing cells (MC). Planners can perform virtual walkthroughs of factory models and furthermore modify them directly from within the VE by interactively placing new or rearranging existing shop-floor equipment. While doing so, planners receive textual feedback if certain layout constraints have been violated, such as when access points or the like are being obstructed. The system by Neugebauer et al. (2011) offers similar functionality. However, instead of realizing the planning by means of interaction within the VE, users perform planning operations, like machine placement or arrangement, using a commercial planning tool that runs on a touch sensitive display table (similar to the planning cockpit by Fraunhofer IPA). Changes made within this tool are immediately reflected in the VE where they can be reviewed subsequently. Additionally, the system assists planners in avoiding energy waste by means of a VE-integrated visualization of energy flows between energy consumers and producers.

In contrast to the aforementioned solutions, the system presented by Caputo et al. (2006) uses VR to enable walkthroughs through simulated manufacturing systems. For this, factory models and the simulations of manufacturing processes are first prepared offline using several different commercially available planning and simulation tools. The results can be explored using a Powerwall VR display system. In addition to passive exploration, the system allows the ergonomic evaluation of manual work cells by means of direct manipulation interaction approaches for which, among others, tracked data gloves were used. Similar to this, Schenk et al. (2005) proposed to use VR as a means for assembly procedure training of workers. However, while they briefly describe general requirements toward such a system, they do neither discuss a concrete realization nor give any information on how an appropriate VR solution would have to be realized.

Aurich et al. (2009) mentioned the usefulness of Immersive Virtual Reality (IVR) in the context of Continuous Improvement Processes. They discussed interaction aspects of IVR but did not give concrete details on their implementation.

Sacco et al. (2010) presented the VF Framework which tries to establish a base for the implementation of a next-generation VF. Its core component is the Virtual Factory Manager (Sacco et al. 2011) that integrates a variety of different planning applications into a larger planning workflow. It allows concurrent access to a common versioned data repository by means of web services. A proof of concept prototype is discussed, but an extension to IVR is not considered.

One important aspect of the planning process is communication between the involved planners. In this context, Menck et al. (2012) discuss VR as a means to support the collaborative factory planning process and particularly name data annotation as an important communication tool in this context. They indicate that no comprehensive approach exists so far, and define important requirements. However, they neither present concrete interaction approaches nor evaluate the applicability of their classification.

One annotation solution for architectural planning has been presented by Jung et al. (2002), who allowed the creation of text-based annotations which can be shared within a globally distributed team. An early VR-based annotation system called *The Virtual Annotation System* was presented by Harmon et al. (1996). It allowed leaving audio markers within a virtual scene but did not offer much functionality aside from that. A more elaborate approach was recently proposed by Guerreiro et al. (2014) who used data annotation to support the planning of offshore oil platforms by remote collaborators. Their system offered a lot more functionality in the form of advanced annotation types. However, they did not clearly discuss effective means for CAVE-like VR systems to create these annotations. Previously, Abbott et al. (2011) presented a similar annotation system for the discussion of cultural heritage sites among researches. However, details on solutions for interaction problems were not thoroughly discussed.

4.3.3 Design Domain Machine

4.3.3.1 Modeling of Laser Applications in Manufacturing

Laser Cutting and its Simulation

In many sectors of production, laser technology has already become a state-of-the-art technology, where laser cutting is the most established one (Belforte 2015). Laser cutting is a thermal separation process widely used in shaping and contour cutting applications. The most relevant industrial laser cutting process is the fusion metal cutting process, as the cutting of large metal sheets into smaller pieces with specified contours is addressed in many branches of the manufacturing industry (especially metal working industry like automotive, aircraft, and ship-building industries). Laser cutting surpasses conventional cutting techniques since it is faster, more accurate, and at the same time more flexible with the optical tool laser not being exposed to any wear.

The ablation process in fusion metal cutting is mainly based on thermodynamics and hydrodynamics. At first, the absorbed laser energy is converted to heat that melts the material, and second, this melt is driven out of the cut kerf by a gas jet, coming out of a cutting nozzle coaxially aligned with the laser beam. Some process evaluation criteria are of major interest in the context of this manufacturing technology. These include, for instance, cut quality, adherent dross, and maximum cutting speed.

When laser cutting was invented (in the 1970s with CO_2-Lasers as those were the most powerful laser systems at that time), laser technology was so new that the developers of the laser and the cutting system were both necessary to operate and maintain such a laser cutting machine. Due to insufficient reliability, it was impossible to use laser cutting machines in production at that time. The new technology had to be validated to find out how to use laser cutting adequately for given materials and cutting tasks. This meant that configuration parameters for laser cutting machines had to be found (e.g., minimal laser energy/power necessary to perform a cut at all, necessary gas pressure to drive out the molten material, etc.). At this stage, only highly trained people were able to apply laser cutting technology.

On the way to industrial use, the laser was used in niche applications, specialized for one single purpose/cutting task and even only as a supplementary tool (such as in laser-assisted oxygen jet cutting of titanium for aerospace applications). So it was combined with already established technology (in this case oxygen cutting) to get to know operating conditions. Even having identified the laser's establishment in the industrial cutting applications, it was still a job for highly trained people to run laser machines and cut the material given to them, to choose a working configuration of laser, handling, and gas flow parameters.

Even nowadays, when using laser cutting systems in production, choosing the appropriate machine parameter set (comprising parameters for the laser optical system, nozzle design parameters, and other process design parameters) has become a crucial ingredient in coping with complex cutting tasks as a result of fast changing market demands. Laser cutting machine manufacturers have started to attach working parameter settings for specific predefined cutting tasks onto their machines.

The processing parameter values for each cutting task are stored in empirically determined technology tables and simply chosen by the operator (advanced operators may even be able to adjust those settings slightly) for achieving different market/product demands, such as minimum ripples, no dross formation, fast cut. Those technology tables, which are generated by every laser cutting machine manufacturer for their machines specifically, are expensive, labor-intensive, vastly time-consuming (due to the high number of cutting experiments) and finally reveal only a discrete set of potentially beneficial operating points of the machine. The data contained in these tables are produced by numerous experimental tests performed by experts or highly trained employees.

The data contained in these tables are produced by numerous experimental tests performed by appropriate Design of Experiment (DOE) techniques as well as other, experience-based procedures. Recently, a modern approach to reduce the time and costs for those experiments has gained considerable importance. It is based on using the computational methods and simulation applications in the field of production technology. These simulation applications have positively influenced R&D in the industrial environment (Schulz 1998). They turned out to be useful for production planning as they enable the user to cope with the complexity mentioned above.

The conventional technique in modeling and simulation of manufacturing processes is performing several sets of individual simulations, and knowledge is extracted directly via post-processing of the simulation results. Each individual simulation is characterized by a set of parameters in a high-dimensional parameter space. At this point, it is important to mention that the parameter–criteria relationship in this stage is just revealed by a set of discrete data and thus may already be indicated by taking advantage of appropriate scatter-diagrams mapping parameters on criteria. However, this data might not be characterized in sufficient detail in order to obtain a deep understanding and accomplish any parameter optimization.

Metamodeling

In order to overcome the limitations of the costly simulations and the discrete nature of either experimental or simulative data, researchers are recently using approximation models that reproduce the behavior of an originally physical simulation up to a required accuracy. These models, also known as metamodels, are not only faster but also less expensive in post-evaluation than physically motivated simulation models and can be constantly questioned when running an operation on the model (data).

With the computational power of today's high-performance computing systems, commonly maintained by research institutes, it is possible to execute simulations on predefined points in the parameter space, which may be called seed points (as they are seeding either the process understanding as well as parametric optimization procedures), within a reasonable amount of time. In order to understand and optimize the process, the simulation has to be performed on different seed points within a wide parameter design space. This allows a complete overview of the solution properties that also contributes well to design optimization processes.

To find useful applications of such an approach in industrial environments, it is crucial to represent the process know-how learned with these simulations in a form that can be handed over to end users of a certain manufacturing technique. This is part of the concept of metamodels and process maps.

The concept of metamodeling techniques is an innovative approach that is forcing a change in the way production planning is realized. It is applied in a lot of manufacturing and production industries (Booker et al. 1999; Martin and Simpson 2002; Forsberg and Nilsson 2005). Metamodels create cheap numeric surrogates that describe cause–effect relationships between setting parameters as input and product quality variables as output for manufacturing processes. It supports the direct transfer of the knowledge from experts in research and experiments to the machine operator in a real production environment and vice versa via a user interactive tool. Such a tool provides a landscape or process map that can be used as an integrated, dynamic, accessible, and visible navigation system that aims for a more reliable and more effective decision-making procedure. This guarantees a mutual benefit since scientific advances and economical needs are assured, especially when production demands are rapidly changing or new manufacturing systems are developed.

Metamodeling techniques rely on preselected sampling data known as training data. The procedure to select the best coordinates for the training data is addressed by DOE techniques. Although the name DOE suggests real-world experiments, it may also be used in the context of *virtual* experiments, such as in simulations.

A survey of DOE methods can be found in Box and Draper (1987). The basic form is the Factorial Design (FD) where data are collected for all possible combinations of different predefined sampling levels of the full parameter space (Box and Hunter 2005). However, for high-dimensional parameter space, the size of FD data set increases exponentially with the number of parameters considered. This leads to the well-known term curse of dimensionality defined by Bellman (1957) which means that an unmanageable number of runs are consequently conducted to sample the parameter space adequately. Many researchers confirmed that the experimental design for deterministic computer analyses should be space filling. Well-known space filling designs are the Orthogonal Arrays, Latin Hypercube designs, Hemmersley sequences, and uniform designs (Kleijnen 2008; HassounaYounis 2010).

After the selection of the training data that contains the parameters-criteria pairs, a global approximation needs to be performed. The global approximation is equivalent to finding the best continuous mapping of the discrete training data. Due to the fact that the method will be applied to deterministic computer models, the criterion that is considered in this context is an exact match (interpolation) of the function to be guessed (metamodel) and the given output variables (simulation). Approximation techniques evolve from the DOE theory in which polynomial functions are used as response surfaces or metamodels.

Besides the commonly used polynomial functions, Sacks proposed the use of a stochastic model called Kriging (Sacks et al. 1989) to treat the deterministic computer response as a realization of a random function with respect to the actual system response. Neural networks are also applied to generate the response surfaces for system approximation (Haykin 1999). Other types of models include Radial Basis Functions (RBF), Multivariate Adaptive Regression Splines (MARS), Least Interpolating Polynomials, and Inductive Learning (Gorissen 2010).

After a metamodel is generated, it is validated before being used as a surrogate of the computation-intensive processes. Model validation and assessment is an interesting and yet challenging task in the typical computational models (Kleijnen 2008). Validating a metamodel is done through two methods:

(i) the use of an additional sample point set to check the predicted function value with the real ones, and
(ii) the cross-validation method that includes leave-one-out or leave-k-out approaches.

Once built and validated, the metamodel is used to predict the model responses at unproven designs quickly and repetitively. A survey of metamodeling application in manufacturing and production tasks can be found in Kleijnen (2008), Gorissen (2010), HassounaYounis (2010) and Al Khawli et al. (2015).

4.3.3.2 Visualization of Multi-dimensional Data

Metamodels represent multi-dimensional functions that are inherently hard for humans to understand. While statistical methods help in gaining an overall understanding of such functions, deeper and more detailed insights can be provided by means of visualization. A huge research body already documents this topic. However, no solution has been presented so far that suits all the needs for the analysis of multi-dimensional metamodels.

Kehrer and Hauser (2013) provided a recent survey on visualization techniques which covers both multi-dimensional and multivariate data. Based on the notion of small multiples, Tufte (1983) as well as Becker and Cleveland (1987) proposed the direct selection of data points (brushing in a scatterplot matrix), in order to facilitate the discovery of relationships between variables, i.e., sensitivity analysis. While we use a scatterplot matrix to facilitate sensitivity analysis of metamodels, the concept of brushing and linking is replaced by dynamic point generation based on user-defined generation rules. Following a similar layout as the scatterplot matrix, van Wijk and van Liere (1993) introduced HyperSlice, which is also adapted as one element of our proposed visualization approach. Based on the idea of the scatterplot matrix, Elmqvist et al. (2008) focused on interactive navigation in the parameter space.

Sedlmair et al. (2014) established a conceptual framework for visual parameter analysis. With regard to the terminology proposed in their framework, our solution provides analysis tasks for optimization, uncertainty, and sensitivity on the predicted outputs of surrogate models (i.e., metamodels) for the physical models of manufacturing processes. Several solutions incorporated multiple linked view designs (Roberts 2007) for visual parameter analysis and addressed similar analysis tasks that we do. Piringer et al. (2010) presented HyperMoVal, which provides a combined visualization of a regression model in combination with validation data to assess the match between both. While we base our work on similar visualization techniques, we face different prerequisites and goals in our solution. We visualize metamodels in order to provide an understanding of the underlying manufacturing process and to allow the identification of parameter configurations that meet desired production criteria. A solution for finding suitable parameter combinations for image segmentation algorithms was introduced by Torsney-Weir et al. (2011).

Based on the exploration of Gaussian process models, they proposed an approach to iteratively refine and explore such models in order to identify parameter combinations for image segmentation algorithms. While we use similar methods for the visualization of the parameter space and enable users to identify ideal parameter combinations, we face different challenges since our metamodels can contain by far more samples, and iterative manual refinement is not feasible due to long simulation times.

Berger et al. (2011) presented an approach for the uncertainty-aware exploration of continuous parameter spaces. They employed 2D scatterplots and parallel coordinates augmented with additional information on the uncertainty of predicted results between sampling points. While their solutions for the visualization of uncertainties are well suited for the used visualization methods, they can hardly be adapted to the continuous data representations of our metamodels. Instead, we visualize aspects of uncertainty that are encoded inherently in the metamodels themselves.

Vismon, Booshehrian et al. (2012) published a design study that tailored to the needs of analysis in fishery management. Here, they analyzed the effects of two input variables on many output variables, thereby incorporating sensitivity and constraint-based analysis as well as analysis of tradeoffs and uncertainty. The key difference to our work is that we usually face metamodels with more input than output variables, what implies the need for a different visualization design.

For two-dimensional scalar field visualization, color-coding over a plane is a standard technique. A three-dimensional scalar function can be efficiently visualized by means of direct volume rendering (Engel et al. 2006). In this work, we rely on both, color-coded 2D slices and direct volume rendering, which depict 2D and 3D cuts through the multi-dimensional domain.

The gradient field is of key importance for the understanding of a scalar function (Maxwell 1870; Smale 1961). Specifically, for more than one input variable, gradient trajectories facilitate a better understanding of the general behavior of a scalar field and its local sensitivity since they directly show the direction of the strongest change. In scientific visualization, topological approaches have enjoyed significant success in a variety of settings. In particular, recent developments based on Morse theory (Milnor 1963) have led to a variety of approaches for the computation and visualization of the Morse-Smale complex (MSC) of scalar fields (Edelsbrunner et al. 2001; Bremer et al. 2004; Edelsbrunner et al. 2003; Gyulassy et al. 2007, 2008). Oesterling et al. (2010) and Gerber et al. (2010) adapt ideas rooted in topology to the exploration of multi-dimensional data. These and related approaches have been proven to be a versatile tool for the examination of scalar functions. However, metamodels for production processes are often monotonic or with low polynomial order for individual parameters. Hence, some of them do not contain local extrema within the process domain. Moreover, ideal parameter settings are not always characterized by local extrema. Thus, existing topology-based visualization approaches have been analyzed and could provide useful overviews on metamodels, but were not capable of revealing details to a reasonable amount.

4.4 Results

This section contains the presentation of results we obtained in the RA VPI. Therefore, we followed the information management cycle by Krcmar (2011), which is shown in Fig. 4.1. As mentioned above, this RA focuses on the two design domains *Factory* and *Machine*. Within each design domain, the information management cycle defines four phases addressing the development of information systems enabling the integration and the explorative and interactive analysis of planning information with the aid of appropriate analysis algorithms. In both design domains, production engineers are the users. For both design domains, the next sections present these phases within the subsections *sources of information*, *resources of information* and *information products*.

4.4.1 *Design Domain Factory*

4.4.1.1 Sources of Information[1]

Application Scenario: Condition-Based Factory Planning

To demonstrate the concept of VPI and our information products in the application domain of factory planning, we implemented a VPI-driven information system to support the Condition-Based Factory Planning (CBFP) approach (Büscher et al. 2014). The main idea of CBFP is the modularization of different planning tasks not with regard to a temporal chronology but instead to their contents (Schuh et al. 2011). In contrast to the existing approaches that were introduced in Sect. 4.3.2.1, this enables the development of an individual and timely efficient project plan for each factory planning project which considers the precise tasks of the project with regard to their required intensity. Hereby, a module encloses a single planning task with defined input and output information, respectively parameters (see Fig. 4.6). These parameters contain the actual planning information. Hence, the CBFP is much more flexible than the established but rigid planning procedures.

So far, the CBFP approach provides a construct for the information flow. Furthermore, it provides the basis for an information model describing the necessary and the optional information as well as their relations along the planning process. Therefore, several types of information are differentiated:

- *Input information* of a module that is a planning result (output information) from a previous one
- *Input information* that has to be generated before starting with the planning task of the module (e.g., by data export from ERP system, by expert interviews, or by workshops)

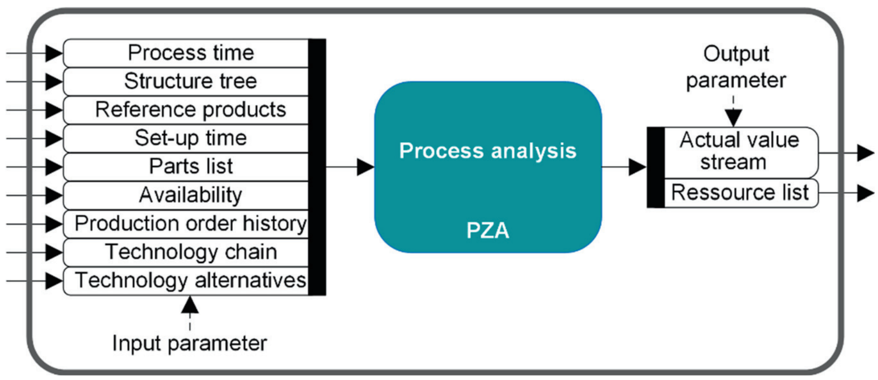

Fig. 4.6 CBFP module *Process analysis*. Adapted from Nöcker (2012)

[1]The results presented in Sects. 4.4.1.1 and 4.4.1.2 have been previously published in Büscher et al. (2016).

- *Output information* is the result of a certain planning module, generated in the end of the planning step, and used in further modules or as a final planning result.

This overall landscape of modules is the basis for an IT-based analysis of the planning process. Still, the management of the data and the pieces of information within a precise planning project is complex. CBFP does not provide an information system to support the planner on a data level. There is distributed data storage within the individual planning and simulation applications. Hence, the transfer of data between the sources in order to perform an evaluation is time-consuming and error-prone.

Therefore, we realized the coupling of the CBFP approach and the VPI, which has been introduced in Büscher et al. (2014). The objective is a continuous and consistent information modeling along whole planning projects to support planners with methods for automated information evaluation and analysis. Thereby, firstly seven CBFP planning modules from the area of production structure planning are considered. The main challenge is to reach interoperability of the heterogeneous data sources by information integration techniques. Both processes of information modeling and integration are presented in the following sections.

The Process of Information Modeling

The general process of information modeling that we pursue consists of the following four steps (Büscher et al. 2016):

(i) Definition of the domain-specific information model
(ii) Explicit formalization of the concepts, relationships, and constraints within a domain ontology
(iii) Derivation of the logical data model of the concrete application
(iv) Derivation of validation rules for consistency checking.

The first step of the modeling process comprises the definition of the information model of the respective domain—in our case the domain of factory planning. By means of analyzing the identified data sources and performing interviews with domain experts, the objective of the information model is to reach a common language and understanding of the concepts used in the domain. Therefore, the model is firstly created and visualized by classical modeling languages like the Unified Modeling Language (UML).

To reach the desired machine interpretability of the business logic of the domain, the concepts, relationships, and constraints are explicitly formalized in the next step by means of the semantic technology of ontologies. Besides of structural ontologies, the main part consists of the domain ontology. Through this, description logic-based reasoning becomes conceivable so that the automatic identification of constraint violations and the extraction of unspecified but implicitly valid information by the system become realizable.

This generic information model is the starting point for the logical data model of the concrete application, which can be derived from the information model. As a next step, the mapping between the ontology and the logical data model is defined, to assign concrete data to the corresponding concept of the information model directly. Therefore, the data model defines the object-relational mapping, for instance, by concretizing many-to-many relationships of the information model. Within this step, the implicit information of the domain ontology gets lost, as it cannot be represented within the data model.

However, the constraints and relations within the information model allow the extraction of validation and consistency rules that we use to realize a consistency check of the planning data during the integration. This process is fully automated so that the integration process automatically adapts to changes in the information model (and the corresponding changes required in the underlying data model). Hence, we can ensure high data quality within the information base of the *VPI platform* as the integration process only completes if no consistency violations occur.

Based on this generic process of information modeling, the precise process of information integration of planning data from the sources within the specified application scenario is described in Sect. 4.4.1.2.

4.4.1.2 Resources of Information

The Process of Information Integration

After having completed the modeling process for factory planning, which is described in the previous section, the baseline is created to realize the integration of the different data sources. Again, this process is divided in the following three steps:

(i) Definition of standardized data sources for all parameters
(ii) Implementation of the integration of each data template
(iii) Storage and visualization of data within the *VPI platform.*

The first step comprises the definition of standardized data sources for all parameters and corresponding information. This shows a high potential for the data management efficiency within planning projects as well as for the knowledge management regarding several projects within a company. Current factory planning departments often face troubles with an inconsistent data management due to several reasons: application of different software applications along the planning process, insufficient documentation within the project, use of different data templates, etc. This leads to higher planning efforts and a lower learning curve between two projects.

To overcome these challenges, data sources for all information within the planning landscape of CBFP are defined, which is based on the experience of factory planning experts. Therefore, common export interfaces or specific templates for Microsoft Excel© as a widely used planning application or the Complexity Manager by Schuh & Co. GmbH (2016) serve as data sources in order to satisfy the business user requirements. By analyzing the data structures of several projects in the past and further optimizations, the basic templates are identified. The single templates hereby fulfill the following requirements:

- Completeness: Templates have to cover all necessary information to fulfill the required planning task
- Exclusiveness: The different sub-information of overall planning information must be exclusive and not redundant
- Specificity: All information in the templates must be clearly defined and specific so that a planner or user of the application can directly fill in the template.

After having identified the relevant templates for the planning information in a first draft, templates and the overall planning landscape were analyzed regarding the mentioned three requirements in total. Especially the exclusiveness is an important challenge as redundancy and doubled information often lead to incoherent data structures and multiple data management. Thus, in addition to the consistency checking during the integration process, the adequate definition of data sources already provides high data quality.

Based on these sources, we use the technology of adaptive information integration in terms of the actual integration process, which provides several integration services with two main functionalities (Meisen et al. 2011): First, the services facilitate the autonomous extraction, transformation, and loading of data from the data source into the information base. Second, they map the loaded data automatically to the corresponding concepts of the information model and enrich the data with the implicit information of the ontology. This process of semantic annotation is followed with the aforementioned consistency checking. In case of inconsistent data or other unexpected problems, the user interface informs the business user. In case of a successful integration instead, the integrated data are loaded automatically into the user interface that provides visualization and interactions for a further analysis.

This approach provides the ability to connect different kinds of data sources to the *VPI platform* without relying on standardized data exchange formats. This is to reach a consolidated information base along the entire planning process. In terms of the following evaluation and visualization, the planning information and the corresponding templates were analyzed regarding possible visual illustrations of the data within the *VPI platform*. For example, a product structure can be represented by means of a simple data view or it can even be visualized as a product structure tree, which helps the planner to understand the gathered information much faster. A more detailed discussion of the evaluation and visualization techniques of the *VPI platform* and the demonstrator flapAssist is described in Sect. 4.4.1.3.

Information Model and Ontology for Factory Planning

As described in the previous section, the first step of the modeling process is the definition of the information model of the respective domain. Therefore, based on the abstract information model of the CBFP, we analyzed the different data sources and conducted interviews with domain experts. The result is the explicit specification of the vocabulary and the valid constraints of the specific domain, which we generalized to a generally accepted model. This is firstly modeled in a UML class diagram (see Fig. 4.7). The figure shows the main concepts of the domain of factory planning at the highest level, including their relationships. Furthermore, we

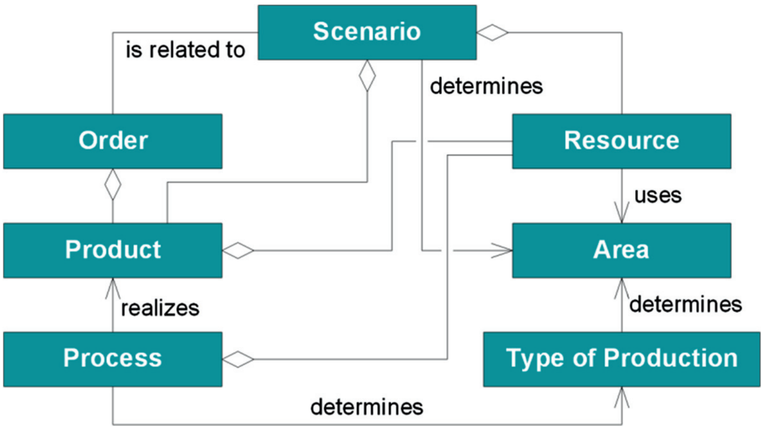

Fig. 4.7 Main concepts of the information model for factory planning

describe each of these concepts by additional meta-attributes and specify the information model (Büscher 2015), which is not shown in the figure.

Afterward, we formalized the information model as an ontology using the Web Ontology Language (OWL) (Büscher 2015). At first, we defined a formal (upper-level) ontology as a template to create specific domain ontologies that are based on the same concept, relationship, and attribute types. Thereon, we transferred the domain-specific information model for factory planning shown in the figure to an ontology. Additionally, we formalized the abstract information model of the CBFP as another ontology with the two base concepts module and parameter (see Fig. 4.8). Besides, the figure shows the relation between modules and parameters and precise individuals in terms of parameters of the module Process analysis from Fig. 4.6. By that ontology, we can validate the structure of a planning project, when creating it by means of the *VPI platform*. Thereby, we decouple the business logic of the domain and the technical implementation of the planning system within an application scenario. This procedure provides a generality and transferability of the business logic and a flexible adaption of planning modules and data sources.

4.4.1.3 Information Product

VPI Platform for Factory Planning

The integration and validation process of planning data, as described in Sect. 4.4.1.2, can be triggered within the *VPI platform*, which is accessible via smartphone, tablet, and personal computer. For each module and parameter, the planner can upload the corresponding data source with the standardized data templates to the platform and start the integration process (see Fig. 4.9). The list on the left side contains the enabled modules and parameters of the planning project.

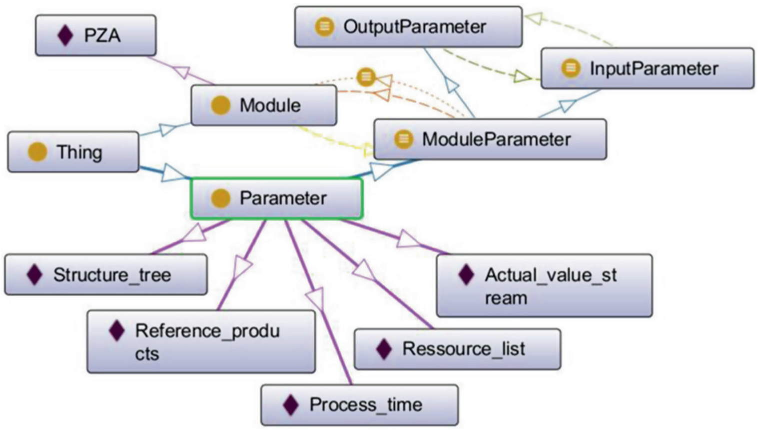

Fig. 4.8 CBFP ontology with selected individuals

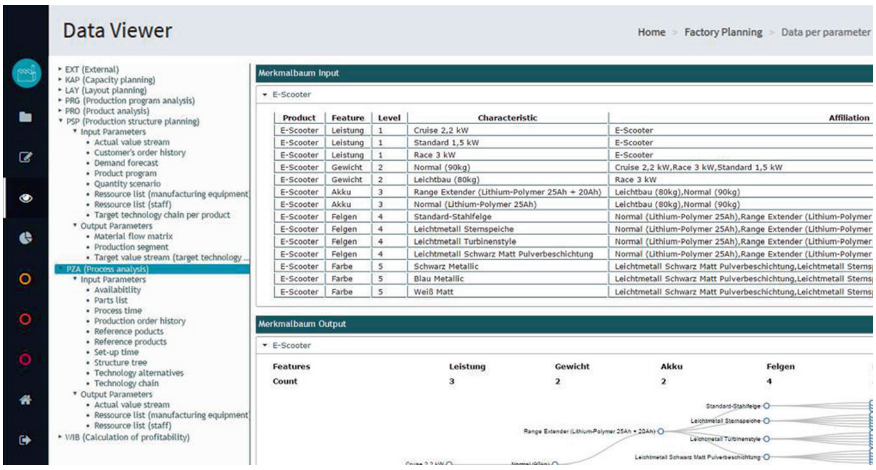

Fig. 4.9 *VPI platform* for factory planning

By selecting one of the modules, the user can view the module structure and manage the data integration on the right side. Furthermore, since the automated integration process has successfully completed, the user can directly access the data and start the evaluation, which is indicated with the exemplary product structure tree downright.

Further analysis and evaluation of factory planning processes is possible by using the KPI cockpit, which summarizes important KPI concerning a precise planning aspect or the whole planning project from the perspective of a typical user. These KPI are generated and calculated automatically from the integrated planning data and can be adapted to the requirements of the user (see Fig. 4.10).

Fig. 4.10 KPI cockpit for factory planning within the *VPI platform*

Virtual Reality-Based Factory Layout Planning

A key target of this project was the elaboration of methods and tools to support the factory planners in their daily work. As one key element especially in layout planning phases, often some kind of factory planning table is used, which basically consists of a 2D touch screen that shows the 2D layout of a factory and a projection with a virtual 3D view into the planned factory. In the past, these tools were just able to show a static picture of the new production facility but could only rarely present further information.

With other ERP tools getting more and more powerful within production environment especially concerning *Industrie 4.0* solutions, it is getting possible to include results of previous planning steps from other planners or software tools in such layout planning solutions. With the *VPI platform* as a powerful tool to structure and organize factory planning information within a project, this demonstrator combined the pure display of a current 3D planning situation with further meta information within specific sights. The result is a monitoring cockpit for the factory planner, which gives him a broad overview of the planning situation showing different kinds of KPIs for the current planning situation using IVR. By using the VPI in this context, not only static data could be integrated into the monitoring cockpit of the tool, it could also processed and calculated in the background.

Especially the IVR is a valuable addition to the factory layout planning process in that context. Specialized display and interaction technology allows planners to perform realistic, life-sized virtual walkthroughs of entire factories long before they have been built. This way, it becomes possible to compare design alternatives in a cost-effective and timely fashion. Korves and Loftus (2000) have even shown that

IVR can clearly outperform traditional non-immersive approaches in certain design review tasks of the layout planning process. To further increase the usefulness of IVR-based factory planning solutions, they can be combined with visualizations that offer access to additional planning-relevant data. More recently, a need for appropriate data annotation functionality to support the collaborative planning process has been indicated in Menck et al. (2012). Here, we present a prototype of such an extended IVR-based solution called Factory Layout Planning Assistant (flapAssist). *flapAssist* offers traditional functionality—such as virtual walkthroughs—but combines them with visualization concepts that have been newly developed to better support the planner. In addition, advanced data annotation functionalities are available.

Core Application

flapAssist is a factory layout planning support tool that utilizes various concepts of IVR. As such, its base functionality is realistic virtual walkthroughs through digital factory models with the goal of performing design reviews. To facilitate *flapAssist*'s integration into established planning workflows, it was built to support a variety of platforms ranging from large-scale immersive CAVE-like VEs to non-immersive desktop systems. A walkthrough within a CAVE-like VE is shown in Fig. 4.11.

As mentioned above, one important aspect during the development of *flapAssist* was its integration into existing workflows. Consequently, we integrated *flapAssist* with tools that were already in use by the planners involved in the project.

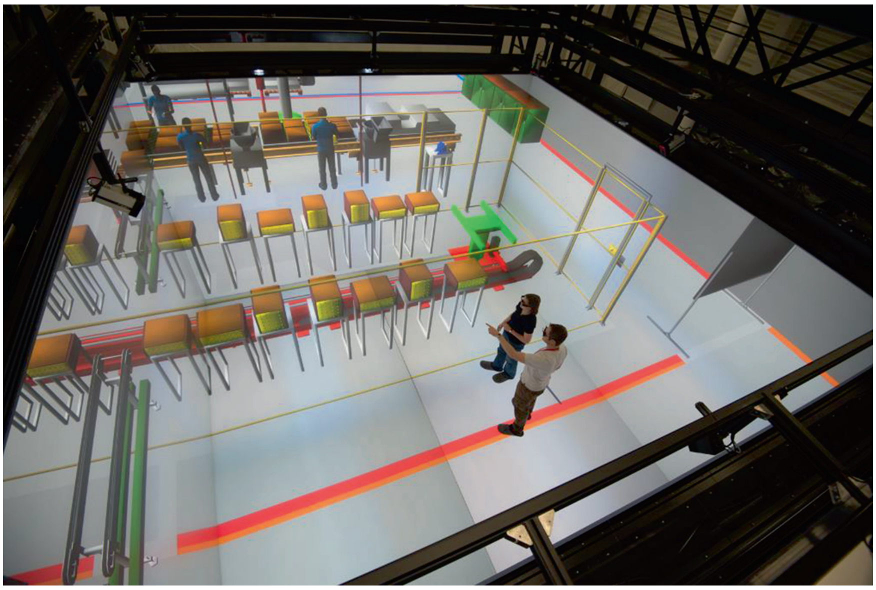

Fig. 4.11 Two users perform a virtual walkthrough through a digital factory model within the aixCAVE of the RWTH Aachen University

Fig. 4.12 The factory model shown in *flapAssist* is synchronized in real time to the one being edited using visTABLE® touch via a network interface

In particular, we combined *flapAssist* with the commercially available factory layout planning software visTABLE® touch[2] (visTABLE®). It allows multiple users to simultaneously participate in planning sessions by means of a so-called planning table, which consists of a touch sensitive tabletop display (see Fig. 4.12). The models created using visTABLE® are made available within the VE using an approach similar to that of Neugebauer et al. (2011), who used a network connection to transmit model data as well as changes to their VR application. The benefit of this solution lies within the possibility to perform walkthroughs during planning sessions, thus allowing planners to immediately evaluate design changes as they are made.

The main target platforms of *flapAssist* are CAVE-like VEs as they offer certain benefits over other available VR systems. For example, they can support multiple users at the same time and offer a more realistic and qualitatively better experience than desktops or HMDs, respectively. However, for the aforementioned integration-related reasons, *flapAssist* also supports other common platforms, such as desktop and HMD-based systems. Technically, the different platforms are supported through the use of the VR toolkit ViSTA (Assenmacher and Kuhlen 2008). It enables applications that are based on this to target different display systems and input devices by means of configuration files. As a result, applications do not also have to be adapted programmatically. However, for an effective solution, it is also

[2]http://www.vistable.de.

essential to provide adequate interaction concepts for each platform as they usually feature different interaction devices. The base foundation for *flapAssist* is a point-and-click interaction approach. For system control tasks, we rely on hierarchical pie menus (Gebhardt et al. 2013) as they have been shown to work well on all the chosen target systems. Users can change all application settings, such as visualization parameters, through pie menus. Navigation is solved differently on every platform. In CAVE-like VEs, we follow a point-and-fly style metaphor using tracked 6-degree-of-freedom (6-DoF) input devices, such as the A.R.T. Flystick 2. For HMD-based systems, we mainly rely on a gamepad-based approach as it is familiar and tracking probably not available. On desktop systems, we adapted the navigation approach from visTABLE®'s 3D viewer to provide users a consistent interaction experience across the two applications. In addition, we also provide a Google Maps-like dragging navigation approach for fast navigation on every system. For this, we reuse the respective input devices of each platform.

Visualization of Planning-Relevant Data

In addition to virtual walkthroughs, the visualization of additional planning-relevant data can help to make sound planning decisions. For this reason, *flapAssist* allows to add visualizations of additional planning data.

One important type of data is material flows. In *flapAssist*, planners can have the different material flows displayed directly on top of the 3D representation of the factory model as shown in Fig. 4.13. Here, material flows are represented in two different forms. On the one hand, inter-machine material flows are visualized using color-coded arcs. Each arc represents the directed material flow between two

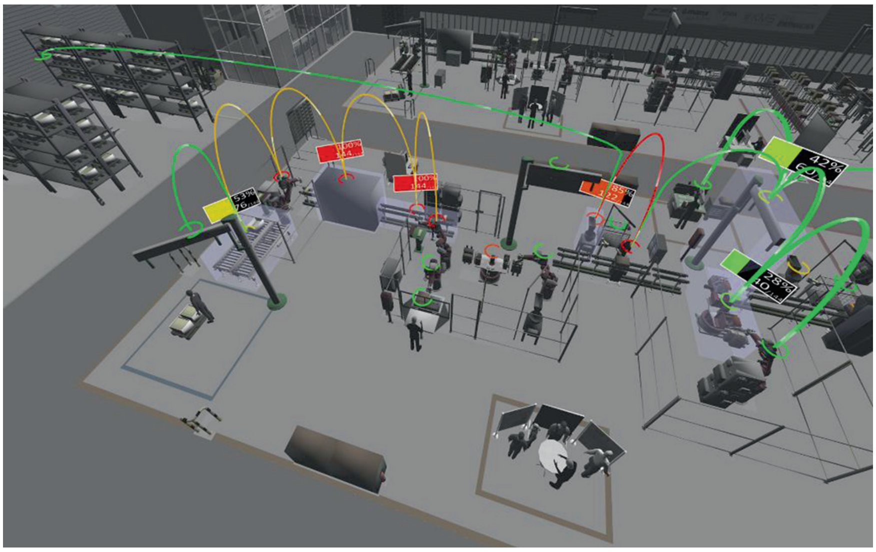

Fig. 4.13 Material flows are visualized via color-coded arcs for inter-machine material flow and an information card for accumulated per-machine material flow

machines. In case of bidirectional material flow between a pair of machines, two distinct arcs are added and placed right next to each other (see left half of Fig. 4.13 with right side). An additional animation of a particle moving along the arcs indicates the flow direction. The speed of the animation is one of two indicators of the intensity of the material flow represented by an arc. The other indicator is an arc's color. By using distinct colors for high and low values, it is possible to get a good overview of material flow distributions at a glance and, for instance, to identify hot spots. In addition, card-style visualization is used to visualize the accumulated material flow in which machines participate. We use the same color-coding as for the arcs and provide numerical values such that users have access to precise material flow values. Since visualizing an entire material flow matrix at once leads to a lot of clutter, users have the possibility to filter out those machines for which they do not want to see material flow information. In Fig. 4.13, material flows are only shown for selected machines and workplaces, which are indicated.

Based on material flow data, we developed a visualization whose goal is to aid the planner to optimize the position of individual machines with respect to their neighbors as defined by the material flow matrix. Generally, it is advisable to place two machines close to each other to reduce the costs produced by the material flow between them. However, since material flow matrices can become rather complex (see Fig. 4.13), it is usually not possible to perform such an optimization by simply looking at the material flow and deduce new positions from that. To solve this conundrum, *flapAssist* provides a visualization that takes the entire material flow for a selected machine into account, and offers the planner a suggestion for instance to which place the machine should be moved in order to optimize its location with respect to material flow costs. Since material flow costs are not the only kind of data affecting the position of a machine, we refrained from using an automated approach. The visualization is shown in Fig. 4.14. Here, the central machine was selected and the blue region indicates areas for which material flow costs can be reduced: The deeper the blue, the lower the costs. In short, the visualization compares the material flow costs at the current location to those of a potential new location using a discretely sampled grid. Based on this grid, the blue regions are extracted.

While looking at this visualization, planners can modify the layout using visTABLE® as described in the previous section. While doing so, the optimization suggestions are updated in real time using a parallelization scheme based on Intel® Threading Building Blocks[3] (TBB). This way, planners get immediate feedback on their changes and can thus quickly iterate over different optimization scenarios.

One of the strengths of VR-based walkthroughs is the life-sized impression that users obtain. This can be used to check workplace visibility in a rather natural fashion and thereby ensure important lines of sight between related workplaces. To speed this process up, we provide a visualization approach specifically for checking

[3]https://www.threadingbuildingblocks.org/.

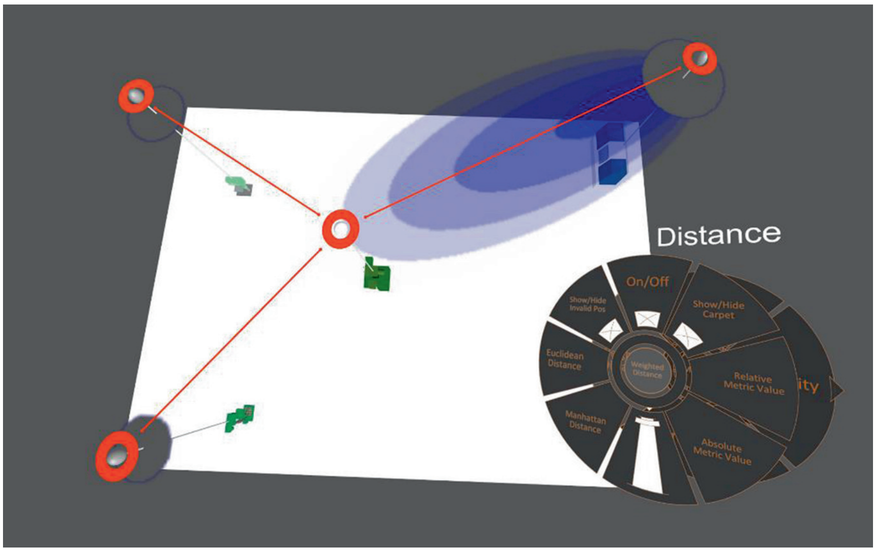

Fig. 4.14 A visualization offering planners guidance in how they can reduce material flow costs. In the example shown, the dark area indicates the region into which the central machine should be moved to reduce material flow costs

lines of sight. The visualization is shown in Fig. 4.14. Here, planners can represent individual work areas by simple geometric shapes, like cuboids. To check the visibility between two such workspaces, users first connect the desired pair of workplaces A and B. Next, an algorithm samples the approximated workspaces into a set of discrete points (see Fig. 4.15). After that, lines are shot between all pairs of points (a, b) for which a belongs to A and b to B. The ratio between lines that *do not* intersect with objects in the factory and the overall number of lines is provided visually to the user using color-coded arrows. Since the required intersection calculations are computationally quite expensive, we again employ a parallelization approach based on Intel® TBB.

Data Annotation for Collaborative Work

Recently, Menck et al. (2012) discussed the need for appropriate data annotation techniques for immersive CAVE-like VR systems to facilitate the collaborative factory planning process. One of the issues in this regard is the lack of efficient workflows for the creation and access of annotations. To alleviate this situation, we developed an annotation framework for *flapAssist* that provides the required functionality (Pick and Kuhlen 2015). One of its central benefits is that annotation workflows can be easily defined in a platform-independent manner.

In general, the annotation system of *flapAssist* allows users to create a variety of annotations, like labels or viewpoint annotations, and fill them with various types of data, such as text, voice comments, images, or sketches (see Fig. 4.16). To capture all these different data types, the annotation system provides a series of interaction

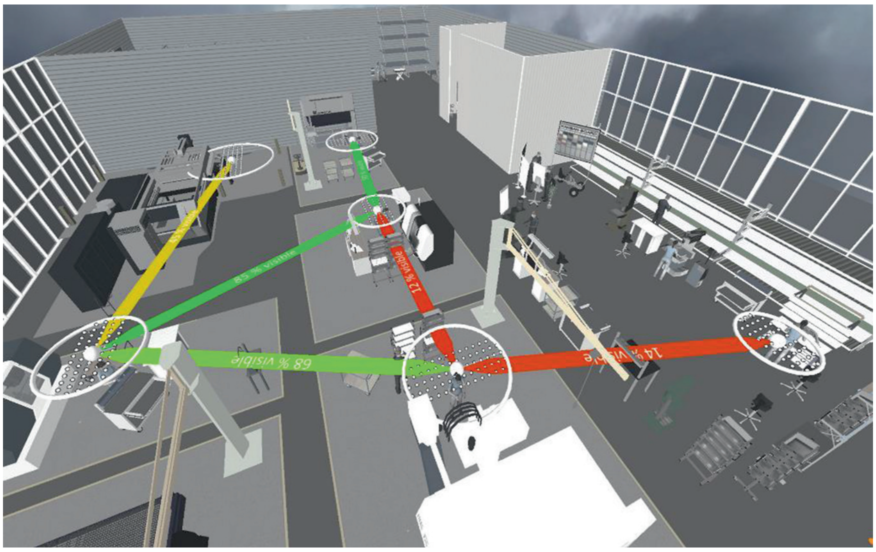

Fig. 4.15 A line of sight visualization is provided to help planners identify visibility issues between related workplaces

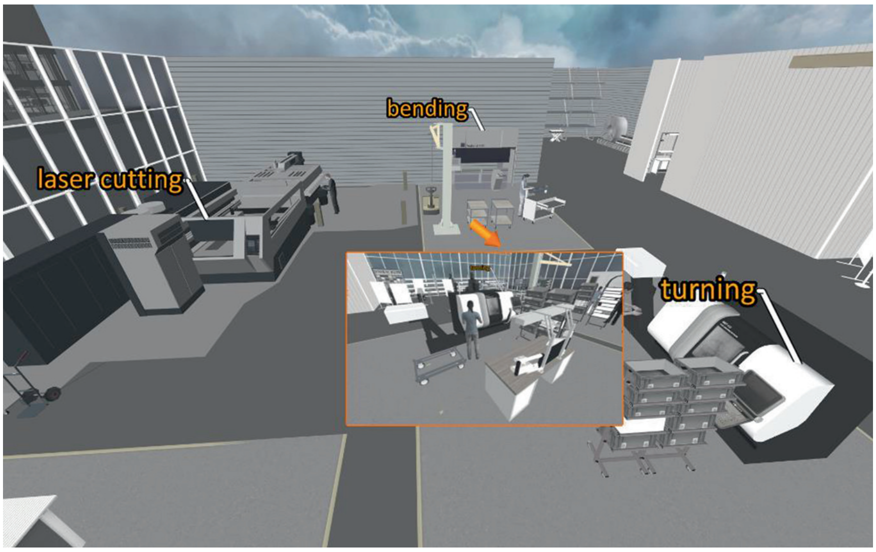

Fig. 4.16 Users can create different types of annotation like labels or viewpoint annotations to capture comments or design changes

metaphors. On desktop systems, data are captured in the usual style using basic mouse and keyboard interaction approaches. On immersive VR systems, however, such input devices are usually unavailable. Therefore, we developed a smartphone application that provides all the tools to perform the required input operations. In addition, several input metaphors using 6-DoF interaction devices are also made available. One such example is a novel multimodal text input metaphor presented in Pick et al. (2016a).

To be able to integrate all the different interaction approaches into consistent workflows, we devised a workflow description mechanism that is based on Android's Intent system.[4] The Intent system allows separating input tasks, such as *input text* from the concrete interaction technique, such as *use smartphone app*. We employ the same approach, but extend it in such a way that entire interaction sequences—like *take screenshot, sketch onto screenshot* and *add text comment*—can be described with it. An evaluation of this interaction workflow design has been performed in Pick et al. (2016b), confirming its usability.

The captured annotation data are organized in the annotation system's own data format, which is independent of the used storage mechanism. For use with *flapAssist*, the annotation system can be configured into one of two modes. An XML storage mode stores all annotation data locally. This storage mode is used for individual use of *flapAssist*, for instance, when no server-based storage is available. Another web-service-based storage mode provides central access to annotation data. In this mode, an annotation data server stores all the data in a standardized fashion using SOAP-based web services. This storage mode was designed in a way that it can be easily integrated into an existing infrastructure like the *VPI platform*. As a result, annotations become accessible to all involved parties, thereby supporting the collaborative factory planning process. It is also the default way to access annotations that have been created in immersive VR systems, such as CAVE-like VEs.

4.4.2 Design Domain Machine

4.4.2.1 Sources of Information

Developed Metamodeling Procedure in the Design Domain Machine

For the design domain, *Machine* metamodeling techniques have been identified as being crucial for the VPI approach. So the methods for generating, validating, analyzing metamodels have been elaborated and are presented in the following paragraphs.

Generating a metamodel, as mentioned in Sect. 4.3.3, requires different aspects and tradeoffs to judge if it is acceptable or not. An acceptable metamodel is defined by a balance or compromise between the user predefined criteria (Franke 1982), which mainly are:

[4]http://developer.android.com/guide/components/intents-filters.html.

(i) **Accuracy**: The measure of deviation of the predicting metamodel from the original data source (e.g., a numerical simulation).
(ii) **Robustness**: The degree of achieving good accuracy for different use cases. This degree indicates whether a modeling technique is highly problem dependent.
(iii) **Timing**: The measure of the computational time required for generating the metamodel and predicting a response to a certain parameter setting.
(iv) **Sensitivity** to parameters: The capability of extracting information regarding the main effect (which is the sensitivity on a single parameter) and the interaction effect (which is the sensitivity on a combination of parameters) on the output criteria.
(v) **Ease of implementation/usage**: Simple usage and easy user-interaction are generally required in instantiating and applying the metamodels efficiently.

In many manufacturing processes, the functional relationship between the input parameters and the output criteria is not steady due to digital changes in the solution properties (e.g., topology changes like a material cut-through), and the system response is often described by a piecewise continuous function. Identifying the region of the discontinuity is not explicit, since it is usually not defined by any functional relationship between parameters (Meckesheimer et al. 2001). When applying metamodels to responses with discontinuity, they might provide poor predictions, since metamodels are generally applied to only continuous responses, because they mostly apply fully steady basis functions.

After defining the design objectives, identifying the input parameters and output criteria of the problem, and defining the lower and upper bounds for the domain space, a metamodel representing the piecewise response can be generated according to the one-shot approach illustrated in Fig. 4.17:

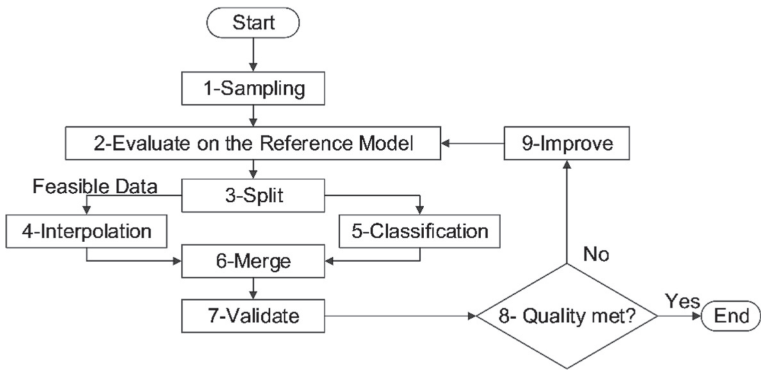

Fig. 4.17 Flow diagram of the one-shot metamodel approach for the output with a piecewise response

The nine steps typically involved in constructing a one-shot metamodel are:

(i) Sampling the design space;
(ii) Evaluating the response of the reference model and assigning an exemplary criterion value for the infeasible region beyond the discontinuity;
(iii) Splitting the data into feasible and infeasible parts;
(iv) Interpolating of the feasible data part;
(v) Classification of the domain space;
(vi) Merging the classification model and the interpolation model;
(vii) Validating the metamodel with the reference model;
(viii) Checking if the quality is accepted or not;
(ix) Improving the metamodel through either resampling or adjusting the parameters of the interpolation technique.

These steps are described in more detail as follows:
Step 1: The procedure to efficiently sample the parameter space is addressed by the DOE techniques discussed previously in Sect. 4.3.3. It addresses mainly where to place the sampling point in the design space. When the sampling points are generated all at once, the metamodeling approach is called a one-shot approach. The sampling set that represents the input parameters and the output response is called the training data set T and is defined by

$$T = \{(x_i, y_i)\}_{i=1}^{n}, \tag{4.1}$$

where n represents the total number of data pairs and i is an index of the runs that ranges from 1 to n.
Step 2: A reference or original model—which might even consist of analytical functions, a reduced model, a full numerical simulation or experimental data—is required for metamodeling. The more information available about the reference model, the better and more efficient the metamodeling generation becomes. Helpful information includes: (i) the state of the model implementation (for example, if the numerical implementation is stable or possible to interface with the metamodel-generator), (ii) the usage requirements (licensing information), system type (deterministic or stochastic), information of the inputs (dimensionality, ranges, or sensitive parameters), and information about outputs (discontinuities, non-linearities) (Gorissen 2010). The main assumption in this context is that a validated reference model with an adequate quality is used. A low-quality reference model would of course generate a low-quality metamodel. This highlights the popular expression among computer scientists: "Garbage In, Garbage Out" (GIGO). In this step, an exemplary criterion value "DiscVal" is set by the user to represent and distinguish the region beyond the discontinuity in the domain space.
Step 3: Split the sampling data according to the value "DiscVal" to two training data sets T_F and T_C such as

$$T_F = \{(x_{F_i}, y_{F_i})\}_{i=1}^{n_F} \qquad T_C = \{(x_{C_i}, y_{C_i})\}_{i=1}^{n}, \tag{4.2}$$

where indexes F, C, n_F, and n represent the feasible sampling data (no discontinuity values), the classification data (full data set), the number of feasible sampling data, and the number of the full data set, respectively. The values of the vector y_C are rescaled to either -1 that corresponds to DiscVal, or 1 that corresponds to feasible values.

Step 4: A scattered data approximation technique for mapping the discrete sampling points to a relationship is required. In scattered data approximation, which is one of the most common problems that arises in many scientific disciplines (Wendland 2005), the true response y is replaced by an approximated response (metamodel) $f_F(x)$. For an arbitrary design point x, the continuous relationship of the metamodel and the true response is defined by

$$y - f_F(x) = \varepsilon, \tag{4.3}$$

where ε is the approximation error. In this work, the Radial Basis Function Network (RBFN) is used as the main interpolation technique. An RBFN, shown in Fig. 4.18, is similar to a three-layer, feed-forward neural network. It consists of an input layer, which is modeled as a vector of real numbers, a hidden layer that contains nonlinear basis functions and an output layer, which is a scalar function of the input vector (Al Khawli et al. 2015).

The output of the network $f(x)$ is given by

$$f_F(x) = \sum_{i=1}^{n} w_i h_i(x), \tag{4.4}$$

where n, h_i, and w_i correspond to number of sampling points of the training set, the ith basis function, and the ith weight, respectively. The RBFs are a special class of functions for which their response increases or decreases monotonically according to a distance from the central point. In this work, the multi-quadric function is defined by

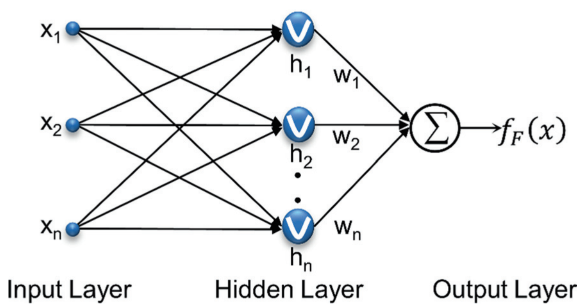

Fig. 4.18 Architecture of RBFN

$$h_i(x) = \sqrt{1 + \frac{(x - x_i)^{\mathrm{T}}(x - x_i)}{r^2}}, \tag{4.5}$$

where x_i and r represent the ith sampling point and the width of the basis function, respectively. The shape parameter r controls the width of the basis function; the larger or smaller the parameter changes, the narrower or wider the function gets.

The learning process of the network is performed by applying the method of least squares with the aim of minimizing the sum-squared-error with respect to the weights w_i of the model (Orr 1996). Thus, the learning/training is done minimizing the cost function C, defined by:

$$\min_{w_i} C = \min_{w_i}\left(\sum_{i=1}^{n}(y_i - f_F(x_i))^2 + \sum_{i=1}^{n}\lambda w_i^2\right), \tag{4.6}$$

where λ is a regularization parameter which determines the relative importance of the smoothness of the function and y_i is the criterion value at point i. Solving Eq. (4.6) leads to

$$w = \left(H^{\mathrm{T}}H + \Lambda\right)^{-1}H^{\mathrm{T}}y, \tag{4.7}$$

with

$$H = \begin{bmatrix} h_1(x_1) & h_2(x_1) & \cdots & h_n(x_1) \\ h_1(x_2) & h_2(x_2) & \cdots & h_n(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ h_1(x_n) & h_2(x_n) & \cdots & h_n(x_n) \end{bmatrix} \Lambda = \begin{bmatrix} \lambda & 0 & \cdots & 0 \\ 0 & \lambda & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda \end{bmatrix} y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}. \tag{4.8}$$

The chosen width of the RBF plays an important role in getting a good approximation. The r value is selected according to Hardy (1990) and defined as

$$r = 0.81d, \quad d = \frac{1}{n}\sum_{i=1}^{n} d_i. \tag{4.9}$$

Note that d_i is the distance between the ith data point and its nearest neighbor. **Step 5**: Perform a classification task in order to first decompose the design space into feasible and non-feasible regions and second detect the discontinuity between them. By applying Cover's theorem (Cover 1965), the domain space that is formed by a set of n vectors x_C, can be split into two classes Ψ_1 and Ψ_2 by assigning a so-called dichotomy of surface. This is done in Step 3 where a value of -1 is assigned to non-feasible regions and a value of 1 is assigned to feasible regions. An RBFN metamodel is used to perform a classification task. The domain space Ψ is said to be separable if there exists a vector w_C such that

$$C(x) = \sum_{i=1}^{n} w_{C_i} h_{C_i}(\|x - x_C\|) > 0, \quad x \in \Psi_1,$$
$$C(x) = \sum_{i=1}^{n} w_{C_i} h_{C_i}(\|x - x_C\|) < 0, \quad x \in \Psi_2, \tag{4.10}$$

The discontinuity in the domain space is defined by the equation

$$C(x) = \sum_{i=1}^{n} w_{C_i} h_{C_i}(\|x - x_C\|) = 0, \tag{4.11}$$

where w_i is defined similar to Eq. (4.7) by considering the whole data set of size n. The first-order linear spline basis function is defined by

$$h_{C_i}(x) = |x - x_i|. \tag{4.12}$$

Step 6: Merge the classification model and feasible interpolation metamodel in one function, such as:

$$f(x) = \begin{cases} f_F(x) & \text{if } \ C(x) > 0 \\ \text{DiscVal} & \text{if } \ C(x) \leq 0 \end{cases}, \tag{4.13}$$

Step 7: The validation techniques are mainly used to estimate the quality of the metamodel in terms of the prediction accuracy. For quantifying the model accuracy, the mean squared error (MSE) coefficient and the coefficient of determination (R^2) statistical measures are calculated on an additional data. MSE percentage represents the deviation of the metamodel from the reference model, and is defined as

$$\text{MSE} = \frac{1}{n\text{VS}} \sum_{i=1}^{n\text{VS}} (y_i - f(x_i))^2, \tag{4.14}$$

where nVS is the number of the validation data set, y_i is the output dependent variable of the validation set, and $f(x_i)$ is the metamodeling function of the parameter vector x_i. The smaller the MSE value, the more accurate the metamodel is. Additionally R^2 is an error performance measure which takes into account the variance and captures how irregular the sample data are (Meckesheimer et al. 2002). R^2 is calculated according to

$$R^2 = 1 - \frac{\text{MSE}}{\sigma^2}, \quad \sigma^2 = \frac{1}{n\text{VS}} \sum_{i=1}^{n\text{VS}} (y_i - \bar{y})^2, \tag{4.15}$$

where $\bar{y}$ is the mean and σ^2 is the variance of the validation set. R^2 ranges from 0 to 1, the closer the value of R^2 gets to 1, the more accurate the metamodel is.

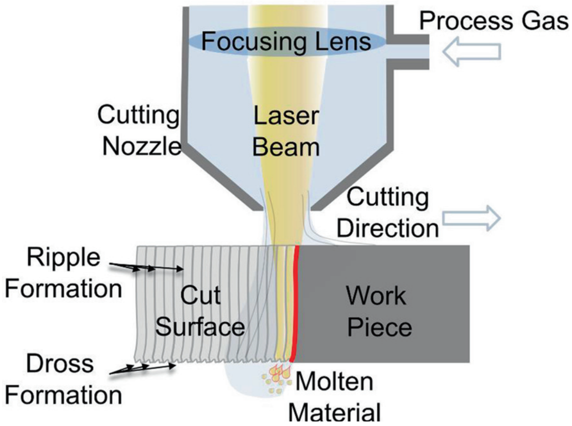

Fig. 4.19 Schematic representation of conventional laser cutting process

Step 8: Check if the acquired accuracy is accepted or not. If it is accepted, terminate or else go to Step 9, which is improving the metamodel. This is done by either increasing the number of sampling points, resampling strategy, or adjusting model parameters of the interpolation method such as the width of the basis function.

Application to Laser Cutting

During the fusion cutting process, a high energy density laser beam is focused on a work surface. The thermal energy is absorbed which heats and transforms the work volume into a molten, vaporized, or plasma state that can easily be removed by the flow of a high-pressure assisting gas jet (Radovanovic and Madic 2011; Dubey and Yadava 2008). The schematic representation of the laser cutting process is shown in Fig. 4.19.

Important degradation of the cut quality is due to the onset of unevenness and roughness of the cut edges, the appearance of adherent dross, as well as other properties like gas consumption and robustness with respect to sensitive parameters, such as nozzle standoff distance and others. These defects share in common that they originate from the dynamical behavior of the cutting process (Schulz et al. 1997). There are gaps in understanding the dynamics of the process—especially with regard to issues related to the cut quality. Numerical modeling and simulation of laser cutting improved the understanding of the process without the need of executing numerous experimental tests (Schulz et al. 2009). The three elements involved in laser cutting are the gas jet, the laser beam, and the material to be cut. Therefore, the modeling of the cutting gas flow, the radiation propagation, and the ablation of the material (in fusion cutting: removal by melt ejection) has to be accomplished, as well as the numerical solvers of these models have to be implemented. One of the current challenges in R&D is to design beam-shaping optics such that the ripple structures on the cutting kerf surface stay minimal, as shown in Fig. 4.20.

As mentioned previously, QuCut reveals the occurrence of ripple formation at the cutting front and defines a measure for the roughness on the cutting kerf surface.

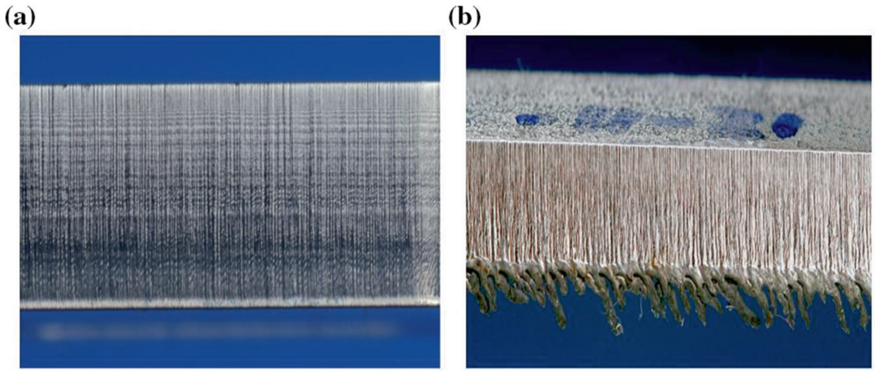

Fig. 4.20 Smooth (**a**) and non-smooth (**b**) cutting surface with ripple structures

Table 4.1 Process design domain

Beam parameters	Minimum	Maximum	Sampling points
Beam quality M^2	7	13	7
Astigmatism Ast [mm]	−15	25	9
Focal position fp [mm]	−8	2	11
Beam radius x-direction w_x [μm]	80	200	6
Beam radius y-direction w_y [μm]	80	200	6

The tool is based on a numerical model, which involves two coupled nonlinear partial differential equations. The model is fully numerical and will be considered in this work as a black-box model. For further details on the mathematical analysis, the reader is referred to Vossen et al. (2013). It takes QuCut about 6 min to estimate the roughness for one parameter set (depending on computational hardware).

Thus, the total computation time required for learning from simulation, for example optimization, or sensitivity analysis, or data mining by executing only 1000 iterations, would be around 3 days. This makes it technically undesirable to perform an online exploration with this model through the full design space for industrial use. With the help of a fast metamodel, a process map is generated from that reference model, rather than experimental data as the experimental costs and effort would be even greater. So the metamodel is generated from a discrete data set of simulation runs. It provides the operator with a continuous relationship between the quality (roughness) and the optical beam parameters. The goal of this use case, which is later presented in Sect. 4.6.2, is to find the optimal parameter configuration of certain laser optics that result in a minimal ripple structure (i.e., roughness).

The five laser optical design parameters examined here are the beam quality, the astigmatism, the focal position, and the beam radius in x and y directions (as an elliptical laser beam was used). The properties of the sampling design are listed in Table 4.1.

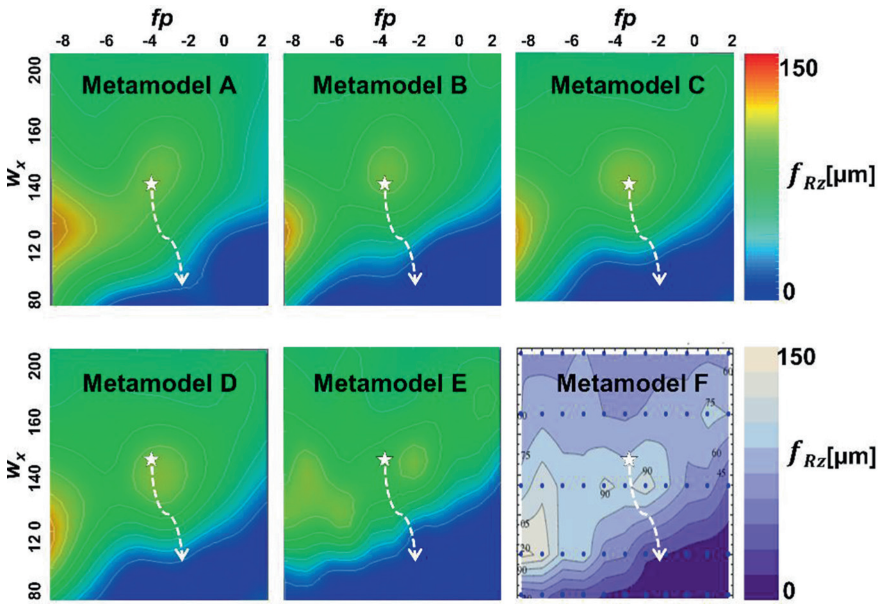

Fig. 4.21 2D contour plots of different metamodels at $M^2 = 10$, astigmatism = 25 mm, beam radius y = 134 μm. The polynomial linear regression metamodel (F) on the bottom right contains more sampling points and is shown here for evaluation of the metamodel quality (A–E)

The selected criterion is the surface roughness (Rz in μm) simulated at a 7-mm depth of an 8-mm-thick work piece. The full data set is 24,948 samples in total. In order to assess the quality of the mathematical interpolation, 5 different RBFN metamodels are generated according to 5 randomly selected sample sets of size 1100, 3300, 5500, 11,100, and 24,948 data points from the full data set. As shown in Fig. 4.21, the metamodels are denoted by Metamodel A–E. Metamodel F, which is used as a reference for comparison, is a two-dimensional metamodel with finer sampling points denoted by the dots in the lower right sub-figure.

The advantage of using a metamodel in this process over the full-scale simulation is denoted in Table 4.2. As stated before, a single evaluation run requires 6 min on QuCut and less than 1 ms on all of the above-generated metamodels. So

Table 4.2 Quality of the metamodels

Metamodel	MSE/ [μm]	R^2	Generation time	Metamodel loading time [s]	Single evaluation time [ms]
A	19.69	0.89	~30 s	0.026	0.012
B	17.89	0.90	~5 min	0.084	0.023
C	15.50	0.92	~1 day	0.132	0.033
D	14.91	0.93	~3 days	0.259	0.057
E	13.63	0.94	~1 week	0.564	0.120

generating a two-dimensional 10 × 10 grid (100 evaluations) contour plot, similar to the contour plots shown in Fig. 4.21, would require less than the tenth of a second by using a fast metamodel or 10 h by using the simulation model.

In order to validate the accuracy of the metamodel, a twofold cross-validation method is applied. A 10 % of the training point sample is left out randomly of the interpolation step and used for validation purposes. The results are listed in Table 4.2.

MSE of the criterion surface roughness and R^2 are calculated and compared to each other. As mentioned earlier in the introduction, the smaller the value of MSE, the more accurate the metamodel is. Additionally, the closer the value of R^2 gets to 1, the more accurate the metamodel is. The results show that the quality of the metamodel naturally depends on the number of sampling points; the quality is improved when the number of training points is increased. However, this will require a longer metamodel generation time as shown in the Table 4.2.

In Fig. 4.21, the contour shapes in the metamodels A–E (five-dimensional) become similar to the ones in Metamodel F (two-dimensional) by simply adding more sampling points to the metamodel. Additionally, the region (resembling large roughness) at a focal position corresponding to 8 mm and for a beam radius between 100 and 140 μm becomes progressively smaller from A to E. This is a consequence of using more sampling points in the vicinity of the (Beam Radius *x*-direction, focal position) slice. In the special application case studied here, the minimum number of sampling points with an RBFN model is already a good choice for giving an optimized working point for the laser cutting process. These metamodels have different accuracy values but similar tendencies that can already support the developer in decision making.

4.4.2.2 Resources of Information

Section 4.4.2.1 described the sources of information in this design domain, which are metamodels on the basis of discrete data sets of simulation runs of the laser cutting process. These data sets contain the process criteria outputs for various input parameters. They form the basis for a data-driven process analysis that examines the relationships between parameters and criteria and provides a validation of the process models. The analysis is complementary to the concepts of metamodeling. It is implemented in the VPI platform for the design domain *Machine*. This section presents the underlying data model. The model describes all relevant issues of the analysis in a formal way. Figure 4.22 illustrates the data model.

The first entity is the object set *lcproject*. It represents an analysis project a user can create. This table has a 1:*n*-relation to the object set *lcprocess*. This means that a single project may contain several processes (i.e., simulation data sets). This connotation ensures that at least 1 % information of funded analysis project is available for the performance of an analysis. In addition to the information of this process there is also the need for statistical details of the considered physical quantity,

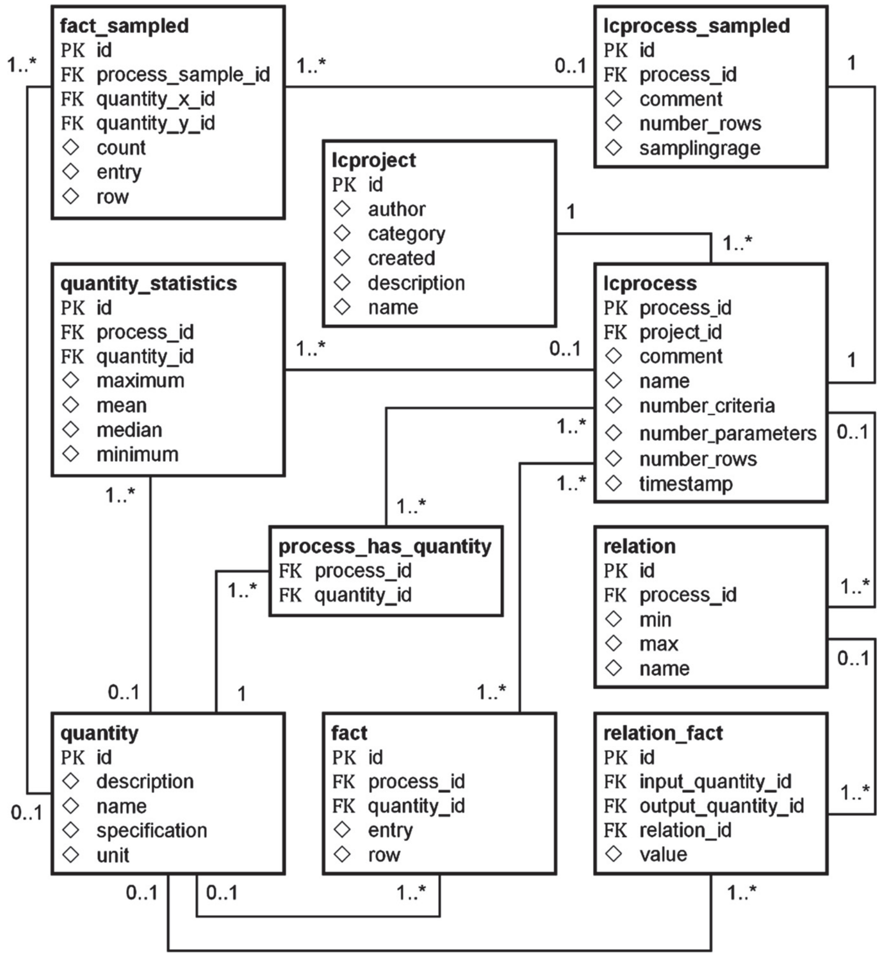

Fig. 4.22 Data model for the VPI platform in design domain machine

which are located at the object set *quantity_statistic*. A quantity may be either an input parameter or an output criterion of the process. Examples include the focal length of a laser, nozzle diameter or outlet velocity of the ablation gas at the nozzle. As mentioned in Sect. 4.4.2.1, there are several physical quantities involved in a process. A 1:*n*-association is defined between these object sets as a consequence.

The value of a physical entity persists within the object set *fact*. Likewise to the previous object set, there is a 1:*n*-association defined between this object set and the object set *lcprocess*. Another object set with an association with the object set *lcprocess* is the object set *relation*. The latter includes the values of the key indicators, which describe the cause–effect relation between process parameters and criteria. An amplification regarding the used key indicators is possible because the attribute *name* of the object set relation identifies the respective key indicator. During a process, a key indicator is gathered several times so that there is a 1:*n*-association between object set *lcprocess* and object set *relation*.

The numeric values persist in object set *lcprocess_sampled*. Between this object set and the object set *lcprocess* exists a 1:1 association. The object set *quantity* gives the characteristic of the entity unit that describes the unit of process parameters and criteria out of a process. Two object sets realize the link to object set *lcprocess*. On the one hand, it is the object set *quantity_lcprocess* that remains a 1:*n*-association with object set *quantity*. On the other, it is object set *process_has_quantity*, which summarizes the considered variables of a process.

In Sect. 4.4.2.3, it will be seen that the analysis contains a visualization of the value distribution in a scatterplot. This visualization relies on the object set *fact_sampled*. It has the two foreign keys *quantity_x_id* and *quantity_y_id*. Due to that, there is a 1:*n*-association between object set *fact_sampled* and object set *quantity* defined. The two foreign keys are used for the distinction between process parameters and criteria. Furthermore, the calculation of cause–effect relations between several process variables reverts to object set *relation_fact* that undertakes the allocation of a process variable of the object set *quantity* to their character of the object set *fact*.

The entity's process parameter and process criteria are not explicitly considered. As a result, there are no object sets with such names. The use of the attribute *specification* and object set *quantity* realized this discrimination. If a process variable is persisted in this object set, this attribute is assigned with value 0 in case of a process parameter and with value 1 in case of a process criterion.

The data model presented in this section forms the basis for the compliance of all requirements laid down in an implementation of analysis concerning virtual production. The implementation of methods of a sensitivity analysis presented below—as well as iterative analysis methods—refers to this. In addition, the implemented graphical user interface, which enables explorative and interactive analysis of process information within a virtual production, uses this data model.

As explained above, the object set quantity manages process variables. These are either process parameters or process criteria. The information model is generically designed so that maximum flexibility concerning process models can be guaranteed. In doing so, the analysis is not restricted to a certain data set with specific variable names. The *VPI platform* provides the integration and analysis of all kinds of relational simulation results.

4.4.2.3 Information Product

***VPI Platform*: Machine**

Examining the relationships of various input parameters and process criteria within the laser cutting process is a complex task. Within the design domain Machine, two information products were developed to support the user to analyze the process: the *VPI platform* and the visualization of metamodels. The latter one is described in the next section. This section provides an implementation of a data-driven validation of the process models within the *VPI platform*. The validation is a complex task that requires several steps for data integration and analysis. Therefore, we adapted the Visual Analytics approach that combines automated statistical computing with interactive visualizations for the user. As the statistical approach for model validation, we chose the classification of influence of process parameters on process criteria. As the classifying method, we use the Elementary Effects method by Morris (1991) and Campolongo and Braddock (1999). Based on simulation data, this method maps a pair of parameter and criterion into one of the classes *negligible*, *linear*, or *nonlinear*. The visualization elements for the user interface are bar charts, scatterplots, and chord graphs.

Validation of Process Models

The modeling of laser cutting processes considers various process parameters and process criteria. These models are marginal and initial problems of partial differential equations. Concerning the validation of process models, an analysis, which calculates the correlation and classification of the cause–effect relationship between the considered process variables, is used. Regarding a process criterion that is in quadratic proportion to a process parameter, however, in the process model, a linear cause–effect relationship is performed. In this case, an adaption of the process model is necessary for depicturing the cause–effect relationship correctly.

In the described use case, the operator interacts with the *VPI platform* that integrates this kind of process data and enables its evaluation over a graphical user interface. Likewise, the use case allows the reply of the research questions of the domain *Machine*. The successfully realized implementations presented below provide the respective answers.

The implementation of the information system takes place in a relational database like it was formulated in Codd (1990). The *VPI platform* uses this information model as the base for inter alia the persistence of a funded or changed analysis project, process information and their allocation to an analysis project. Additionally, the system calculates results of cause–effect relationships between process parameters and criteria within an iterative analysis method that is necessary for an explorative and interactive information analysis. This section refers to the models of Morris and demonstrates how the calculation of elementary effects can be realized. They serve as a basis for calculation of so-called sensitivity indicators, which give a statement about the question how a cause–effect relation of an input variable x_1 to a model y can be categorized.

Calculation of Sensitivity Indicators

The calculation of sensitivity indicators between model parameters and model criteria requires the answers to following questions: How can the utilization of elementary effects define sensitivity indicators? How many grid stairs should be used? How should atypical distributed values for the examined quantities be treated? In the following, these questions are discussed.

The sampling strategy results in the establishment of r trajectories in Ω. Each trajectory corresponds to $k + 1$ accomplishments of the model and allows the calculation of an elementary effect for each model parameter x_i, $i = 1, \ldots, k$. If $x^{(\ell)}$ and $x^{(\ell+1)}$, $\ell \in \{1, \ldots, k\}$, are two points of the j trajectory defined by the sampling strategy which defer in their ith element, the elementary effect of input variable x_i. is given by

$$\mathrm{EE}_i^j\left(x^{(\ell)}\right) = \frac{y(x^{(\ell+1)}) - y(x^{(\ell)})}{\Delta}, \tag{4.16}$$

in case the i element in $x^{(\ell)}$ is increased by Δ, and by

$$\mathrm{EE}_i^j\left(x^{(\ell+1)}\right) = \frac{y(x^{(\ell)}) - y(x^{(\ell+1)})}{\Delta}, \tag{4.17}$$

in case the i element in $x^{(\ell)}$ is decreased by Δ (Saltelli et al. 2008). After performing samplings of using r trajectories of the existing simulation results, there are just as much elementary effects for one model's parameters. They constitute the set $\{\mathrm{EE}_i^j | i = 1, \ldots, k; j = 1, \ldots, r\}$. With its help, the measure μ_i (average) and σ_i (standard distribution) for the distribution functions F_i of elementary effects presented calculate the input variable x_i as follows:

$$\mu_i = \frac{1}{r} \sum_{j=1}^{r} \mathrm{EE}_i^j. \tag{4.18}$$

The measure μ_i^* (average) of the distribution function G_1 of the absolute values $\left|\mathrm{EE}_i^j\right|$ is to be calculated as follows:

$$\mu_i^* = \frac{1}{r} \sum_{j=1}^{r} |\mathrm{EE}_i^j|. \tag{4.19}$$

Critical in carrying out the calculation of the elementary effects is the selection of the parameter p, which controls the number of stages, and the parameter Δ, which controls the grid width for Ω. The choice of p directly affects the choice of r. A detailed example for the impact of the selection of values p and Δ on the calculating of elementary effects has to be found in Saltelli et al. (2008).

If the values are equally distributed in all model parameters, the number of stages is determined by the given greatest common multiple of the number of accepted values for each input variable. If the values are not evenly distributed for the input variable, the sampling is not carried out directly for this input variable. Instead, the space of the quantiles of the distribution function is used; this is the k-dimensional unit cube $[0, 1]^k$. The actual values for the corresponding input variable will be derived from the distribution function (Campolongo and Braddock 1999). An example of the procedure for non-uniformly distributed values of model parameters can be found in Saltelli et al. (2008).

If Δ is selected uniformly for all model parameters, its importance is irrelevant for the definition of the elementary effect with regard to the determination the sensitivity. In this case, Δ^{-1} becomes a constant, which is multiplied with an elementary effect and has no influence on the results of the calculations for the elementary elements.

For this purpose, following model is considered: $Y = X_1 + X_2$. With the following conditions: $X_1 : [0,1] \to A \subset \mathbb{R}$, $X_2 : [0,10] \to B \subset \mathbb{R}$. The values assumed in A and B are uniformly distributed. It is expected for this model that the input variable X_2 has greater interaction with the model than input variable X_1. Due to the wider definition range of X_2, a change in the values of X_2 affects the model Y to a greater extent than X_1. To calculate elementary effects, we select $p = 4$ and $\Delta = 1/3$ and one trajectory through Ω, thus, $r = 1$. That is, for each input variable an elementary effect is calculated, so that these two apply as sensitivity measures. For the further process, it is assumed that a trajectory is generated of the following quantiles of X_1 and X_2: $(0, 1/2)$, $(0, 2/3)$ and $(1/3, 2/3)$. Inverting the distribution function, the following grid points for both model parameters are generated: $(0, 10/3)$, $(0, 20/3)$ and $(1/3, 20/3)$. In each case, the elementary effects below can be determined for one input variable:

$$\mathrm{EE}_1(X) = \frac{Y(1/3, 20/3) - Y(0, 20/3)}{\Delta} = \frac{1/3}{\Delta} \tag{4.20}$$

and

$$\mathrm{EE}_2(X) = \frac{Y(0, 20/3) - Y(0, 10/3)}{\Delta} = \frac{10/3}{\Delta}. \tag{4.21}$$

Both formulas (4.20) and (4.21) represent the impact of Δ on the calculation of elementary effects. In case Δ gets a change in value from primary $1/3$ to $10/3$ during the calculation of EE_2, the value of both elementary effects would be equal 1. In turn, this implies that both model parameters have the same influence on the model Y. Now, we consider the choice of $\Delta = 1/3$ to calculate both elementary effects. That means, we ignore the stronger variation in the value range of X_2, and an elementary effect for X_2 in relation to Y might be calculated ten times larger than for X_1.

This example illustrates the flexibility of this measure for sensitivity of a model concerning a variable. Regarding its ability to deal with both the requirements of a model as well as with the different distribution functions, the model parameters involved. In addition, it also illustrates that the choice of Δ has to take the distribution function for the range of values of an input variable into account regardless of the definition range of this input variable. The strategy for selecting the grid points with which the elementary effects are calculated influences computational costs. How this selection has to be made is explained in detail by Morris (1991).

Iterative Analysis Method

This section provides the adaptation of the method of Morris to the models of the use case. It focuses on the selected parameters for the method and their

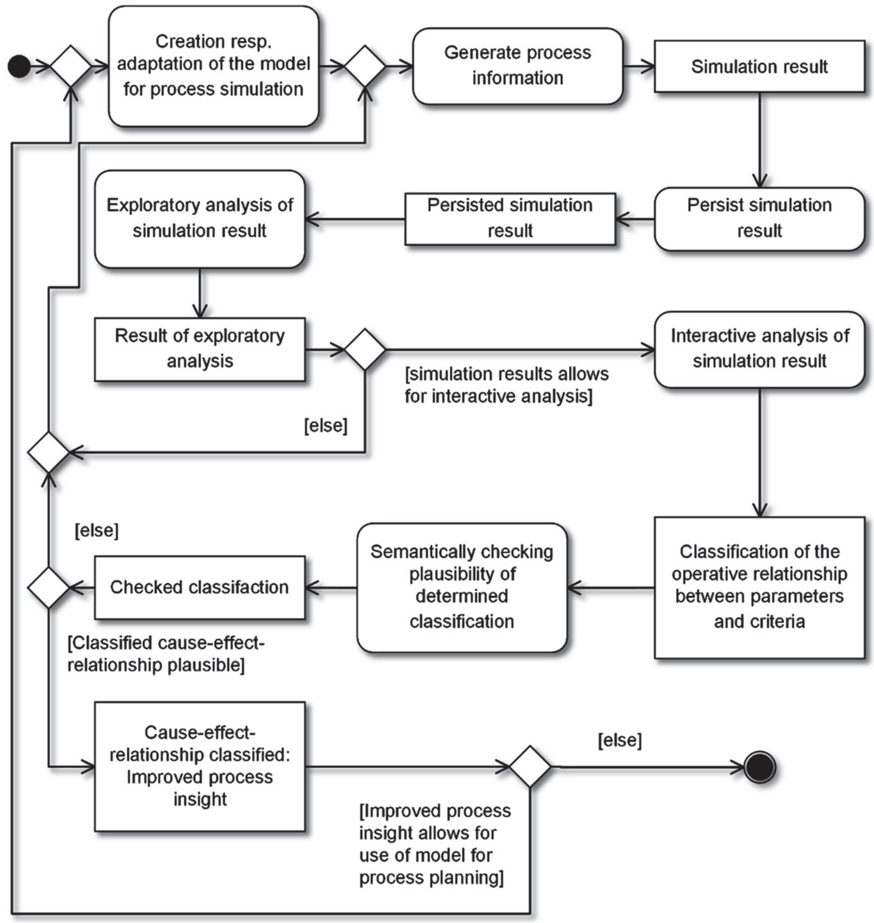

Fig. 4.23 Iterative analysis for the validation of manufacturing models

improvement through Campolongo. The integrated data sets consisted of 10,000–100,000 samples. The number of process parameters was not more than ten, the process criteria maximum twelve. The following allocations for the setting parameters of the method are used for the classification of the cause–effect relationship: $\Delta = 3r = 300$, $p = 6$. In the following, the iterative analysis that comprises the methodology for the classification of cause–effect relationship is described. The single actions and artifacts are presented and described below. The implemented iterative approach is shown in Fig. 4.23.

According to the developed concept, the first action of the iterative method is the *Creation resp. adaptation of model for process simulation* that prepares the subsequent action. The second action *Generate process information* refers to the execution of a simulation of the manufacturing process. Here, models are the basis for the implementation of simulation application. The artifact of this action is the *simulation result* and is presented as a file for the successful implementation of the subsequent action in an established structure. In the present use case, the simulation results are available as CSV resp. XML file. The specific column resp. elements contain the terms of the within the underlying model considered parameters and criteria. Furthermore, the selected user parameter values and the calculated criteria values of the underlying model are also part of the simulation results.

The *VPI platform* enables the user to examine these simulation results through data integration and interactive analysis. Once the simulation results are generated, the next step is to upload them to the platform through its web-based graphical user interface. This step is depicted as *Persist simulation result*. The user may link the simulation results with an existing or newly created analysis project as a process. Furthermore, the user has the possibility to give more information concerning the process such as the term or a description of the process. Once the data is uploaded, the platform performs the data integration and analysis calculations in the background. All information that is required for the subsequent explorative and interactive analyses are automatically prepared and persisted in the respective database entries. These entries form the artifact *Persisted simulation result*, which is used in the next step: *Exploratory analysis of simulation result*.

Appropriate visualizations support the user determining inappropriate process parameter ranges, which is crucial for carrying on further examinations based on these simulation results. Frequently, the selection of an inappropriate model or implementation errors in the simulation application on which the simulations results were generated causes such unsuitable ranges. At the end of this action, the user has the artifact *Result of exploratory analysis*. If an irregularity or an error is detected, such as an invalid value range for the considered process parameters, the procedure provides the first feedback to the second action. Thus, the user reruns the simulation application. Otherwise, the user continues with the next action *Interactive analysis of simulation result*.

First, the user makes a selection of the criteria of the process that need to be visualized and initiates its visualization. Subsequently, a view of each chosen criterion of the correlations determined by correlation calculation between the previously selected criteria and all parameters of the process is presented. Figure 4.24 shows the implementation in the *VPI platform*.

The presentation is done in two ways: quantitatively and qualitatively. For the quantitative representation, a bar graph is used (top left). Each bar shows the signed correlation between the selected criterion and all the parameters of the process. The qualitative representation is made via a chord diagram. Between the criteria and all parameters of the process, one chord appears each. For the representation of the correlation level, two types of visualization are used. On the one hand, this is the strength of the chords. The length of each chord remains unaffected. A high correlation corresponds to a wide chord, a low correlation to a narrow chord. On the other, there is the color-coding of the chords. The color scale used ranges from green for a high correlation to yellow for an average correlation to red for a low correlation. The representation of the elementary effects between each criterion and

Fig. 4.24 Interactive analysis within the *VPI platform*

any process parameters is also visualized. The interactive examination is carried out for several criteria. The artefact of this action is called *Classification of the operative relationship between parameters and criteria*, and represents the next action *Semantically checking plausibility of determined classification* available.

This action provides the review of the interdependency determined by the interactive analysis by the user. Thereby, the user conducts a semantic examination of the result and puts it in relationship with its existing knowledge. If the classification proves as non-plausible, the analysis method provides a return to the second action *Process Simulation*. In this, the user makes an adjustment of the value range of the parameters or selects a new model, which is based on the simulation.

If the classification is plausible, the improved understanding of the process allows the validation of the process model, which enables an adaption of the process model or the completion of the investigation. The description of the implemented iterative analysis process has been completed.

Visualization of Metamodels

As already outlined in the state of the art, visualization is a powerful way of analyzing multi-dimensional data. As stated, for instance, by van Wijk (2005), it facilitates obtaining insight in complex data by addressing the human visual system that is effective and efficient in detecting interesting features and patterns. Among existing solutions that have been examined for the visualization of metamodels, the solution by Gerber et al. (2010) in particular provided useful overview information. However, since it focuses on revealing general interdependencies, it is not well suited for the examination of details in the data space. Furthermore, a combination of improving the general process understanding in combination with capabilities for identifying improved process configurations is needed for the current use case. For that reason, a new visualization concept is presented that is illustrated in the form of a prototypical implementation, called Metamodel Slicer (*memoSlice)*.

The focus of the visualization concept is fostering the understanding of manufacturing processes by providing features for overview and in-depth analysis of metamodels. Furthermore, support for the fast and easy identification of improved process configurations is included. By default, *memoSlice* is a stand-alone application. However, to make the benefits of metamodels already available in the planning phase of factories, *memoSlice* is also integrated in *flapAssist*, where it serves as a widget for machine configuration.

As depicted in Fig. 4.25, *memoSlice* is based on a linked-multiple-view design, which tightly integrates several visualization techniques for the analysis of metamodels. To facilitate correlation analysis, a scatterplot matrix is included. A HyperSlice view (van Wijk and van Liere 1993) enables the detailed examination of metamodels, while more context is provided by means of a 3D view.

To facilitate interactive exploration and to be able to integrate *memoSlice* into *flapAssist*, a high degree of responsiveness is of key importance. Thus, the application relies on task-based parallelization techniques with a new user-centered prioritization scheme and streaming updates to guarantee fast update rates, without impairing the user's workflow.

In summary, the contributions of the approach are, first, a novel multi-view visualization approach for the analysis of metamodels; and second, concepts and techniques for a high degree of interactivity, including parallelization techniques.

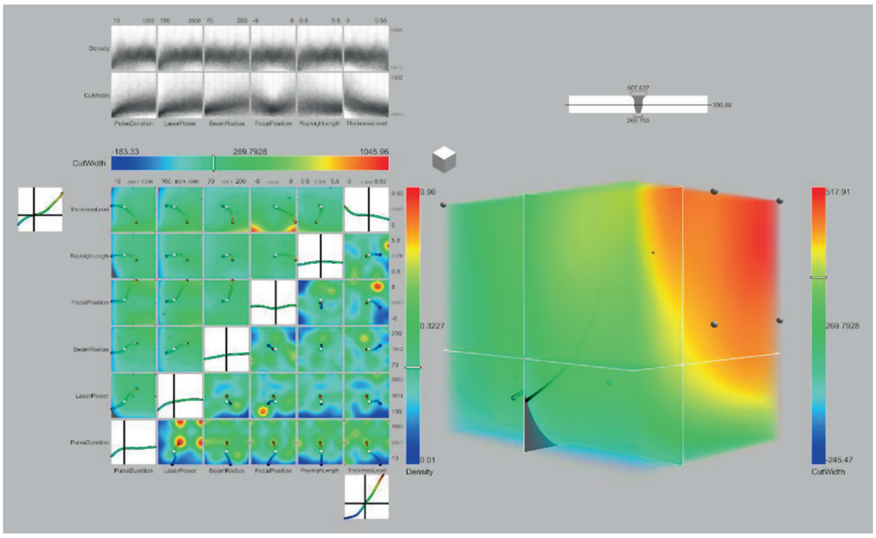

Fig. 4.25 Screenshot of *memoSlice*. The visualization components are the scatterplot matrix (*top left*), the HyperSlice view (*bottom left*), the cutting profile view (*top right*) and the 3D view (*bottom right*). The so-called EpoxyCut metamodel is visualized. It illustrates the effects of six parameters of a laser cutting process on the criterion *cut width*

Supplied Data

memoSlice visualizes metamodels as they are described in Sect. 4.4.2.1. For the analysis of a manufacturing process, an RBFN metamodel has to be provided for the visualization of process criteria of that metamodel. An optional second RBFN metamodel, the so-called feasibility metamodel, can be provided for the visualization of the separation into the feasible and the infeasible domain, respectively. In case both metamodels are provided, parameters have to be identical in both metamodels. This applies for the number of parameters and their names, as well as it does for the covered ranges of the data space. The number of criteria and training points may yet be different in both metamodels.

As outlined in Sect. 4.4.2.1, metamodels cannot directly classify Boolean values, but instead continuous scalar values. For this reason, the feasibility metamodel contains values in the interval [−1, 1], where 1 represents a feasible parameter combination, while −1 represents an infeasible combination. Since the evaluation of the feasibility metamodel returns interpolated values in the interval [−1, 1], positive values are interpreted as feasible and negative values as infeasible by default.

However, the exact separation of the domains is unknown due to interpolation, so results in the interval [−1, 1] indicate values with an uncertainty about whether the process yields a feasible result, depending on how close the value is to either −1 or 1. To account for this, a threshold different from 0 can be chosen for the domain separation to exclude areas with high uncertainty from the feasible domain. Infeasible regions are grayed out in all visualizations. However, in order to account for the implied uncertainty, a blending with the original coloring can be applied that depends on the distance to the certain values −1 and 1. This way, the user is made aware of getting close to regions where feasibility might be uncertain.

Visualization Design

This section gives an overview of the visualization design of *memoSlice* and describes its single components and the most important interaction aspects. To support the user in the fast assessment of metamodels, different views are combined that give an overview of the supplied metamodel, but can also be used to inspect details. These are described in the remainder of this section. Additional landmarks, which are extrema and training points, help to maintain orientation in the data space. These visualization primitives are used in most of the described views.

As done in other approaches before, such as van Wijk and van Liere (1993) as well as Torsney-Weir et al. (2011), *memoSlice* uses *focal points* as a key concept. A focal point is a tuple of parameters that determines which parts of the metamodel are to be displayed in the single visualizations. By changing it, all affected views are updated. By default, all views are linked by means of a common focal point. However, the focal points for every single view can be decoupled from the common focal point. This way, different regions of the data space can be analyzed simultaneously, thereby supporting comparisons of different candidates of parameter combinations or different behaviors for varying process configurations. The focal point can be adjusted either via menus or via direct manipulation where applicable. Another important concept in *memoSlice* is the usage of slices, which are incorporated in several visualization primitives. These are 1D, 2D and 3D slices that are axis-aligned cuts through the data domain with the respective dimensionality.

HyperSlice View

The HyperSlice view gives a comprehensive overview on the multi-dimensional vicinity of focal points. It enables the user to improve the overall understanding of the data while exploring it. Only a brief overview over the HyperSlice layout is given here, for detailed information the reader is referred to the publication of van Wijk and van Liere (1993).

HyperSlice is a matrix of axis-aligned 1D and 2D slices through the parameter space of the metamodel. It consists of three parts: the upper part, the lower part, and the diagonal. Additionally, axis captions and color legends are shown.

As illustrated in Fig. 4.25, the upper and lower part each show all possible axis-aligned 2D slices through the respective focal point, represented as color-coded squares. Here, the *x*-axes of the slices correspond to the respective labels on the bottom of the matrix, while the *y*-axes correspond to the respective labels on the left. In contrast, the diagonal of the matrix shows all 1D slices through the focal point as graphs, with the *x*-axis corresponding to the labels at the bottom and the *y*-axis corresponding to the value of the displayed criterion. This layout also implies that the upper and lower part display transposed views on the same data. Though this might seem redundant at first, this layout features several advantages for metamodel analysis. It is possible to emphasize different aspects of the data by using different color mappings in the upper and lower part. Alternatively, two different criteria or two different focal points can be analyzed simultaneously, thus supporting a better overview and comparisons.

The 2D slices are superimposed with additional information. This includes a projection of the common gradient trajectory, which originates from the focal point. Furthermore, projections of training points and local extrema are shown in each 2D slice.

Scatterplot Matrix View

The scatterplot matrix view gives an instant overview over a metamodel. It contains one scatterplot for every possible pair of parameter–criterion combinations. The displayed points are created via evaluating the metamodel at random locations within the working limits. The concept of *brushing* (Becker and Cleveland 1987) is often used with scatterplot matrices. It allows for filtering in several linked scatterplots by direct selection of points that then get emphasized in all plots. However, due to the possibility of evaluating metamodels in fractions of milliseconds, the concept of brushing was replaced with generating points based on user-defined generation rules. To this end, the user can define parameters to be locked to a distinct value or define the minimum and maximum values of parameters and criteria that are considered for point generation. This procedure maintains the density of the scatterplots. Thus, detailed insights can be gained—even for small subspaces of the whole metamodel.

3D View

In contrast to the HyperSlice view, the 3D view visualizes a single three-dimensional slice instead of several two-dimensional ones. Thus, it does not give an overview over all dimensions, but instead shows all information along three visible parameters, thereby providing more context than 2D slices. The corresponding focal point defines the values of the remaining parameters. Additionally, the user can freely choose the displayed parameters.

The 3D view is composed of several visualization primitives. Three crossed 2D slices are shown within the volume of the 3D view. They are axis-aligned and their intersection point matches the location of the projection of the focal point. Additionally, a direct volume rendering of a 3D slice is superimposed over the crossed 2D slices. It fills the area that is not covered by the 2D slices. Training points, local extrema, and a color legend are displayed as additional information.

Cutting Profile View

Metamodels are applicable for various manufacturing tasks. However, cutting tasks are (especially within the scope of this reported work) a common object of research for metamodels. An experienced analyst can easily judge if a parameter configuration might be considered for a certain process by having a short glance at the resulting cutting profile. To account for this, *memoSlice* contains the cutting profile view. As the name suggests, it displays the cutting profile for the currently selected focal point, as long as the information can be derived from the metamodel. However, this is only possible if the metamodel contains the cutting depth as parameter and the resulting cut width as criterion. Consequently, the cutting profile view is only visible if a metamodel is loaded that meets these criteria, while it is not visible otherwise.

Interactive View Updates

The main computational load for *memoSlice* is generated by metamodel evaluations. These are assessed by probing the RBFN. For each evaluation, the contribution of all RBFs has to be computed for the metamodel and, if provided, also for the feasibility metamodel. Apart from tuning the metamodel evaluation itself, several strategies had to be examined to guarantee a highly interactive workflow for the user who should not be hindered by waiting times.

Asynchronous Parallel Updates

RBFN evaluations are parallel in nature. Each evaluation can be performed independently and the contribution of each RBF can thus be computed in parallel. These observations have been translated into a layered, task-based parallelization scheme. On the top level, a task comprises the update of a single 1D, 2D, or 3D slice or the calculation of samples for the scatterplot matrix, respectively. Tasks for updating a slice are decomposed into sub-tasks, each of which provides several samples for the slice. Each of these tasks in turn spawns sub-tasks that evaluate individual RBF kernels. Finally, data for the scatterplot views are created from sampling the parameter domain space. However, this task is decomposed analogously to slice updates with random sampling positions.

Load balancing across CPU cores is realized by the Intel® TBB runtime. The task engine runs asynchronously to the frame loop, hence not interfering with continuous rendering updates. Tasks are triggered whenever depictions need to be updated and updates are displayed as soon as they become available.

Streaming Updates
Parallel updates alone do not guarantee highly interactive user feedback within fractions of a second. However, most metamodels feature relatively smooth gradients over extended parts of the domain. Hence, it is possible to gain a first overview of the data field based on a relatively coarse sampling of the parameter space. At the same time, precision adjustments, such as when modifying the focal point close to the working limits, require a more accurate depiction of the data. In order to reduce perceived system latency and update the visualization in the vicinity of the focal point as quickly as possible, a progressive computation of slice-based views is proposed. Slice updates start with a user-defined minimum resolution and are refined by interval bisection until a maximum resolution is reached. The progressive update scheme provides nearly instant overviews, with further refinements being streamed in upon availability. To make the user aware of this process, slices that are out of date are grayed out, while slices that are currently getting refined are emphasized with a colored border.

Expert User Feedback
The development process of *memoSlice* is not finished yet. However, to further improve the underlying visualization concept, two domain experts that use the application on a regular basis have been interviewed. The qualitative feedback from the interviews reveals the strengths of *memoSlice*, but also helps in identifying shortcomings that will be refined in future revisions.

The experts specifically mentioned that a first-glance assessment of metamodels with *memoSlice* provides insights that could only be gained with a high amount of manual work beforehand, namely running many simulations and then analyzing the results with MATLAB® or ParaView. These insights include the instant identification of the boundaries for parameters and criteria, assessment of the sampling strategy by visualizing the density function of a metamodel, and being able to directly identify the physical limits of a process.

Feedback on the actual analysis process included that the comparison capabilities, like using different focal points and displaying multiple criteria, helped a lot in their decision making process. Even if this feature was an explicit request in the design phase of *memoSlice*, the experts admitted that they rarely used the 3D view until now. However, they see a potential of using it in the future for analysis tasks that include the identification of optimized configurations, when 2D slices only reveal a limited spatial structure.

After looking at the main project results within the two designs, domains Factory and Machine in the phases of the information management cycle, the next section is concerned with the economic advantages of the presented demonstrators.

4.5 Profitability Assessment as a Contribution to the Theory of Production

This section assesses the profitability of the three demonstrators *VPI platform*, *flapAssist*, and *memoSlice*.

The *VPI platform* is the information product of the different planning information systems using the VPI approach. It uses web technology to provide interaction with the users and is therefore highly adaptable and accessible. Within the *VPI platform*, the whole integration and analysis process of planning data is available for a unified access to all functionalities. Besides user-centered visualizations within the platform, it provides interfaces to further planning tools such as the other demonstrators.

The demonstrator *flapAssist* is a VR application that supports the factory layout planning process. It allows planners to perform virtual walkthroughs and provides access to further metadata in form of interactive visualizations right from within the VE. Users can create annotations to capture and exchange results as well as planning decisions.

The demonstrator *memoSlice* was created not only to enable users to improve their understanding of production processes that are represented as metamodels, but also to identify improved process configurations. Both are enabled by means of an interactive explorative visualization approach that can be used stand-alone or as configuration interface in *flapAssist*.

In order to evaluate these three demonstrators, it is necessary to consider the different scopes, which are required, since the products are located in different positions within the value chain (see Fig. 4.26). Thus, the demonstrators have to be analyzed separately. Moreover, the consideration of the profitability of *memoSlice* is split into two scenarios. The first one deals with the case that a machine

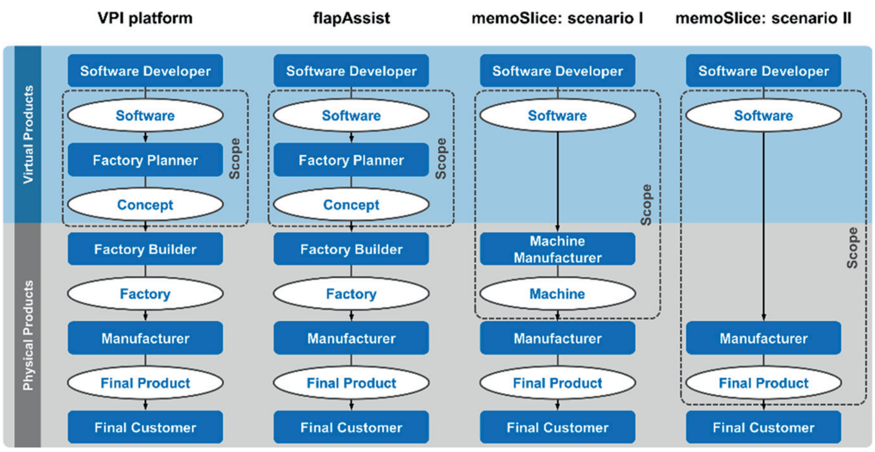

Fig. 4.26 Overview of all demonstrators as located in the entire value chain

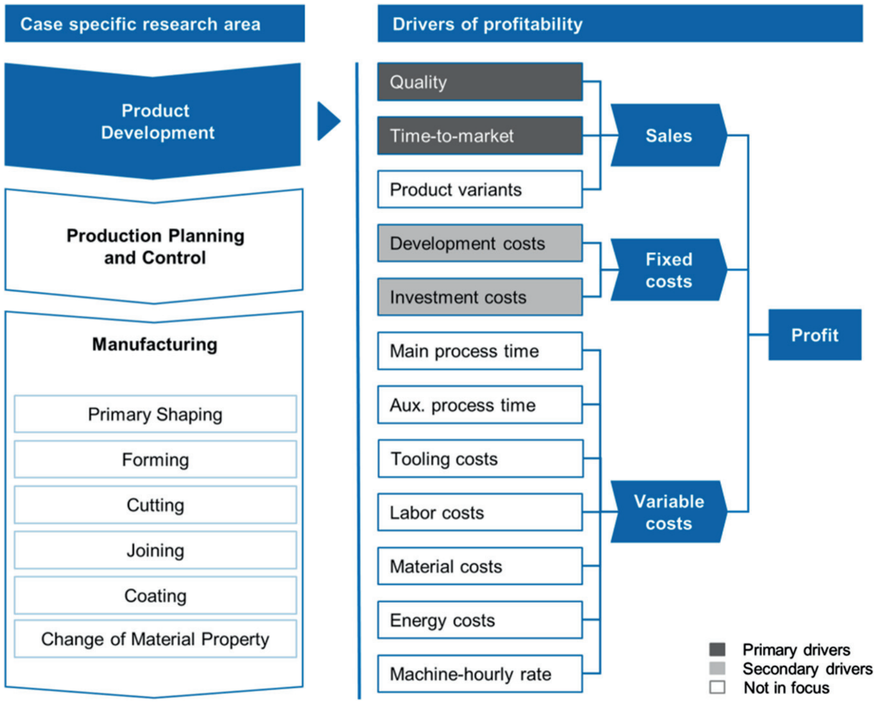

Fig. 4.27 Drivers of profitability within RA "virtual production intelligence"

manufacturer configures the machines with the software and sells them as a user interface tool to manufactures. The second one represents that manufactures themselves use the software for their own machines.

All of the cases are mainly described in the following sections based on four drivers: time-to-market, quality, development costs, and investment costs (see Fig. 4.27). We chose these drivers due to their major significance with regard to the profitability study. The analyzed demonstrators mostly affect these drivers as the following research shows. Since time-to-market and quality have the greatest impact on profitability, they are considered as *primary drivers* of profitability. Hence, the reduction of time-to-market and the increase of quality caused by the implementation of the demonstrators are described in detail afterward.

4.5.1 Reduction of Time-to-Market

Virtual Production Intelligence (VPI) Platform

We mainly developed the *VPI platform* in order to support the factory planner planning a new factory. Thus, factory planners are the customers of this platform and the factory concept is considered as the product (see Fig. 4.28). *VPI platform* is

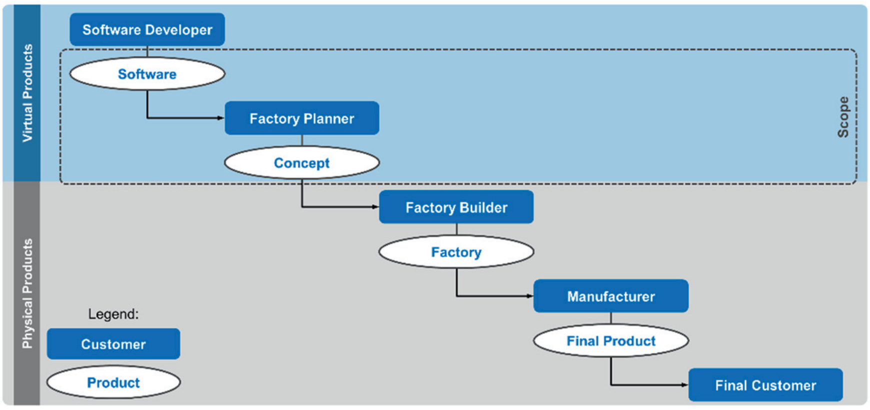

Fig. 4.28 *VPI platform* and *flapAssist* in value chain

analyzed by means of the two primary drivers—*quality* and *time-to-market*—which both are changing positively. In addition, the platform can be evaluated based on development costs and investment costs.

Due to automatic data acquisition and consolidation, customers can save time during the planning processes, as all planning data as well as evaluation results are saved in a standardized way. Manual created analyses of data and other non-productive operations can therefore be reduced. This leads to a reduction of the driver time-to-market.

flapAssist

The profitability study of *flapAssist* focuses on the same scope as the analysis of *VPI platform*. The location in the value chain is identical: The factory planners are the customers, and the product is the concept of the factory to be built (see Fig. 4.28).

Different machine settings and layouts can be evaluated much faster. Consequently, a reduced time-to-market is observable. Due to a faster planning process, the factory planner has less financial requirements. A shorter time-to-market facilitates the adaption of products according to market demands.

memoSlice—Scenario I

With *memoSlice*, a proper parameter configuration for machine settings can be identified more efficiently than with existing solutions. This improves decision making and thus reduces time-to-market concerning the production of final products. In scenario I, *memoSlice* is an analysis and visualization tool used by machine manufacturers who are considered as the main customers. Their products are the machines that are sold to manufacturers. The scope of the profitability assessment is shown in Fig. 4.29.

The use of a metamodeling technique allows reducing the required time invested to find a suitable machine-set-up working point. Moreover, the customer/user can

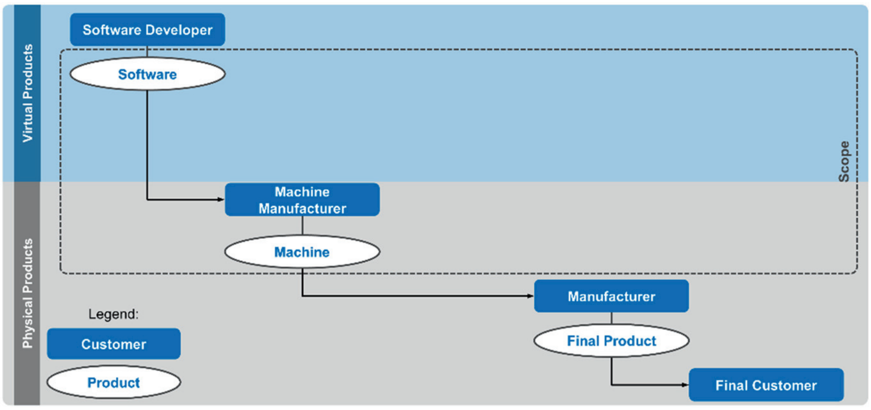

Fig. 4.29 memoSlice scenario I in value chain

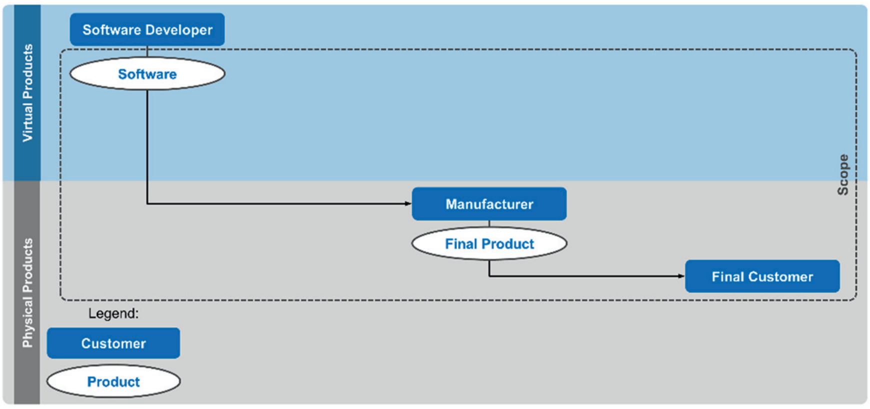

Fig. 4.30 memoSlice scenario II in value chain

attain an understanding of the process more easily through visual exploration/experimentation. This ultimately leads to a reduction of development time so that the product can enter the market faster.

memoSlice—Scenario II

As mentioned before, the position in the value chain is a different one in scenario II. In this scenario, *memoSlice* is used from manufacturers, who in turn use it on their machines to improve production of their end product (see Fig. 4.30). Therefore, in this case the drivers relate to the final products.

Due to a proper configuration of the machine parameters, the production time of each final product is reduced. The time for setting up a machine for a certain manufacturing operation as well as production time is shorter. Therefore, the final product can get into the market faster.

4.5.2 Increase of Quality

VPI Platform

The quality of the factory planning process and the results improve as a result of using the *VPI platform*. Referring to the driver quality, two different aspects can be underlined. In respect of objective dimensions, data quality improves. There is the possibility of an integrative information evaluation by means of a consistent and coherent modeling of factory planning data. Respecting the subjective dimension of quality, we can point out the distinctiveness: The information management process certainly stands out from the competition. In addition, the possibility of an automatic calculation of KPI along the whole planning process is poised for realization in the future.

flapAssist

The goal of *flapAssist* is to facilitate layout planning by means of a CAVE VR system. The high degree of immersion offered by such a system allows users to judge spatial relations in entire factories through cost-effective virtual walkthroughs. These walkthroughs through life-sized VF models allow planners to get a realistic impression of the product without the need of constructing them. As a result, the quality of the planning process improves.

Additional information can be visualized to comprehensively review the factory layout. In conformance with the factory builder, the factory planner can realize a completely customized layout. All in all, the performance of the product (objective dimension of quality) improves.

memoSlice—Scenario I

Using metamodeling techniques, manufacturers master manufacturing processes easier and with better results. Process insight increases due to the visual support during the analysis of process models and process maps. In consequence, the quality of chosen machine settings increases.

memoSlice—Scenario II

There is an augmentation of quality by the implementation of the optimal working point in machine parameter configuration. The result is a better quality of products as well as a better operational understanding and process behavior.

4.5.3 Effects on Development and Investment Costs

VPI Platform

The automation of the whole information processing cycle (from data consolidation over data processing to information provision) causes fewer personnel requirements so that personnel costs are reduced. This fact implicates a reduction of the development costs, whereas required investments rise in the first place, which has a negative influence on the profitability. Costumers have to integrate the information system and realize the implementation—meaning to buy the software—and train the staff. This short-term effect is probably overlapped by all of the other benefits and should be completely compensated for in the long-term.

flapAssist

Time-to-market and the quality of the factory increase due to *flapAssist* and development costs decrease. The visualization supports the optimization of the layout in the same way as it optimizes the development process of the factory. Furthermore, a visualization of KPI concerning the layout is possible and can be done quickly. A result of the efficient planning process is a shorter development time. In this case, the planning period corresponds to development time. Consequently, development costs decrease. Investment costs rise because the factory planner has to buy the software and pay for potential training courses before using *flapAssist*. Nevertheless, the short-term effects should be overcompensated in the long-term here.

memoSlice—Scenario I

Quality, time-to-market, and development costs have a positive influence on the profitability. A shorter development and production time leads to a reduction of development costs. Distributed planning requires the implementation of a performant application and information integration. Thus, it represents an essential investment that is redeemed in the medium-term.

memoSlice—Scenario II

The software requires less time and fewer resources for the optimization of the process compared to an experimental trial-and-error approach. This results in a major reduction of the setup costs and thus in a reduction of the development costs. Additionally, the labor costs can be decreased because employees need less time to adjust the machine. The investment in the software will shortly be balanced by benefits of greater quality, smaller development costs, and shorter development and machine-setup time scales. Investment costs rise because the manufacturer has to buy the software and pay for potential training courses before using *memoSlice*.

4.5.4 Conclusions on Profitability

The different independent applications have differences concerning their profitability. As mentioned previously, the primary driver time-to-market has a major impact. Regarding all demonstrators, time-to-market is reducing—albeit slightly less in the first scenario of *memoSlice*. The analysis of quality has also positive impacts on the profitability of all products. In equal measure, all demonstrators cause a reduction in development costs.

Only the investment costs have negative impacts on profitability. However, the listed benefits of these different software tools compensate for the initial investment: *flapAssist* provides the opportunity of a virtual visit of the factory; *memoSlice* enables to find an optimal machine configuration. The *VPI platform* supports these applications by the integration, processing and evaluation of data and information. Finally, the demonstrators *VPI platform*, *flapAssist*, and *memoSlice* have positive effects on profitability and the value-added of the products.

After the description of profitability of the elaborated demonstrators in the current, the next section focuses on this project's industrial relevance.

4.6 Industrial Relevance

4.6.1 Virtual Production Intelligence (VPI) in Factory Planning

As the VPI and its demonstrators in factory planning are still under development, the precise industrial implications and market chances still have to be estimated. However, from different interviews and meetings with experts from production planning departments in practice, it can be said that especially the approach of a consolidated data platform and an automatic exchange of information between different planning modules (and hence software solutions) may be seen as a great chance.

As mentioned, a key enabler to reduce planning time and costs is the establishment of an overall data and information processing tool that at least partially automates the planning tasks within a project. If this approach comes into force, the changes to factory planning projects might be dramatic: Key challenge in factory planning projects would then be able to supply all relevant data in the required data format and enter this input into the *VPI platform*. The rest of the calculation could be automated to a large extent so that—using the required calculation capacities—the planning times might decrease dramatically. Of course, the complete automation is a keen vision and will never be realized completely, since a factory planning project is highly complex, with strong sociocultural influences. The possible extent of automation must be evaluated for every planning module of the CBFP. In this project, especially the module layout planning was analyzed in further detail.

For layout planning with its demonstrator *flapAssist*, the industrial relevance was already discussed with industrial experts. Especially the approach to gather information and arrange them collectively within different sights in a 3D layout is a highly interesting approach for companies that only rarely see factory planning projects within their company. As bigger companies with their own factory planning departments often use a high number of tools and already know how to manage the interfaces between those tools by experience, *flapAssist* with the VPI as a basis is a great tool for smaller companies that are looking for an all-in-one solution.

In summary, the industrial relevance of the *VPI platform* and especially the demonstrator *flapAssist* can be estimated as high. As the *flapAssist* was already discussed with experts from the industry, a further development of this tool toward an overall layout planning and assessment tool is promising. As this demonstrator only addresses the module layout planning, a further investigation of other planning modules is also necessary to enable a higher automation of the planning processes on the basis of the VPI.

The idea of a continuous and consistent information modeling is not only highly relevant in factory and production planning but also in production itself. Nowadays, every automated production *produces* vast amounts of data, *Big Data*, with the same challenge of heterogeneous data and incompatible IT systems. The semantic annotation and consistent aggregation of production data is again the necessary basis. We have already combined the methods of the VPI with the industrial communication protocol OPC Unified Architecture (OPC UA) and have implemented use cases in industrial practice (Hoffmann et al. 2016). Furthermore, the analysis of such information with the aim to optimize production processes is currently discussed and prototypically implemented with several industrial partners. Technologies such as data mining and machine learning that we implemented in the VPI context again serve as a basis.

4.6.2 Metamodeling of Laser Cutting Processes

As a fundamental metamodel for laser cutting is now developed, we can take a look at a real-world application example, where the metamodeling methodology is applied for achieving additional benefits from this newly gained knowledge:

Fundamental research in modeling and simulation showed that increasing the beam diameter in feed direction should be beneficial to the surface quality in laser cutting, as it should reduce the ripple-forming instability on the cut front and thereby decrease the roughness amplitude on the cut edges. This idea inherently leads to the concept of an elliptic beam—that is, a beam with elliptic cross-section. However, this concept needs to be quantified for testing in the real world. Therefore, the question is which minimal diameters the beam should have, and at which position with respect to the workpiece the focal points corresponding to these minimal beam diameters should be placed. Together with the beam quality giving a measure for the beam divergence, this makes five parameters to choose beneficially —a perfect task for the process map presented in previous sections, where the metamodeling concept can prove its strengths.

Looking at the process map for laser cutting, shown in Fig. 4.31, the star-shaped marker denoting the seed point of the analysis represents the current cutting parameter settings, and the arrow trajectory shows how an improvement in the cut quality is achieved.

The more detailed results presented in Fig. 4.31 show that in order to minimize the cutting surface roughness in the vicinity of the seed point, astigmatism should be increased, while the beam radius in the feed direction x should be decreased, and the focal position should be raised. The fact that the minimal beam radius in x-direction is decreased to get a lower roughness value is actually no contradiction to

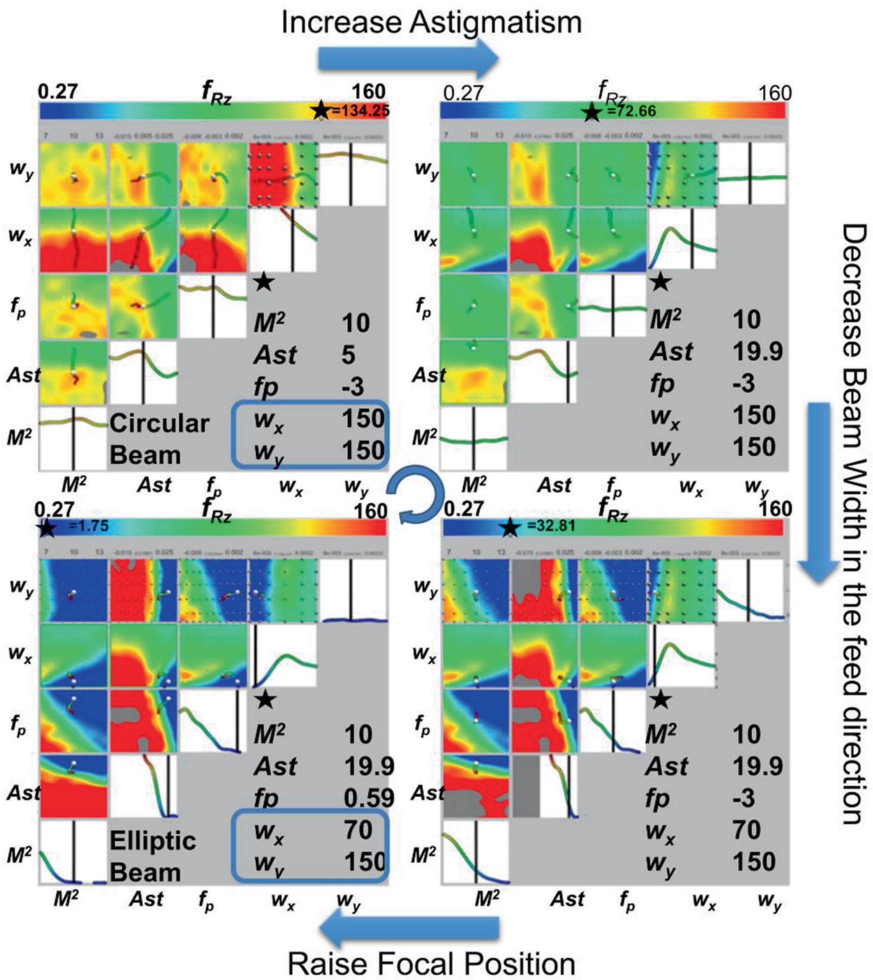

Fig. 4.31 Use of the metamodel and process map in the design of a new focusing optics (for elliptic beams) with the goal of reducing roughness in laser cutting; the dark color indicates regions in the domain space where smaller roughness values could be expected

the premise of increasing the beam radius in feed direction, since the focal position is such that the beam radius in feed direction at the position of the workpiece is actually increased.

Having determined the beam parameters for a beam that promises improvements in cut quality, it is a straightforward optics-design task to conclude the optics that produces that kind of beam. For an elliptic beam, the beam parameters (i.e., the beam radii and the astigmatism value) are directly and analytically related to the focal lengths of two cylindrical lenses and the distance between those lenses (see Fig. 4.32).

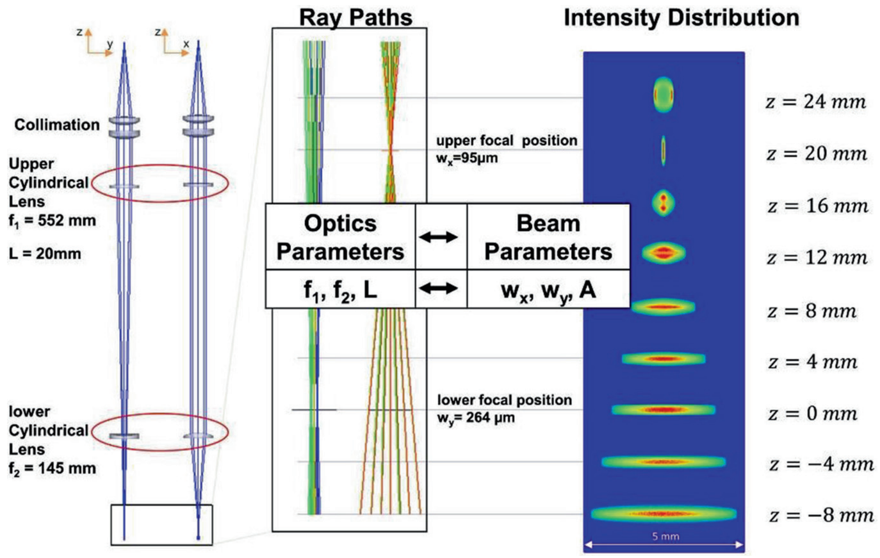

Fig. 4.32 Laser focusing optics derived from the metamodel: the beam parameters that have been extracted from the process map as being optimal can directly be transferred to optics parameters

This concludes the presentation of a direct application of metamodeling techniques in a real-world example that evidently reveals the implications for industrial use. At the moment, the optics designed with the help of metamodeling techniques is built up and tested in a lab environment.

After examining the industrial relevance, the next section deals with future research topics in the two design domains covered.

4.7 Future Research Topics

4.7.1 Design Domain Factory

The factory planning use case has demonstrated the applicability of the *VPI platform* by showing how all of its modules and functionalities can be used. The environment for the demonstration is a factory with typical production from the industry sector of mechanical engineering. Several different products have to be produced on different machine types following different value streams. In contrast to the current understanding of factory planning (which is characterized as a unique and terminating process), factory planning in this use case is performed periodically using predefined planning workflows to assess the production structure and identify needed changes (due to, for example, changes in quantity demand or production program).

A factory planning workflow is defined to assess the factory structure and configuration periodically. Changes in layout or technology are not allowed by assumptions—thus, the periodic planning workflow focuses on capacity planning and machine configuration. The basis for the assessment workflow is the predefined, static technology stream and working plan for every product, the current quantity forecast received from production control and planning, and configurable parameters describing targets like utilization or availability for production. Based on this information, the maximal process time per process step can be calculated. This information is sent to the process simulation module, which is able to find one or multiple machine configuration sets/operation points that fit the targets. After calculation, the results are reviewed from experts on a *factory dashboard* in order to make a decision and apply the new configuration to machine configuration and production control and planning.

In this way, the available process time can be used more efficiently compared to a static machine configuration, which focuses on highest operation speed. Line-balancing losses are avoided by using the available time to achieve several advantages compared to a static operation point, like saving energy, material, and machine wear while producing at higher quality (see Fig. 4.33). By applying periodic assessment and reconfiguration workflows to all factory resources, the factory can be kept at a global and permanent optimum.

Regarding the information processing of the *VPI platform* in factory planning, different research focuses result from our scientific findings. The *VPI platform* provides semantic information modeling so that the domain knowledge is represented in the system and heterogeneous planning data are transformed into information. One future focus is to provide more intelligence in the system not only for decision support but also in terms of decision making. On the one hand, this refers

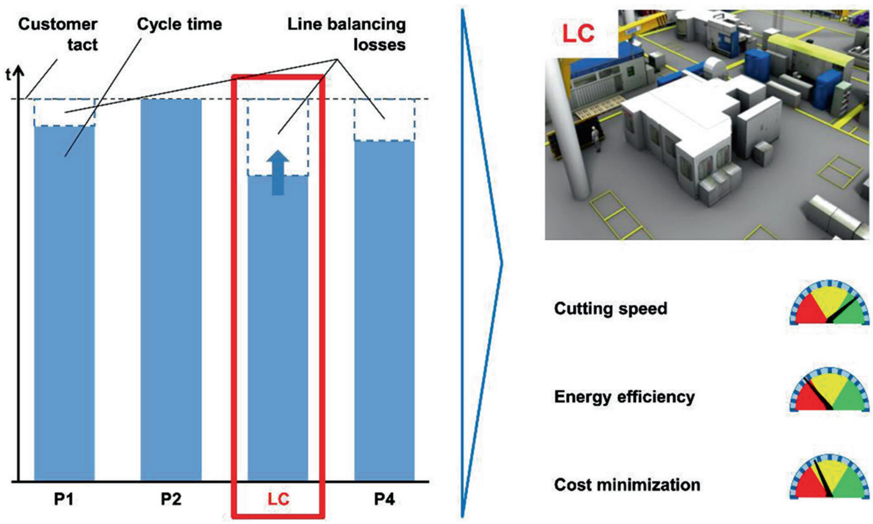

Fig. 4.33 Using line-balancing losses to achieve optimization potentials

to the automated linkage of data sources to the information model, which is currently done by experts. Using *text mining* technologies, data sources might be analyzed automatically to extract their meaning and context (Feldman and Sanger 2007). On the other, the *VPI platform* might develop planning scenarios based on planning profiles instead of only visualizing planning information in terms of KPI cockpits. Therefore, past planning project serve as a basis for a learning process, in which the system develops the planning profiles based on the decisions of the experts in that projects. Therefore, the *VPI platform* has to be used in real planning scenarios to generate the necessary base data. A further research focus has been indicated in Sect. 4.6.1. The linkage of the virtual production and the automated production is of great interest. Hence, the information systems of the VPI have to be extended so that they match the requirements of future cyber-physical production systems (CPPS).

The immersive VR application *flapAssist* for factory layout planning will be extended in several ways. Already, the application works in parallel to the visTABLE®Touch software, so that changes to the factory layout will directly become visible in the immersive VR system, similar to the solutions that were discussed in Neugebauer et al. (2011). Furthermore, to enrich the VE, metadata that are essential in decision making of the factory planning process will be retrieved from the *VPI platform* and visualized along the main factory model, like machine utilization rates or process chain definitions. For this, a web-service-based approach similar to the one in Sacco et al. (2011) in a more generalized scope will be developed.

Another important topic is interaction in the VE. As already pointed out in Menck et al. (2012), several classes of interaction tasks need to be addressed. The concrete realization of suitable interaction techniques is one of the next steps in the development process of our application. One central aspect in this regard is the inclusion of remote participants to better integrate the CAVE into the planning process, thereby not requiring all participants to be physically present at the CAVE's installation site. Important questions in this context are through which means participants are best integrated into the VR-supported layout planning process and how efficient communication among participants is realized. Another aspect, which is especially interesting in the aforementioned situation, is the use of annotations to convey messages related to the factory model and indicate points of interest among remote participants (see Menck et al. 2012). To analyze the applicability of immersive VR to the factory layout planning process in general, and our approach in special, we will perform user studies.

4.7.2 Design Domain Machine

After the elaboration of a new (computational) technique for machine planning tasks (i.e., metamodeling in the sense that was presented in previous sections) that has proven to be applicable not only for finding suitable machine working points but also to boost technology development via analysis of the underlying physical system, next steps in the further development of that technology will be twofold: One part will certainly be the further scientific advance of the technology. whereas the other is the industrialization of the elaborated concepts and technology.

Concerning the scientific working fields, it is necessary to consolidate the status quo already reached by constant improvements and extensions which, for example, should comprise of the enhancement of already existing physical models which form the scientific base for any metamodeling. At the moment, the majority of physical base models is mostly related to laser manufacturing, although the procedures themselves are not exclusive to that field of manufacturing but instead can be applied to any other physical system for which a physical and numerical modeling has been done. In addition to a widening of the application area of metamodeling, the possibilities for extracting knowledge from the system are about to be improved further, for example, via the incorporation of a domain-decomposition module that gives the overall structure of the system response in the high-dimensional parameter space (e.g., via the Morse-Smale-Complex). Further technical improvement is already on the way via an enhanced annotation concept that will enable the user to mark and give remarks to certain points in the parameter space of user-specific interest (e.g., foreseen machine working points for specific tasks). The developers of the metamodeling concept are also working on a fundamental extension of metamodeling that will enable it to model spatially distributed quantities in addition to scalar quantities, which is the status now. For this challenge, a combination of the classic metamodeling concept together with the concept of Proper Orthogonal Decomposition (POD) is intended. POD decomposes a spatially distributed quantity (a quantity field) into pre-computed modes (so-called snapshots) that this specific distribution can exhibit within a certain physical system. This decomposition actually corresponds to a reduction (or compression) of the valuable dominant information about the system's state, which can then be expressed by only a few mode coefficients, which are in fact scalars. So these scalars can in turn be handled by metamodeling as usual. Together with the computed and stored snapshots or computational modes, this opens up the possibility to model whole distributions of quantities while not having the computational effort to generate these again and again for different parameter requests, since they appear in any kind of analysis work on the model. In summary, the major scientific work on metamodeling in the future will be domain space decomposition and mode decomposition aspects.

With respect to the industrialization of the developed concepts and (numerical) tools, it will be necessary to undertake further work on the usability of those procedures, which surely have to be adapted for the industrial usage in specific manufacturing fields other than those already prepared in the demonstrator. A usual approach to get acquainted to user requests in applying the elaborated procedure to their daily work would be to invite industrial users to interviews to find out about specific needs for a certain manufacturing branch. In a next step, a licensing concept has to be established that makes it easy for industrial users to operate the machine planning tools. In some cases, for example, it makes sense to use these tools directly at the production machine, but still Internet access is not guaranteed at all of these working places. Therefore, these cases certainly require other licensing concepts than the usage of such tools does in a typical office environment, where nowadays Internet access can usually be expected.

Concerning the interactive analysis of process models and simulation results within the web-based VPI platform, further techniques in the field of machine learning and data mining will be implemented. Data mining techniques automatically extract previously unknown but valuable knowledge from simulation results. They will extend the existing statistical analyses to provide an extensive and profound knowledge of the production process (i.e., laser cutting process). The goal is not only to analyze the relationships between input parameters and process outputs but also to identify similarities between different simulation results of the same process. As a result, the user will be able to select certain simulation runs of major interest (e.g., high cut quality and high cutting speed at the same time) and to identify the process parameters that lead to these results.

4.7.3 Integrative Scenario

With VPI, a fundamental contribution to the realization of the vision of the digital factory is proposed. The integrative *VPI platform* enables heterogeneous IT tools in the phase of product and production planning to interoperate with each other. Based on information processing concepts, the platform supports the analysis and evaluation of cause–effect relationships. During the modeling of production processes, various boundary conditions and parameters can be taken into account. The *VPI platform* therefore enables an integrative, holistic view on a planning project including different scenarios and thus serves as a sophisticated decision support system.

Since product and production planning are the core areas of virtual production as part of the digital factory, the contribution focused on this part. The VPI is the basis to establish interoperability. The main two application domains of *Optimization of the Manufacturing Process Laser Cutting* and of *Factory Planning* presented and illustrated the functionality of VPI. It allows a significant reduction in engineering effort to create customized integration and analysis tools since VPI is an adaptive solution. Nonetheless, it is possible to start with a process-oriented and thereby contextual information processing. So information is no longer based on a single process step, but instead related to the overall process, so that the importance and validity of information can be considered.

Hence, new approaches for information processing, analysis and visualization are necessary—but also feasible for attaining better decision support. A key factor for the success of the VPI is also the user-centered design of information that asks for a domain-specific design to fulfill the requirements of different user roles and contexts of application. This is already done in visualizing the *VPI platform* in terms of a production cockpit.

In the context of optimized production planning, the next steps will consist in advancing the presented concepts with regard to both algorithmic procedures and methodical aspects for an interactive data exploration based analysis. Thus, first, new integration and analysis algorithms as well as enhanced performance indicators will be developed in order consider temporal aspects of the production too. As a methodological improvement, the presented concepts of integration and information management will be extended with respect to the different organizational sectors of a manufacturing enterprise. In particular, data exchange should not only be performed between ERP systems of the management and the tactical (respectively the planning level), but also between the operational and higher levels.

The resulting challenges for the integration and the information management will be approached by an extension of the VPI concepts to new application domains in the field of production planning as well as to real production. In this context, data from the operational level (Cyber-Physical Systems) will be processed in a way that the data can be integrated productively into Manufacturing Execution Systems (MES) as well as into ERP systems. Only through the realization of interoperability between these systems, a holistic digital mapping of the production can be attained. On the basis of this holistic interconnection of data, tools for an active decision support in real-time environments can be derived. These DSS ensure a continuous improvement of the production process development through actual data from the production.

Furthermore, it must be examined how this information can be presented to the user—for instance, in an immersive environment—and how context information can be presented in an understandable and comprehensible fashion. For this purpose, experts assess results of analysis and optimization in various feedback-based techniques. A bidirectional communication is needed: The user gives feedback and this feedback will be used to correct the displayed information. The system will store this feedback to avoid imprecise or erroneous statements.

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