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Decision support system for automated planning of process monitoring in multi-variant assembly

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Editors’ Preface

In times of global challenges, such as climate change, the transformation of mobility, and an ongoing demographic change, production engineering is crucial for the sustainable advancement of our industrial society. The impact of manufacturing companies on the environment and society is highly dependent on the equipment and resources employed, the production processes applied, and the established manufacturing organization. A company’s full potential for corporate success can only be taken advantage of by optimizing the interaction between humans, operational structures, and technologies. The greatest attention must be paid to becoming as resource-saving, efficient, and resilient as possible to operate flexibly in the volatile production environment.

Remaining competitive while balancing the varying and often conflicting priorities of sustainability, complexity, cost, time, and quality requires constant thought, adaptation, and the development of new manufacturing structures. Thus, there is an essential need to reduce the complexity of products, manufacturing processes, and systems. Yet, at the same time, it is also vital to gain a better understanding and command of these aspects.

The research activities at the Institute for Machine Tools and Industrial Management (*iwb*) aim to continuously improve product development and manufacturing planning systems, manufacturing processes, and production facilities. A company’s organizational, manufacturing, and work structures, as well as the underlying systems for order processing, are developed under strict consideration of employee-related requirements and sustainability issues. However, the use of computer-aided and artificial intelligence-based methods and the necessary increasing degree of automation must not lead to inflexible and rigid work organization structures. Thus, questions concerning the optimal integration of ecological and social aspects in all planning and development processes are of utmost importance.

The volumes published in this book series reflect and report the results from the research conducted at *iwb*. Research areas covered span from the design and development of manufacturing systems to the application of technologies in manufacturing and assembly. The management and operation of manufacturing systems, quality assurance, availability, and autonomy are overarching topics affecting all areas of our research. In this series, the latest results and insights from our application-oriented research are published, and it is intended to improve knowledge transfer between academia and a wide industrial sector.

Rüdiger Daub   Gunther Reinhart   Michael Zäh

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I am grateful to all my colleagues at the *iwb* who have contributed to making this time an unforgettable and formative period of my life. The pleasant working atmosphere, engaging discussions, and occasional late-night sessions will be fond memories for me. Additionally, the support and camaraderie from the *iwb* family, especially my research group Assembly Technologies and Robotics, have been invaluable. The commitment, creativity, and enthusiasm of my colleagues have been a constant source of inspiration and motivation for me.

Special thanks go to Joachim Michniewicz, Veit Hammerstingl, Philipp Bauer, Lisa Heuss, Fabian Konwitschny, Maja Lehmann, and Daniel Baier for their valuable advice and thorough review of my work. I am grateful for their input, which has helped me refine my research and improve the quality of my dissertation.

Finally, I would like to express my gratitude to my family, who have always been my greatest supporters and made my education possible. Their support and encouragement have been a constant source of strength throughout my academic journey.

Munich, 2025-02-03 *Clemens Jasper Richard Gonnermann*

Abstract

Process monitoring in assembly has become more complex and important due to increasing demands on product quality, individualization, and regulatory requirements (e.g., medical production regulations). Planning process monitoring is time-consuming, expensive, and requires expert knowledge. This is due to the complex decision-making process involved in selecting appropriate monitoring and analysis methods, monitoring plans, as well as ensuring compliance with quality standards. It requires extensive research, expertise, time, and additional equipment.

To solve these challenges, this thesis presents a decision support system for automated planning of process monitoring in assembly. The system is specifically designed for highly variable production in a flexible and reconfigurable production system. It combines CAD-based feature recognition methods to identify monitoring requirements and skill modeling methods to determine production equipment capabilities. It also generates process monitoring tasks and creates monitoring plans.

The proposed system offers several benefits by automating the planning of process monitoring. These include time and cost savings, elimination of the need for expert knowledge, customized generation of process monitoring alternatives, integration of quality aspects, and simultaneous assembly and process monitoring planning. In addition, the simultaneous planning of assembly and process monitoring minimizes the planning effort and increases the efficiency and flexibility of the planning process. Validations in research projects confirm the effectiveness of the system and make it a valuable contribution to process monitoring planning in assembly.

Contents

List of Abbreviations

iwb	Institute for Machine Tools and Industrial Management
BOM	Bill of Materials
CAD	Computer-Aided Design
CAIP	Computer-Aided Inspection Planning
CAM	Computer-Aided Manufacturing
CAPP	Computer-Aided Process Planning
CAx	Computer-Aided Technologies
CMM	Coordinate Measuring Machine
CNC	Computer Numerically Controlled
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
DML	Dedicated Manufacturing Line
DRM	Design Research Methodology
EDM	Electrical Discharge Machining
FDA	Food and Drug Association
FMEA	Failure Mode Effect Analysis
FMS	Flexible Manufacturing System
GUI	Graphical User Interface
HAAG	Holistic Attribute Adjacency Graph
IT	Information Technology
LLM	Large Language Model
MDR	Medical Device Regulation
PMI	Product Manufacturing Information
PPR	Product-Process-Resource
PPRS	Product-Process-Resource-Skill
PRD	Product Requirement Description
QFD	Quality Function Deployment
QoS	Quality-of-Service
RD	Resource Description

RMS	Reconfigurable Manufacturing System
ROS	Robot Operating System
SPIN	SPARQL Inferencing Notation
STEP	Standard for the Exchange of Product Model Data (ISO 10303)
SWRL	Semantic Web Rule Language
TUM	Technical University of Munich
UI	User Interface

Chapter 1

Introduction

1.1 Motivation and Current Challenges

Manufacturing companies operate in a dynamic and competitive environment where the traditional mass production approach with long product life cycles is no longer sufficient to meet changing market demands (ABELE & REINHART 2011; FOIDL & FELDERER 2016; WESTKÄMPER 2009). Customers today are looking for individualized and customized products with shorter life cycles, which requires a shift towards more flexible production processes and systems (ABELE & REINHART 2011; REINHART 2017). This shift requires production systems to quickly adapt to short-term market fluctuations and handle a high number of product variants (BÄCHLER et al. 2015; JÄRVENPÄÄ et al. 2016).

To address these challenges, Reconfigurable Manufacturing System (RMS) has proven to be a viable solution. RMS enables a quick adjustment of their production capacity and functionality in response to changing market demands (KOREN et al. 1999; REINHART et al. 2010). By using RMS, manufacturers can achieve the desired flexibility in their operations, which enables individualized products and shorter production cycles (KOREN et al. 1999; REINHART et al. 2010). If new products cannot be produced, exchanging or adding production resources is necessary. A high flexibility results in a cost-effective production system change (MALAKUTI et al. 2018).

However, RMS implementation is not without challenges. A major obstacle is the planning and integrating equipment from different suppliers into a production system, leading to increased costs and downtime when adding or removing equipment (KOREN & SHPITALNI 2010). Heterogeneous equipment increases complexity and planning effort due to different equipment interfaces, functionalities, and interactions (KOREN & SHPITALNI 2010). Additionally, customer demands pressure companies to produce with high quality, requiring higher control and knowledge of their production processes (BERTHOLD & IMKAMP 2013). Certain production domains, such as medical device production, also require higher production process knowledge due to regulations and provisions (e.g., Medical Device Regulation (MDR) or Food and Drug Association (FDA) (PETER et al. 2020)).

Assembly, typically the last step in the production process, must meet these requirements to a significant degree. To avoid errors, a detailed understanding of the assembly processes and their interrelationships is important (REINHART 2017). Adaptive process monitoring systems can increase controllability and reliability (STAVROPOULOS et al. 2013). KOREN et al. (2018) describe this characteristic of monitoring the production system and processes as diagnosability in RMS. Besides the importance of this characteristic, it is not yet sufficiently considered and supported in the concept of RMS (KOREN et al. 2018). The main constraint is often the manual effort and expert knowledge required to plan and reconfigure these production systems (BACKHAUS & REINHART 2015; KOREN & SHPITALNI 2010).

The complexity of process monitoring planning is influenced by assembly planning. Due to the variety of possible assembly plans, various process monitoring plans can be generated. The number of parts in a product leads to an exponential increase in the number of possible assembly sequences (BAHUBALENDRUNI & BISWAL 2016). The resulting number of possible assembly plans is additionally influenced by the different possibilities of resource allocation. As a result, there are a large number of monitoring plans that are almost impossible to create and evaluate effectively manually.

The challenges associated with individualized production and higher quality requirements can be effectively addressed by integrating the concepts of RMS with a flexible and efficient approach to planning monitoring processes. The execution of assembly processes plays a decisive role in the overall production time and costs (LOTTER & WIENDAHL 2013, p. 6). It is essential to ensure a high-quality execution of these processes and to implement effective monitoring measures. This promotes more sustainable production by reducing waste and minimizing production downtime, as well as failures.

1.2 Objective and Scope

As pointed out, the need for efficient and flexible planning of process monitoring in production has become increasingly important. Current RMSs offer an inherent flexibility, which allows to perform different possibilities of data acquisition at low cost and effort and thus to adapt to changing needs. Due to the high manual effort and required expert knowledge to plan monitoring in RMS, an automated approach is needed. KOREN et al. (2018) highlights the aspect of monitoring as diagnostic capability, which is one of the six core properties of RMS that need further research.

A framework is created to develop a system for automated process monitoring planning that leverages available and industry-known digital data of the product, assembly processes, production system, and resources. This thesis focuses on assembly processes and systems, including manual, hybrid, and automated systems. The development and implementation of the framework include a human-centered toolbox that enables user interaction in the system. Therefore, the background, current state of the art, and need for research action are presented. The objective is to create a framework and system in this thesis that allows an efficient and automated generation of process monitoring plans. The focus lies on assisting the monitoring planner through a demand-oriented monitoring plan generation (e.g., reduced additional sensor reconfigurations and high monitoring accuracy).

An efficient, automated, and human-centered generation of monitoring plans reduces the required expert knowledge, time, and cost expenses.

1.3 Scientific Classification, Research Approach and Structure

The thesis presented here belongs to applied research, which is concerned with applying scientific knowledge and principles to solve real-world problems (ULRICH & HILL 1976). It goes beyond purely theoretical research by focusing on the practical application and implementation of scientific knowledge. This scientific classification shows that the concept is developed theoretically, implemented, and tested in a prototypical format in addition to a comprehensive research analysis. This problem-oriented approach manifests as a cumulative dissertation in which the main contributions and results are presented in publications. Figure 1.1 illustrates the overall structure of the thesis and provides a visual representation of its organization, including the relation to the research approach.

The research approach used in this thesis is based on the Design Research Methodology (DRM) by BLESSING & CHAKRABARTI (2009), which provides a systematic framework for conducting research. This approach includes several key phases. The first phase of DRM aims to identify the research gap by clearly defining the problem and research objectives (*research clarification*) (BLESSING & CHAKRABARTI 2009, pp. 15–17). This is presented in Chapter 1, which discusses the motivation behind the research and the current challenges in today's volatile production. In addition, the objectives of the work are presented, and the scope is defined. The chapter closes with an overview of the structure and arrangement of the content.

Chapter 2 and Chapter 3 cover the second component of the DRM, known as the *comprehensive descriptive study 1*. This part aims to analyze the current state of the art to deeply understand the research problem (BLESSING & CHAKRABARTI 2009, pp. 15–17). Chapter 2 deals with the basics of assembly technology and process monitoring in assembly, including relevant process steps, requirements, systems, and resources. In addition, it provides an overview of the methods and steps of process planning, such as assembly planning, test planning, and monitoring planning. The chapter ends with a discussion of Cyber-Physical System (CPS) and their flexible use, allowing for adaptive planning and integration of monitoring into the assembly. Chapter 3 examines the current state of the art in creating digital twins in manufacturing and automated process planning. It includes feature- and skill-based approaches to requirements identification, resource functionality description, automated assembly, and inspection planning. The chapter ends with a summary of the current state of the art and the identified need for action.

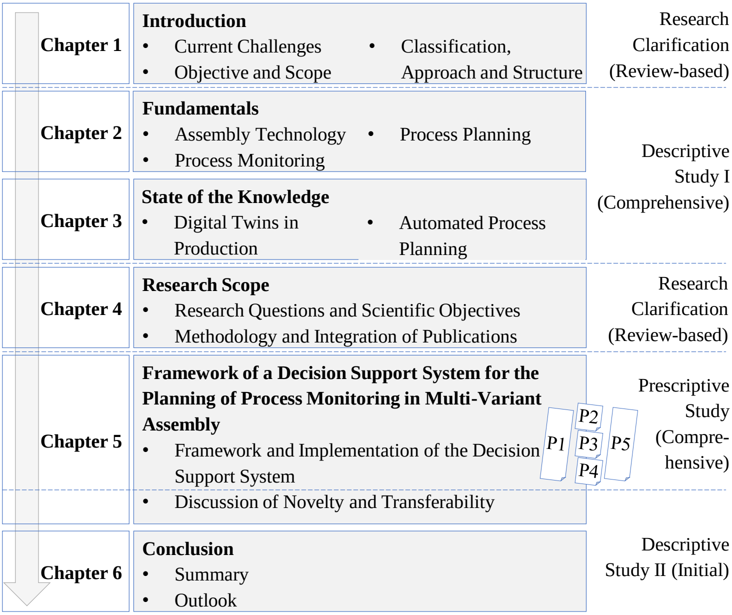


Figure 1.1: Structure of the dissertation including the publications (P1 to P5).

Based on the findings from the *comprehensive descriptive study 1*, Chapter 4 provides a detailed research explanation (i.e., *research clarification*) (BLESSING & CHAKRABARTI 2009, pp. 15–17). This chapter presents the scientific goals of the study, the methodology used, and the integration of publications into the research. It serves as a starting point and reaction to the identified need for action and formulates the intention of the thesis.

The *comprehensive descriptive study 1* is followed by the prescriptive study, in which conceptual and implemented results based on the knowledge gained are presented (BLESSING & CHAKRABARTI 2009, pp. 15–17). In this phase, innovative ideas are developed, implemented, and refined to effectively address the identified problem of efficient planning of process monitoring in the RMS. Chapter 5 covers the prescriptive study by providing reviews of the publications embedded in the research. The chapter discusses the five major publications, including automated setup of process monitoring, feature detection based on Computer-Aided Design (CAD) models, skill modeling in Cyber-Physical Production System

(CPPS), automated generation of process monitoring alternatives, and a skill and feature-based approach to the planning process monitoring in the assembly.

The last phase, the *descriptive study 2*, is about the evaluation and validation of the effectiveness and impact of the proposed system (BLESSING & CHAKRABARTI 2009, pp. 15–17). The results are evaluated, and feedback and an outlook is given. The discussion of this phase is presented in Chapter 5, specifically in Chapter 5.2. Chapter 6 summarizes the main results of the publications and gives an outlook on future research in this area.

Applying the DRM and going through these phases gives this thesis a deep understanding of the research topic. It develops a practical decision support system for the automated planning of monitoring processes.

Chapter 2

Fundamentals

This chapter presents the essential background information on production and process planning, specifically focusing on assembly. The main emphasis of this chapter is on process monitoring and its planning, which is the central theme of this thesis. Chapter 2.1, dedicated to assembly technology, provides a comprehensive overview of various aspects such as assembly processes, process requirements, assembly systems, and production resources.

This section serves as the basis for the subsequent Chapter 2.2, which describes the topic of process monitoring in assembly. Additionally, process planning methods in assembly and how they relate to monitoring planning are shown (Chapter 2.3). To complete the fundamental knowledge Chapter 2.4 addresses CPS. In automated process planning, CPSs play a crucial role and offer numerous advantages in today's volatile production.

2.1 Assembly Technology

As the last production stage, assembly is central in manufacturing companies where earlier production processes and their values are merged (ABELE & REINHART 2011; MICHNIEWICZ & REINHART 2016). According to the definition of C.I.R.P. (2011, p. 2), the assembly can be described as the "action of bringing individual parts into a sub-unit, a unit, a structural group, a machine or a product."

The goal is to assemble components with a given geometric shape. This assembly process includes various sub-operations, including joining, handling, adjusting, testing, and, if necessary, other specialized supporting processes (C.I.R.P. 2011, p. 2). Consequently, numerous value-adding processes significantly impact this stage of production. Processes that contribute to the value of the final product are referred to as primary processes, such as joining. In contrast, other processes that do not directly contribute to value creation are considered secondary processes (LOTTER & WIENDAHL 2013, p. 49).

Assembly processes can be manual, semi-automatic, or automatic (LOTTER & WIENDAHL 2013, p. 3). The equipment and resources required for these processes are commonly referred to as assembly systems and include machines, stations, cells, and lines. As a rule, assembly represents the final stage in the production flow, where all organizational, scheduling, and quality-related aspects of the production process converge.

Although it is responsible for over 70 % of the costs, the assembly itself only actively contributes to 13 % of the production process (LOTTER & WIENDAHL 2013, p. 6). Nonetheless, assembly takes a critical role in production due to its significant cost impact. In addition, assembly often involves customization or individualization processes to meet specific customer requirements (FELDMANN 2014, p. 5).

2.1.1 Process Steps of Assembly

Value-adding processes in the assembly are subcategories of joining (LOTTER & WIENDAHL 2013, p. 49). According to the norm DIN-8593 (2003), joining refers to the "... permanent connection or other bringing together of two or more workpieces of a geometrically defined shape or of similar workpieces with shapeless material. In each case, the cohesion is created locally and increased as a whole."

In the field of joining, there are many subgroups, such as putting together or welding (DIN-8593 2003). The various process steps are based on different mechanical and thermodynamic principles and can be seen in Figure 2.1.

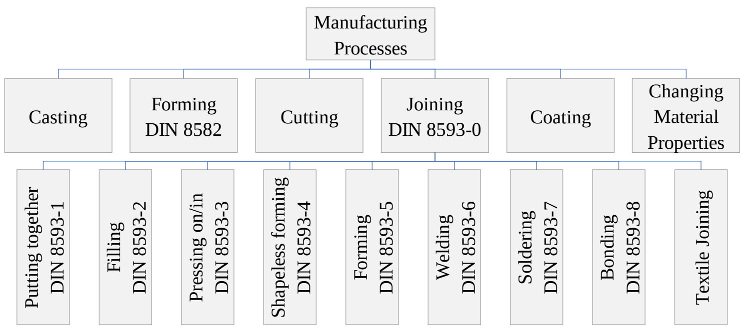


Figure 2.1: Different manufacturing processes focusing on joining according to DIN-8593 (2003).

Certain assembly methods are more widespread and more frequently used than others. As shown in Figure 2.2, screwing, as part of pressing in (DIN 8593-3), and connecting, as part of putting together (DIN 8593-1), are the most commonly used methods (FELDMANN 2014, p. 145). The figure shows the relative frequency of the different types of joining processes as a percentage of the total number of joining processes and the number of workstations allocated to specific joining processes.

Figure 2.2 is intended to illustrate the different utilization of the individual joining processes and the corresponding occupancy of the workstations. It becomes clear that specific processes are executed several times on the same workstation, while other types of joining processes require fewer workstations per execution in comparison (FELDMANN 2014, p. 145). The main focus of this thesis is on these two prominent assembly processes (connecting and screwing). Additionally, welding, which involves thermal physical quantities, is considered.

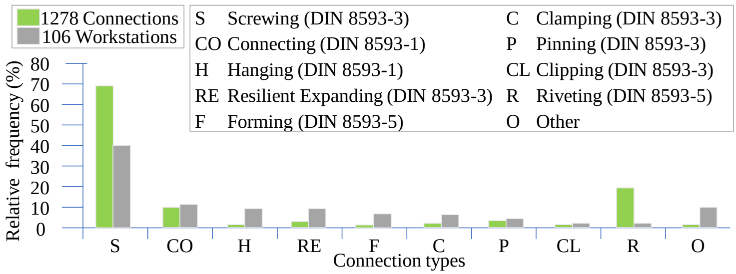


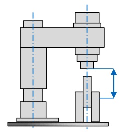
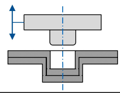
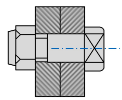
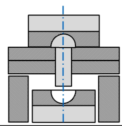
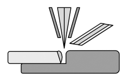
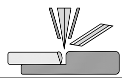
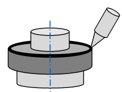
Figure 2.2: Bonding types and their relative occurrence regarding the total number of connections and number of working stations (FELDMANN 2014, p. 145).

2.1.2 Process Requirements in Assembly

Each process type has requirements that need to be fulfilled by the resources executing the process (EVERSHEIM 2002, pp. 57–61). The product developer defines these process requirements. Depending on the process, the requirements vary in terms of topology, geometry, or process parameters (i.e., required torque), as seen in Table 2.1. These requirements hold significant importance not just in the planning and execution of the assembly process but also in its control and monitoring (LOTTER & WIENDAHL 2013, pp. 222–237). This aspect becomes particularly crucial when aiming for high process quality. The quality planner must establish limits or constraints for the parameters to be considered during the monitoring process.

The table briefly overviews the various methods for joining parts in manufacturing processes. Each joining process is described, along with a small schematic figure and example parameters that can be used to evaluate and monitor the quality of the process. Methods covered include joining by pressing/shaping/jacking, screwing, riveting, welding, soldering, and bonding. The parameters listed for each method highlight the most important measurements or factors to consider during the joining process. Monitoring process parameters can help ensure the quality and durability of the joined components. By understanding the various joining processes and their associated parameters, manufacturers can make informed decisions and optimize their assembly processes accordingly (LOTTER & WIENDAHL 2013, pp. 222–237).

Table 2.1: Exemplary assembly processes, schematic diagrams, and parameters according to LOTTER & WIENDAHL (2013, pp. 222–237).

Process type	Description	Exemplary parameters	Schematic diagram
Joining by pressing/shaping	The parts are joined together by forming them with a punch by applying pressure to their contact surfaces so they cannot separate. The measurement of force used in this process is state-of-the-art, similar to jacking. The recorded force can be analyzed to detect material irregularities and damage to the punch.	Force Angle	
Joining by jacking	Joining through jacking involves pressing one part into another by applying force. The process can be evaluated by monitoring the force applied during the pressing movement.	Force Angle	
Screwing	The screwing process is one of the most widely used methods for joining multiple parts. A screw is inserted into a threaded component and connects the parts. The parameters used to evaluate the screwing process are the applied torque and the screwing angle.	Torque Angle Speed	
Riveting	Joining multiple parts by deforming a rivet with force is one method of joining. There are no specific process parameters for monitoring the riveting process. However, in cases where riveting is performed at several points, it is recommended to check the coordinates of these points.	Force Angle	
Welding	Joining two or more components by heating the parts to the melting point and then allowing them to cool and fuse. The process can be performed using various techniques (e.g., arc welding, gas welding). One key aspect of welding quality is the amount of thermal energy applied to the surrounding material.	Temperature Angle	
Soldering	Joining metal parts by adding melted material is similar to welding. In this process, many parameters, such as pressure, temperature, and the amount of added material, can be monitored.	Temperature Pressure Angle	
Bonding	Joining parts by applying a cohesive material to their surfaces is one method of joining. In addition to the temperature and pressure during the pressing process, the amount of adhesive applied is an important parameter. This can be measured either directly by measuring the pressure at the nozzle or indirectly by cameras or other means.	Temperature Pressure	

2.1.3 Assembly Systems and Resources

Assembly processes are carried out in various assembly systems, which can be classified as manual, hybrid, or automated. These systems are designed to assemble products or product families. The classification is based on the level of automation, which includes human operators, robots, or other (non-)automated resources (LOTTER & WIENDAHL 2013, p. 3). These resources play an essential role in the assembly process by facilitating functions such as joining, inspection, handling, and transportation between process steps (C.I.R.P. 2011, p. 256). The selection of an appropriate system depends on the specific requirements of the assembly system based on factors such as lot size, investment, and flexibility. The relationships among these requirements are shown in Figure 2.3, which visually represents their interactions.

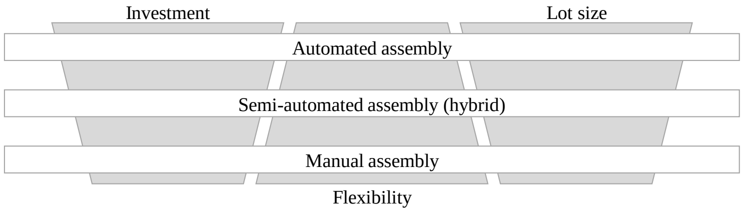


Figure 2.3: The classification of assembly systems depends on the requirements of the assembly system, such as flexibility, loss, size, and investment (LOTTER & WIENDAHL 2013, p. 3).

According to EVERSHEIM (2002), production processes require various resources such as personnel, equipment, buildings, capital, and Information Technology (IT). C.I.R.P. (2011, p. 6) describe the operating resources as the totality of plant, equipment, and facilities used to perform operational tasks without the products entering as substances. Assembly systems consist of various operating resources that can perform different assembly operations. In the assembly environment, the terms operating/production resources, machines, equipment, and devices are often used interchangeably.

In this thesis, resources refer to the equipment required for assembly (i.e., personal, robots, tools). The addition "actorial" emphasizes that the resource is actively performing the assembly process. "Sensorial" resources do not actively perform the process but can monitor it. In manual assembly, additional resources, such as screwdrivers, can be used by workers to perform assembly processes (LOTTER & WIENDAHL 2013). An assembly system can be structurally divided into hierarchical production levels, as seen in Figure 2.4 (WIENDAHL & HEGER 2004). Several assembly systems can form a segment, and a collection of segments can constitute a production site. The production network is the highest level of the organizational hierarchy in the production levels, which includes one or more production sites. An assembly system can be further subdivided into individual cells, stations, and machines.

From a product perspective, production can be broken down into product levels (e.g., features, sub-products, or product portfolios). The level of production chosen determines the specific levels of the product to focus on, such as sub-products or product portfolios (ELMARAGHY 2009). The production network covers the entire product portfolio, while a site focuses on a specific product. Segments deal with sub-products, and systems or cells handle the processing of workpieces. Station and machine level influence the features of the products.

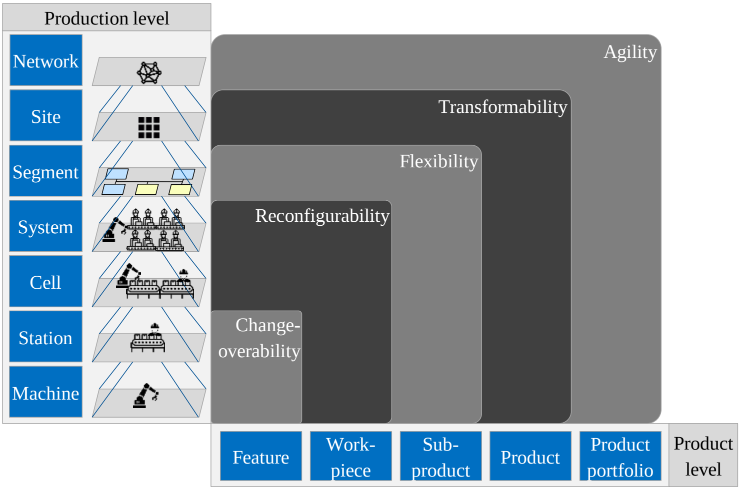


Figure 2.4: The categorization of the different production, product levels, and the allocation of the different types of flexibility is based on WIENDAHL & HEGER (2004). Schematic structuring of the production levels and views according to WIENDAHL et al. (2007).

This thesis focuses on the production level of the system and its sub-levels, such as cells, stations, and machines. The classification of flexibility is determined by the production level and influenced by the specific product level. Different types of flexibility can be determined that specific production levels can inherit, as described by WIENDAHL et al. (2007):

- *Changeover-ability*: Ability of an individual machine or workstation to perform new operations.
- *Reconfigurability*: Ability of a manufacturing or assembly system to quickly and easily switch between different families of workpieces or subassemblies.
- *Flexibility*: Tactical ability of an entire production and logistics domain to switch to new families of components of a similar type with relatively little time and effort.
- *Transformability*: Ability of an entire factory structure to adapt and change to accommodate the production of a different product family.
- *Agility*: Ability of an entire company to explore new market opportunities, develop the necessary products and services, and create the required production capacity.

Different types of production systems offer various solutions and serve different purposes regarding overall flexibility and reconfigurability at the station and cell levels. The distinctions and variations between production systems described by

KOREN et al. (1999) allow companies to address different aspects of flexibility and reconfigurability at several levels of their production processes. The following types of production systems and lines can be classified according to KOREN et al. (1999):

- *Dedicated Manufacturing Line (DML)*: Designed for specific products or a narrow portfolio optimized for high efficiency.
- *Flexible Manufacturing System (FMS)*: Can be customized to produce different products or variants and include modular equipment.
- *Reconfigurable Manufacturing System (RMS)*: Highly customizable and versatile, allowing for quick changes in production setup.

Due to their ability to adapt, scale, and respond flexibly to new market dynamics, RMS was chosen as the system type in this dissertation. The cost-effective adaptability of these systems facilitates the deployment of multi-variant production, which is the requirement for the research of this thesis. New resources can be introduced quickly to adapt production processes required for new product variants. According to KOREN et al. (2018), RMS are characterized by six basic characteristics:

- *Scalability*: Changing production capacity by adding or removing resources and/or changing system components.
- *Convertibility*: Transforming the functionality of existing systems and machines to meet new production requirements.
- *Diagnosability*: Real-time monitoring of product quality and rapid diagnosis of the causes of product defects.
- *Customization*: System or machine flexibility within a part family that enables customization capability within that specific part family.
- *Modularity*: Division of operational functions into units that can be manipulated between alternative production schemes.
- *Integrability*: Fast and precise integration of modules via hardware and software interfaces.

As mentioned by KOREN et al. (2018), there has been limited research on the aspect of diagnosability in RMS. This characteristic is crucial in minimizing ramp-up time and failure rate when adapting an existing production system. As production systems are becoming increasingly reconfigurable and subject to frequent modifications, it is essential to quickly adjust the newly reconfigured system to produce high-quality parts (KOREN et al. 1999).

2.2 Process Monitoring and Inspection in Assembly

DIN-EN-ISO-9000 (2015) defines quality control as part of quality management where the focus is on achieving quality, which is defined as "[the] degree to which a set of inherent characteristics of an object [meets] requirements." To assess the quality of products, both quantitative and qualitative characteristics, known as inspection characteristics, need to be determined.

Quality control is defined by variables that affect processes and can lead to changes in product characteristics. Monitoring these variables is necessary to assess the status of both the machine and the process (COLLEDANI et al. 2014; MORGAN et al. 2021).

There are several strategies for quality control in assembly, such as process monitoring at multiple stations, single process monitoring (e.g., joining), and product quality inspection (LIU et al. 2019). In comparison to process monitoring, inspection focuses on a static checking of individual product characteristics. Process monitoring is the on-machine, run-time assessment of part and process quality based on the observation of the process.

This comprehensive approach can enhance the understanding of the production process, its internal dynamics, and external influences (LIU et al. 2019; RATO et al. 2020; REINHART 2017). The choice of the appropriate strategy depends on the scenario resulting from the availability of sensor data and the complexity of production. Product quality inspection requires additional secondary (i.e., non-value-adding) processes. The inspection planning is described in VDI-RICHTLINIE-2619 (1985).

Direct and indirect process monitoring methods can directly or indirectly monitor the relevant quality characteristics (STAVROPOULOS et al. 2013). For example, a force-torque sensor of a robot serves as a direct monitoring method to record the accuracy of a joining process. Evaluating the sensors in each robot axis based on the current deviations is an indirect monitoring approach.

Direct monitoring methods are generally more accurate because the sensor and sensor data are specifically designed to monitor the process. Indirect monitoring methods, on the other hand, can be more cost-effective and industrially applicable by using existing sensor data and correlating it with process quality (SCHMUCKER et al. 2021; STAVROPOULOS et al. 2013).

More significant variations in process parameters and technologies, as well as different alternatives, lead to increased complexity in process and assembly planning. As mentioned in Chapter 1, monitoring or inspection is often required for certification and safety (i.e., medical goods). According to DIN-EN-ISO-13485 (2021), certification and sale of medical goods necessitate monitoring and quality control of both the product and the process.

2.3 Methods and Steps in Process Planning

Process planning in the manufacturing industry aims to identify the necessary processes and resources required to complete production tasks while maintaining quality standards (ElMaraghy & Nasseh 2019). The manufacturing context covers several areas, including material handling and forming, assembly, inspection, and monitoring.

The goal is to convert raw materials into a final product that meets the required specifications. Process planning includes two levels of planning, namely, macro planning and micro planning. Macro planning is concerned with determining the appropriate sequence of operations and selecting resources. Microplanning involves determining and establishing operating parameters. Figure 2.5 illustrates the various activities in process planning from the product design to the manufacturing.

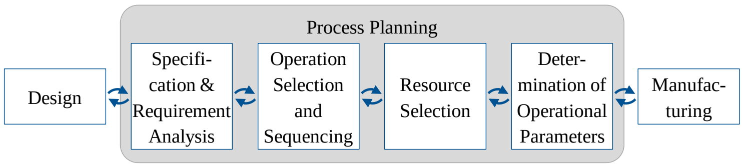


Figure 2.5: Individual process planning steps according to ElMaraghy & Nasseh (2019).

Process planning activities vary by application area and involve a range of outputs, including assembly plans and processes related to inspection or monitoring planning. Additionally, the number of steps in the planning process can vary due to the planning steps' granularity, as seen in the next sub-chapter.

2.3.1 Assembly Planning

Assembly-related process planning includes all steps for planning and validating the processes required to assemble products. The aim is to select the technologies required for production, the most suitable sequence of assembly processes, and the resources required.

One of the results of this process is the assembly plan (Eversheim 2002, p. 59). An assembly plan provides a comprehensive overview of all the processes required to manufacture a product, including the duration and sequence of those processes (Böge & Böge 2021). It also specifies the allocation of work centers, considering the resources and information required to perform the operations (Eversheim 2002, p. 59).

Eversheim (2002, pp. 17–20) describe a well-established and frequently used method for assembly planning that includes five steps. The first two steps of the following approach by Eversheim (2002, p. 59), can be aggregated to the step "specification and requirement analysis" by ElMaraghy & Nassehi (2019), as shown in Figure 2.5 of the general process planning steps.

1. *Planning preparation:* Gather and review information for work plan tasks and act as a coordination point between the design and process planning departments.
2. *Part lists processing:* Identify necessary activities in work planning (e.g., material determination and definition of the manufacturing process by using Bill of Materials (BOM)).
3. *Rough assembly planning:* Identify predecessor and successor relationships to create an assembly plan by using BOMs, assembly drawings, and assembly sequences.
4. *Detailed assembly planning:* Inclusion of material and resource requirements planning and implementation of capacity planning and scheduling of resources.
5. *Control programming or ramp-up:* Development of control programs for machines such as machine tools, industrial robots, and operating equipment.

2.3.2 Inspection Planning

Inspection planning in the assembly field occurs after the rough assembly planning (Eversheim 2002, pp. 17–19). According to DIN-EN-ISO-9000 (2015), it can be distinguished between incoming inspection (i.e., inspections of the incoming material), in-process inspection (in between or during the processes), and final inspection (inspection of the final product) (Eversheim 2002, pp. 62–66). Inspection planning is part of quality management and can be divided into the following steps (Eversheim 2002, pp. 66–68):

1. *Reviewing the documents*: Review the relevant documents and identify the product characteristics that need to be tested (e.g., quality planning process with Failure Mode Effect Analysis (FMEA) and Quality Function Deployment (QFD)).
2. *Recognizing and selecting the test characteristics*: Identify individual inspection characteristics relevant to quality control as described in Chapter 2.2.
3. *Determining the inspection frequency*: Determine the frequency of the tests, inspection time for each characteristic, and the type of inspection (e.g., attribute or a variable inspection, 100 % inspection, or a sample inspection).
4. *Establishing the inspection method*: Select the appropriate testing location and determine who will perform the inspection (e.g., Self-testing by workers with feedback loops between process and testing inspection).

5. *Creating the inspection plan*: Assign the inspection characteristics to a task class and select suitable inspection equipment.

Factors such as the number of pieces, the measurement range, the measurement uncertainty of the inspection equipment, the inspection time, the inspection costs, and the signal power should be considered when selecting the inspection equipment. Based on this process, an efficient inspection plan can be developed (EVERSHEIM 2002, p. 68).

2.3.3 Monitoring Planning

In contrast to inspection planning, process monitoring planning focuses on the on-machine, run-time assessment of part and process quality based on the observation of the process as described in Chapter 2.2. Process monitoring can be categorized as in-process inspection within quality management. Although monitoring processes do not directly add value to the product, they do not constrain productivity because they do not add process time to the primary process (value-adding process) (NEHER 2012, pp. 2–3). The planning steps are similar to inspection planning, but with the added aspect that inspection is performed simultaneously with the execution of the assembly process.

Inspection frequency can vary depending on whether statistical or continuous process monitoring is used. Statistical monitoring typically uses control charts to detect process changes (VARDEMAN & JOBE 2016, p. 107). These control charts display process performance measures. Quality assessment is based on regularly sampled production batches, and statistical measures are used to characterize the samples and compare the current production state with the desired target (NEHER 2012, pp. 39–41). Possible deviations in the process data are thus detected early so that appropriate corrective measures can be initiated (KLOCKE 2018, pp. 456–457).

With continuous process monitoring, every production cycle is considered and monitored, resulting in 100 % online process monitoring (NEHER 2012, pp. 41–44). While continuous process monitoring reduces the need for random inspections, it cannot completely replace them. The monitoring process relies on quality data or process data collected by measurement devices. One advantage over statistical process monitoring is the ability to examine each process step, which allows defects to be detected and corrected in a timely manner or defective products to be rejected (NEHER 2012, pp. 41–44).

The outcome of the planning process for monitoring is a comprehensive plan that outlines the necessary monitoring processes for each process step, along with the required resources (i.e., sensors).

2.4 Cyber-Physical Systems

In recent years, the term CPS has been used in several fields, including manufacturing, logistics, medicine, and cyber-security engineering. CPS are networks of cooperating entities that can process and transmit data while being connected to their physical environment (ACATECH 2011). The interaction between physical and virtual components and their connection to computer and information systems, such as the Internet, is the focus of CPS.

Introducing CPS aims to achieve self-organization, decision-making, increased efficiency, and transparency in production systems (MONOSTORI et al. 2016). CPS have the ability of self-description and self-configuration, which includes information about their own state, knowledge about individual skills, and ability to adapt (VOGEL-HEUSER et al. 2016). According to BAUERNHANSL et al. (2016) the characteristics of CPS can be categorized as follows:

- Communication between CPPS and interaction with smart products.
- Self-description is an inherent property of CPS.
- Functionalities of CPS can be distributed and used through software platforms.
- Ability to configure themselves and make decisions based on situational factors.
- Decoupling of data collection and use from the automation pyramid occurs.
- Detection, search, and integration of missing services and data are performed.
- Assurance of Quality-of-Service (QoS) requirements is guaranteed.
- Access control to original data and services is established.

VOGEL-HEUSER et al. (2012) and CHEN et al. (2018) claim that the use of CPPS will lead to the creation of a smart factory that outperforms classical production systems in terms of quality, time, and cost (ACATECH 2011). CPPS are production systems in which different CPSs work together simultaneously (VOGEL-HEUSER et al. 2012).

Effective exploitation of the potential of CPS can be achieved through the use of appropriate data models, such as semantic descriptions (e.g., ontologies) (NEGRI et al. 2017). These models provide explicit, semantic, and formal representations of concepts within a given domain and play a critical role in incorporating intelligence into CPPS. They also facilitate the integration and sharing of large amounts of collected data (BORGO 2014). Using automated and intelligent analytical tools, CPPSs support decision-making processes by enabling rapid access and analysis of collected data. This ultimately leads to faster decision-making and improved productivity (LEE et al. 2014).

Chapter 3

State of the Knowledge

The following chapter provides an overview of the current state of research relevant to this thesis. First, the modeling and representation of new product variations are shown, which includes their process requirements, the design of production systems, and the skills needed to execute the processes. Feature recognition approaches are then discussed, which play a critical role in improving the virtual representation of products and the identification of process requirements. When discussing production systems and their resources, the primary emphasis lies on assembly skills.

In the final section of this chapter, current methods for automated process planning are presented, with a focus on assembly and inspection planning, as they are closely related to higher-level planning. Finally, a conclusion highlights the identified areas that require attention and action.

3.1 Generation of Digital Twins in Production

Virtual product and production system representations are crucial in production and process planning. These representations are essential tools for product and production system analysis and creating valid process plans (NEGRI et al. 2017). Nowadays, these virtual representations are commonly referred to as digital twins. The digital twin is being applied in product design, prototyping, testing, and simulation of production processes (BOSCHERT & ROSEN 2016). In addition, it can be used to analyze product performance, detect defects, and plan maintenance activities (KAHLEN et al. 2017; ROSEN et al. 2015). The digital twin is a versatile tool for developing and producing products (WAGNER et al. 2021).

To represent the three relevant perspectives in a digital twin and its applicability to production, the Product-Process-Resource (PPR) model is used (DRATH 2010). This model describes the three basic data domains within an overall digital twin framework for production planning. The model illustrates the interdependence between the product, process, and resource domains. In this context, the product is produced by processes and uses resources for its production. The processes are executed through the use of resources. An additional domain in this model is the aspect of skills (Product-Process-Resource-Skill (PPRS) model) introduced by PFROMMER et al. (2013). Skills represent hardware-independent functionalities executed by resources, effectively merging the process and resource domains. The focus lies on the execution of the tasks required by the product, as shown in Figure 3.1 (BACKHAUS & REINHART 2015; PFROMMER et al. 2013).

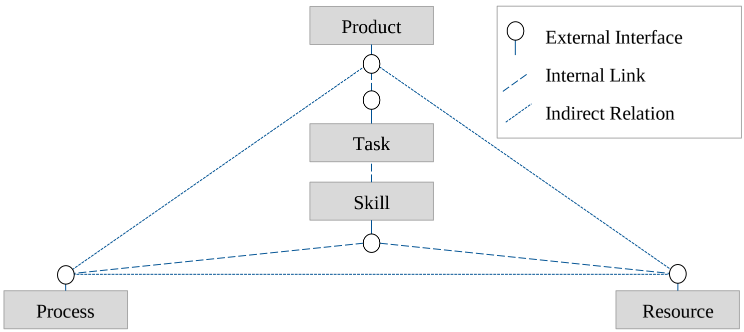


Figure 3.1: The PPRS model according to PFROMMER et al. (2013).

The following two sub-chapters describe current methods for creating data models that include products and resources in combination with process information. These models are intended to simplify decision-making processes in process planning. First, methods for identifying product requirements are presented that enable the creation of the product and process domains to describe task requirements. Second, methods for describing the skills of production resources for process execution are explained. The third chapter provides an overview of approaches to using these data models, including product and process requirements and production system and resource skills.

3.1.1 Feature-based Approaches for the Recognition of Product and Process Requirements

To increase the effectiveness of process planning, various methods utilize different features in both manufacturing and assembly, depending on the application throughout the product life cycle (HASAN et al. 2016). Product features can be derived from CAD models and provide a detailed representation of product geometry, technical functions, and required process parameters. Such features are commonly referred to as Product Manufacturing Information (PMI) and can be saved in CAD files (MOHAMMED et al. 2022). Product features can be classified into low-level features, which relate to the shape of parts and forms, and high-level features, which refer to specific applications like assembly (e.g., features that are characteristic of joining) (NEB 2019). Low-level features describe parts' geometric and topological characteristics, including holes, chamfers, notches, and slots. In contrast, high-level features describe the functionality and use of specific product components.

An example of a high-level feature is an assembly feature that describes the connection between two shape features of different parts within an assembly. The definition of high-level or assembly features can vary in terms of their level of detail and specific use. However, high-level features are critical to the overall process, especially in assembly applications with important geometric, topological, and process parameters. In MULLINS & ANDERSON (1998), joining features are defined as entities that include the joint, the joining process, constraints, and geometric shapes such as grooves and chamfers. Other aspects, such as features of the joining path, tolerances, and gripping positions, also fall under this category (SANFILIPPO & BORGO 2016). This thesis defines assembly features relevant to process monitoring as assembly knowledge that includes geometric, topological, functional, and process features. In recent years, various approaches to feature recognition have emerged, each focusing on a specific application. Some of these approaches are discussed in the following, in which the technology behind them is described.

LI et al. (2010) propose an approach for the feature recognition of aircraft structural parts. A Holistic Attribute Adjacency Graph (HAAG)-based approach is developed, which allows to detect complex features more effectively than other approaches (i.e., single hint-based) in this application. The approach uses a combination of geometric and topological attributes to describe the features of an aircraft component, and these attributes are represented as nodes in the HAAG. The edges in the HAAG describe the relationships between the attributes. The graph is hierarchical to capture and combine the different levels of abstraction of the features. The proposed technology is set up of three main steps:

1. Hint search: The hint database is accessed to get hints for the seed face. The process of hint extension then begins using these seed hints, with the termination conditions being co-determined by both the seed hints and machining knowledge.
2. Hint extension: The extended rule base is used to extend the hints of the seed face into simple features.
3. Feature combination: The rule base combines the simple features and generates complete features.

The authors conclude that the proposed HAAG-based feature detection technology has the potential to be used in the manufacturing and maintenance of aircraft components, as it can significantly improve the accuracy and efficiency of detecting complex features (e.g., free-form surfaces, relationships between faces).

GENG et al. (2016) present a clue-based approach to identify machining features critical to the integration of CAD and Computer-Aided Manufacturing (CAM) into

Electrical Discharge Machining (EDM) process preparation. This approach includes four sequential steps that together enable the identification of machining features that are important to the EDM process. These steps are as follows:

i) Use of internal sharp points within the uncut area to extract the corresponding surfaces.
ii) Classification of the uncut regions based on common features.
iii) Reconstruction of the topological structure of the interacting region by decomposing it into isolated regions.
iv) Merging the original and reconstructed surfaces to produce a closed surface, which can then be solidified to obtain the CAD model of the volumetric feature.

The hint base is categorized as follows: internal sharp points (i.e., reference points), cutting-into points (i.e., intersection points, indicating the wedging of the cutter), interacting points (i.e., the interaction of different machining operations), and uncut regions (i.e., pockets containing internal sharp points and cannot be machined by cutter).

Madurai & Lin (1992) propose a rule-based approach for the automatic detection of part features from CAD data. The method uses a set of rules to identify and extract geometric objects and their attributes, such as planes, holes, and slots, from the CAD model (Figure 3.2). The extracted features are then recognized based on their attributes and geometric relationships to other features. The approach has been tested on several CAD models, and the results show that it can successfully identify and extract part features with high accuracy. The authors conclude that the rule-based approach can be used to develop more complex and intelligent feature recognition systems in the future.

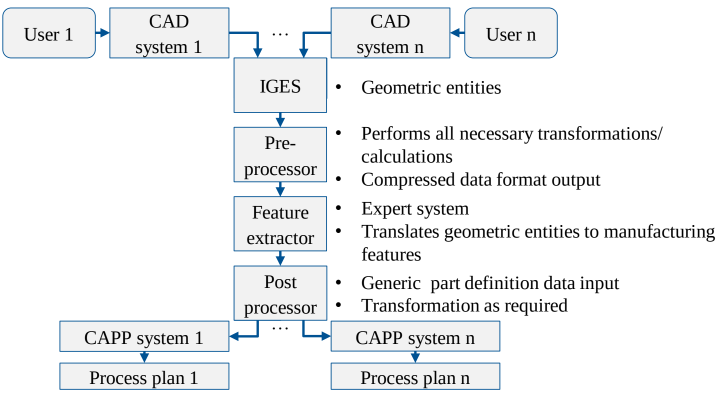


Figure 3.2: Rule-based approach for the automatic detection of part features by Madurai & Lin (1992).

KIM (1992) and KIM & WANG (2002) provide a feature detection approach based on the decomposition of a polyhedron (P) into its constituent parts using convex hulls and set difference operations. In this approach, a part is decomposed into a set of intermediate volumes without concave edges, called convex hull (CH) (Figure 3.3).

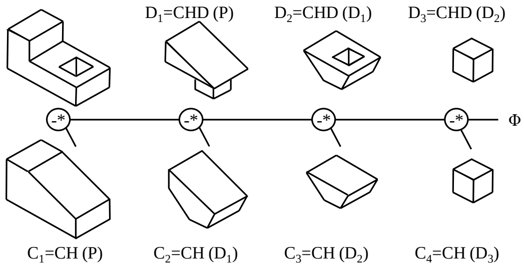


Figure 3.3: Feature recognition approach based on a convex-hull volume decomposition (KIM 1992).

The regularized convex hull difference CHD(P) of P is defined as the regularized set difference between the convex hull CH(P) and P. The basic concept of this approach is that any non-convex object can be expressed as a combination of CH (e.g., in Figure 3.3; P = CH(p) - CHD(P). This process is completed by repeatedly decomposing the part into convex hulls until no more segmentation is possible and form features are detected. A limitation of the convex hull decomposition method is its potential non-convergence for certain components. In addition, the approach is limited to polyhedral parts and parts with cylindrical surfaces and has limitations in handling complicated feature interactions (VERMA & RAJOTIA 2010).

SAKURAI & DAVE (1996) and WOO (2003) present a cell-based approach for the detection of features (Figure 3.4). The method is set up of three steps:

1. Identifying the overall removable volume as the difference set between the blank and finished part.
2. Decomposing this volume into unit volumes by utilizing the extended boundary faces as cutting planes (cell decomposition).
3. Merging all unit volumes that share common or co-planar faces to achieve maximum cells that can be removed in a single tool path (cell composition).

A significant problem arises in the cell decomposition step: the number of cells generated may be enormous, leading to a vast array of possible feature interpretations in step (3).
This process generates many unnecessary cells, and cell-based methods concentrate on dealing with them because they generate multiple interpretations

of potential machining features. The process of cell dissection brings with it a problem. The generation of a large number of cells leads to multiple possible feature interpretations in step three. This generates a significant number of extraneous cells, and therefore cell-based methods focus on solving this problem as it leads to multiple interpretations of possible processing features.

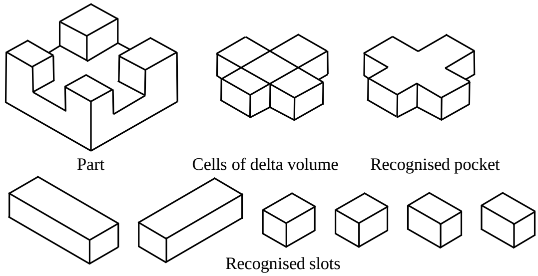


Figure 3.4: Cell-based approach for the detection of features by WOO (2003).

SUNIL & PANDE (2009) describe the development of an intelligent system for recognizing machining features of prismatic parts from CAD models using an artificial neural network (Figure 3.5). A 12-node vector scheme is proposed to represent machining feature families with variations in topology and geometry, and the system is trained with a large set of feature patterns to optimize its performance.

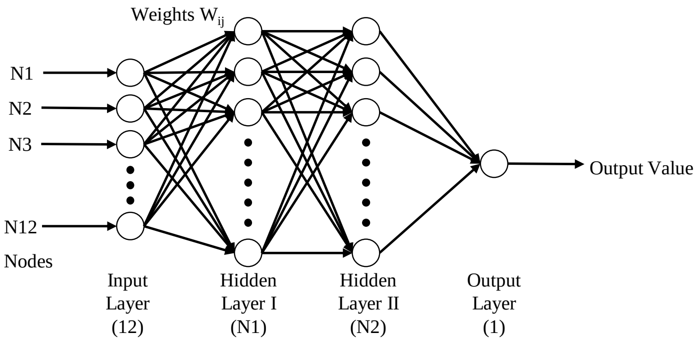


Figure 3.5: Feature recognition approach based on an artificial neuronal network (SUNIL & PANDE 2009).

The system is able to efficiently recognize a wide range of complex machining features and seamlessly integrate with a feature-based Computer-Aided Process Planning (CAPP) system for Computer Numerically Controlled (CNC) machining. There is a seamless integration from a CAD model (ACIS format) to a feature-based automatic CNC code generation. The feature recognition system must be re-trained and tested when a new feature template is added to the training set. The success of this approach depends on the availability and quality of the training data on which the artificial neural network relies.

Besides the continuous development of these approaches, hybrid solutions often come into play. A recent approach has been presented by Guo et al. (2021). The authors describe a new hybrid three-dimensional feature recognition method for detecting machining features in CAD and CAPP systems (Figure 3.6). The proposed method is based on rules and graphs and was developed to overcome the limitations of existing feature recognition methods restricted to a specific set of predefined manufacturing features.

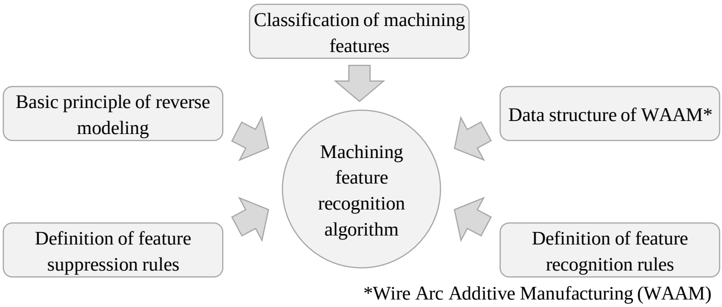


Figure 3.6: Hybrid feature recognition approach by combining a rule- and graph-based approach (Guo et al. 2021).

The approach is based on the reverse modeling method for classifying machining features, representing the three-dimensional model using a weighted attribute adjacency matrix, defining detection and suppression rules, and applying the method to shaft parts as a test case. The results show that the method can detect various machining features. Nevertheless, assembly features are not taken into account.

Conclusion

Different approaches exist to recognize features. Most of these approaches focus on machining or manufacturing features relevant for CNC machines. Some of these approaches can be used for different domains, such as assembly, as pointed out by Neb (2019). An extract of relevant approaches just described in the previous chapter is listed in Table 3.1.

Depending on the focus of feature recognition, the scope of the application differs. Rule-based approaches are most commonly used, some of which are combined with other approaches to form hybrid approaches. However, the rule-based approach is often the primary focus. In addition, the Standard for the Exchange of Product Model Data (ISO 10303) (STEP) format is a preferred CAD format for feature analysis. This is due to the standardization and the text-based structure.

Table 3.1: Different approaches for CAD feature recognition based on form identification (VERMA & RAJOTIA 2010).

Nr.	Approach	Focus
1	*Graph-based approach*	• Nodes and arcs represent faces and edges • More successful for isolated features (i.e., non-interacting features)
2	*Hint-based approach*	• Patterns in the part boundary that indicate the possible existence of a feature • Recognizing machining features from 2D orthographic projections
3	*Rule-based approach*	• Predefined constraints are formalized as rules • Broad applicability due to predefined rules that are required for every conceivable feature
4	*Convex-hull volumetric decomposition*	• Volumetric decomposition into convex volumes • Effective in determining delta volumes for polyhedral parts - difficulties with curved surfaces
5	*Cell-based volumetric approach*	• Volumetric decomposition into minimal cells • Parts with flat surfaces and only in a limited number of cases with convex curved surfaces
6	*Neuronal network-based approach*	• Training algorithms, design of network layers, and number of neurons in each layer • Requires structured data, high-quality data, and a sufficient quantity of data for the training
7	*Hybrid approach*	• Combination of different advantages and limitations of individual approaches • Applicable to different fields

3.1.2 Skill-based Approaches for the Description of Resources and Assembly Systems

Describing the functionalities of resources in production planning through skills or capabilities, and therefore hardware-independent, has gained increasing acceptance in various domains (e.g., assembly or manufacturing planning, robot programming) (KÖCHER et al. 2023). A skill refers to a specific function a resource can or must perform during a specific process. Skills have been incorporated into the PPRS model and used in various planning strategies (PFROMMER et al. 2013).

According to KÖCHER et al. (2023), a capability is defined as a description of a function that can achieve a certain result in either the physical or virtual domain, regardless of how it is implemented. On the other hand, a skill represents the practical implementation of a function encapsulated in a capability. In this context, the terms capability and skill are used interchangeably, and KÖCHER et al. (2023) definition of capability applies to both.

BENGEL (2009), HAAGE et al. (2011), MALEC et al. (2007), and STENMARK & MALEC (2015) focus on the concept of reconfigurability in the context of manufacturing systems, with a focus on skills and knowledge-based techniques. Both approaches are combined in the project SIARAS (Skill-based Inspection and Assembly for Reconfigurable Production Systems), which aims towards an intelligent system (i.e., skill server) capable of supporting automatic and semi-automatic reconfiguration of existing manufacturing processes. The skill server captures production skills and is based on a knowledge-based concept that describes processes and resources using skills. These are compared and prepared for exchange with Computer-Aided Technologies (CAx) programs for simulation and reconfiguration purposes, using an ontology to map skill relationships. To model the resources, the top-down and bottom-up views are merged using various industry standards (i.e., VDI-RICHTLINIE-2860 (1982) and DIN-8593 (2003) according to BENGEL (2009)). The skill hierarchy focuses on the process view and includes sensorial skills.

The following project ROSETTA (RObot control for Skilled ExecuTion of Tasks in natural interaction with humans; based on Autonomy, cumulative knowledge and learning) extends the focus and classification of skills according to the PPR or PPRS model (PFROMMER et al. 2013). This allows a nested hierarchy for processes such as pick or place. However, the transfer of this approach to the development of composite skills and the resulting properties is not discussed in detail. In addition, resource availability is not considered in production planning, and process requirements have to be generated manually.

BACKHAUS & REINHART (2017) present the skill concept to improve the adaptability of robot programming tasks (Figure 3.7). The method involves developing an adaptable task-oriented programming system for assembly systems that can be easily configured and adapted to different assembly tasks, making it more flexible and efficient in industrial environments. The modular system allows easy integration of new components and modules by leveraging skills.

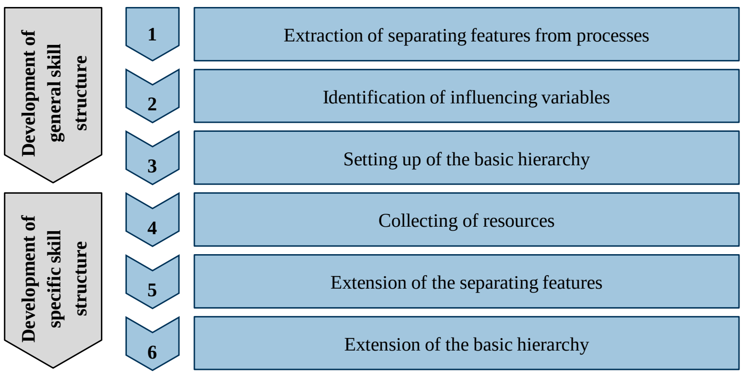


Figure 3.7: Concept of the development of a general skill structure and adaptable task-oriented programming system for robots (BACKHAUS & REINHART 2015).

Figure 3.7 shows two different phases that can be distinguished. The first phase involves the development of the general skill structure based on general process knowledge. The second phase then specifies the skill structure by considering the resources.

A distinction is made between elementary and composite skills. The latter can perform more complex or higher-level processes (e.g., joining). The approach includes testing and evaluating the performance and usability of the system, including its adaptability to different assembly processes. The modeling direction from individual resources to stations, cells, or production lines is not included. The goal is to provide a practical and versatile solution for assembly systems in the industry using a task-oriented programming system that is easy to customize. BACKHAUS & REINHART (2015) define skills mainly from a process perspective, augmented with resource properties. BACKHAUS & REINHART (2015) do not address the use of the model for the development of process monitoring systems.

A further approach to effectively using skills lies in the work of HAMMERSTINGL & REINHART (2018). They present a skill taxonomy developed as part of a Plug & Produce architecture to facilitate the automatic integration of field devices in the industrial environment (Figure 3.8). The skills of resources serve as a virtual representation, and the taxonomy focuses on the assembly domain, considering industrial standards and relevant publications.
The naming of skills and associated parameters is mainly done from a process perspective and refers to resource and product-related data. As shown in Figure 3.8, the individual skills and composite skills are used to match different levels of processes or tasks (i.e., combined processes). Composite skills can be modeled of elementary skills in serial or parallel:

- Serial: handling a part by using retaining and moving skills
- Parallel: checking the height or length of a part with two checking presence skills

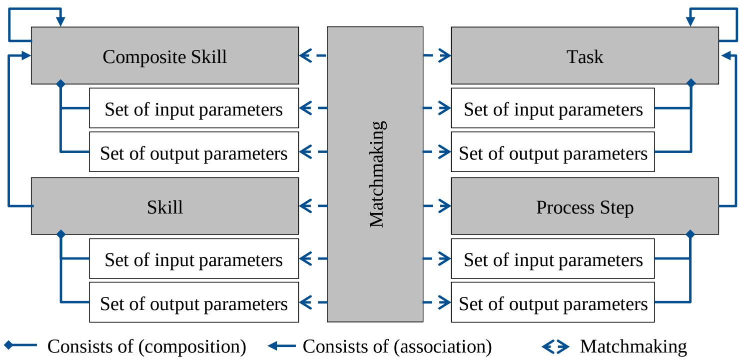


Figure 3.8: Matchmaking system containing a skill taxonomy based on individual and composite skills (HAMMERSTINGL & REINHART 2018).

A semantic and parameter-based description and modeling of the skills are described, which allows a matchmaking process between resource skills and process requirements. However, the authors HAMMERSTINGL & REINHART (2018) identify insufficient structures in the area of sensorial skills. An additional taxonomy for composite skills is also presented. No general procedures for deriving these skills or for resource modeling are explained. The structure with elementary and composite skills allows a preferred modeling direction from components to resources and finally to whole assembly systems. The application areas of the taxonomy are not specified in more detail.

JÄRVENPÄÄ et al. (2016) aim to increase and accelerate the adaptability of production systems by describing the skills of resources. The description of the skills and setup of the ontology is part of a project called ReCaM (Rapid Reconfiguration of Flexible Production Systems through Capability-based Adaptation, Autoconfiguration, and Integrated Tools for Production Planning). The goal is to automatically match a product's process requirements with available resources and their combinations by matching skills with available resources based on their semantic descriptions and parameters (SILTALA et al. 2018). Elementary skills are documented in a taxonomy and directly assigned to individual resources. The skills are saved in an ontology called MaRCO (Manufacturing Resource Capability Ontology). The ontology rules developed for composite skills are particularly innovative and stored in the taxonomy (JÄRVENPÄÄ et al. 2019). These enable the automatic determination of skills and associated parameters of combined resources, as seen in Figure 3.9.
Skills and their physical and technical parameters are defined based on the PPR model, with naming based primarily on the process to be performed. Resource modeling using these skills is performed either according to the top-down approach by describing entire production systems or according to the bottom-up approach by combining individual resources and their skills. The terms simple and combined skills are used to classify skills, as in BACKHAUS & REINHART (2017) and HAMMERSTINGL & REINHART (2018). The transferability of this methodology to sensorial skills and process monitoring is not explained in detail.

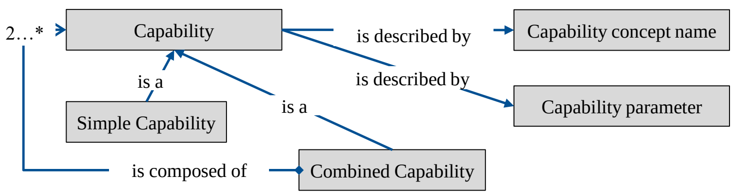


Figure 3.9: Structure of the skill taxonomy developed by JÄRVENPÄÄ et al. (2019).

Conclusion

For a skill-based approach to be used in automated process planning, the approach must be adapted for the corresponding domain and modified according to the specific problem. However, most approaches are domain-specific and are difficult to transfer to other domains, for example, in the approaches by BACKHAUS & REINHART (2017), MALEC et al. (2007) and STENMARK & MALEC (2015).

However, there are generic approaches, such as those presented in HAMMERSTINGL & REINHART (2018) and JÄRVENPÄÄ et al. (2019), that can be used to define skills in other domains, such as process monitoring planning. In particular, sensorial skills with specific parameters, such as accuracy and region of interest, are essential in planning monitoring processes in assembly. The sensorial skills for assembly monitoring must first be defined to apply the generic approach to this domain, including a semantic description and individual parameters.

3.2 Approaches for Automated Process Planning

Various approaches to automated process planning have been developed in recent years, depending on the available information about process requirements and skills of the production system. In this context, CAPP is divided into variant and generative process planning, where variant process planning is based on a master template of a previous production variant (ELMARAGHY & NASSEHI 2019, pp. 339–341).

In contrast, generative process planning starts from scratch and uses rule-based and knowledge-based systems as well as heuristic and problem-specific algorithms. Reconfigurable process planning is referred to as a hybrid approach and is essential for generating a virtual representation of production or digital twin (ELMARAGHY & NASSEHI 2019, p. 341). Since monitoring planning in assembly is closely related to assembly and inspection planning, approaches for automated process and inspection planning are presented in the following sub-chapters.

3.2.1 Automated Assembly Planning

The SIARAS project aims to increase the reusability of resources in production systems by simplifying the selection and reconfiguration of assembly stations through skill-based approaches. In the European research project SIARAS and ROSETTA, as described in Chapter 3.1.2, a skill server was developed that provides the skills of resources in production and makes them comparable by means of an ontology-based description (HAAGE et al. 2011; MALEC et al. 2007). Additionally, a matchmaking approach allows us to automatically match skills with predefined process requirements.
The matchmaking results in process resource combinations due to the usage of the PPRS model (PFROMMER et al. 2013). The matchmaking in this approach is rule-based and has been implemented in Protegé (STENMARK & MALEC 2015). The goal is to increase the reusability of resources and to facilitate the reconfiguration of assembly stations. The approach does not apply to process monitoring planning. The automatic selection of optimal resources according to criteria specified by the user is suggested but not described in more detail (BENGEL 2009).

The ReCaM project aims to improve the adaptability of production systems by describing the skills of resources (JÄRVENPÄÄ et al. 2016) and automatically meeting process requirements with the available resources and their combinations (SILTALA et al. 2018). The approach involves matching the required skills by name and then with the available resources based on required parameters in a rule-based manner (Figure 3.10).

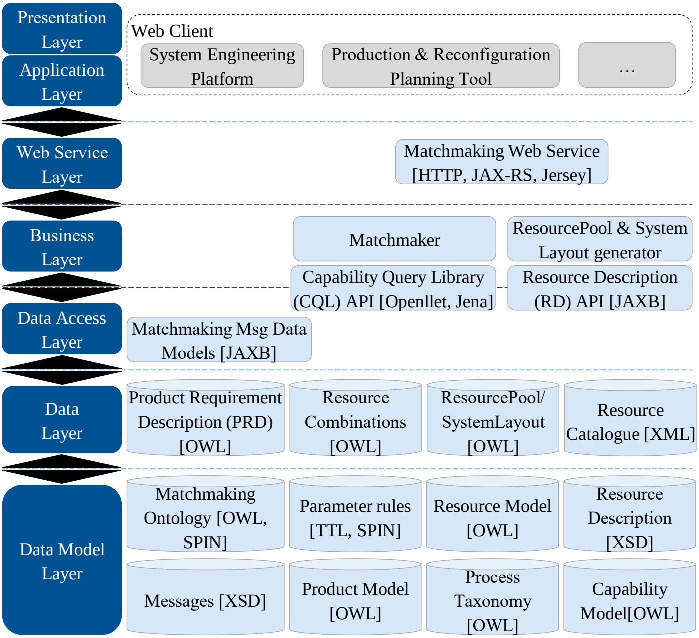


Figure 3.10: Matchmaking system for the identification of process-resource-combinations developed by JÄRVENPÄÄ et al. (2019).

Skills are documented in a taxonomy, can be directly assigned to individual resources, and follow industrial standards (JÄRVENPÄÄ et al. 2019). JÄRVENPÄÄ et al. (2018, 2021) further develop the matchmaking system, focusing on matchmaking by searching through large resource catalogs to find feasible combinations automatically (Figure 3.10). An implementation and combination with external design and planning tools are also given. After the import of the Product Requirement Description (PRD) and set of Resource Description (RD), the rule-based matchmaking generates a new process resource combination. The matchmaking rules are implemented in SPIN rules (SPARQL Protocol And RDF Query Language) (JÄRVENPÄÄ et al. 2018).
As shown in Figure 3.10, different ontologies for the product, resources, and matchmaking rules have been defined. The different layers describe the hierarchy of the data and the user interaction, which is mainly possible via a web client.

However, it should be noted that resource availability is not considered in production planning, skills are not parameterized, and no reference is made to process monitoring in assembly. Additionally, the required input information must be generated manually (i.e., process requirements and resource skills).

In process planning, MICHNIEWICZ (2019) provide an approach to automatically create assembly plans using product and production system information. The approach uses skill- and simulation-based planning to improve and automatize the planning and usage of assembly systems efficiently. The approach focuses on the automatic generation of various assembly plans and their simulation-based validation. The immense solution space offered by the product and production system, due to multiple possible assembly sequences and possible process resource combinations, requires automation. Four domains can be distinguished: 1) product domain, 2) skill domain, 3) resource domain, and 4) matchmaking domain (Figure 3.11).

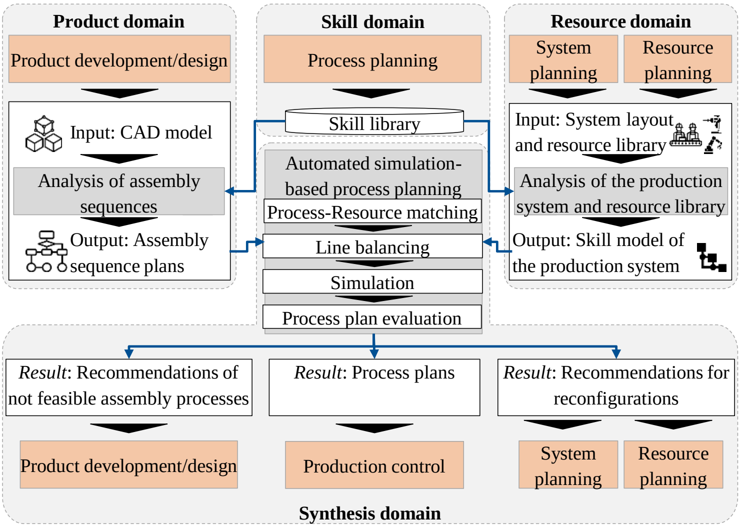


Figure 3.11: Matchmaking system for the generation of assembly processes with allocated assembly resources developed by MICHNIEWICZ (2019).

The product domain describes the product to be assembled, including the individual assembly processes and their requirements. An assembly-by-disassembly approach is used to automatically generate valid assembly sequences of the product in a three-dimensional simulation. The resource domain provides information about the individual resources and the layout of the production system. In combination with the skill domain, which defines process requirements and resource functionalities, process resource combinations and assembly plans can be generated. The matchmaking step is divided into semantic, parameter, and simulation-based analysis. The user can insert criteria (i.e., number of reconfigurations, process time) to reduce the number of assembly plans. The approach does not consider process monitoring planning and focuses exclusively on actorial skills.

Conclusion

Automated assembly planning approaches rely on semantic skill databases and adaptive structures of matchmaking modules for flexible applications, as shown in the work of STENMARK & MALEC (2015), MICHNIEWICZ (2019), and JÄRVENPÄÄ et al. (2019). However, a specific assembly process monitoring approach has not yet been designed. The definition of sensorial skills relevant to process monitoring still needs to be developed. A closer focus on the physical quantities to be measured and a more flexible view of direct and indirect monitoring methods is essential.

3.2.2 Automated Inspection Planning

Approaches for the automated planning of inspection often lie in the field of manufacturing. Here, individual parts are produced, not assembled. Matching process requirements and product quality characteristics with inspection resources are essential to inspection planning. Similar to automated assembly planning, matching algorithms based on rules, knowledge, or heuristics are often used. The following chapter provides insight into recent and promising approaches. KAMRANI et al. (2015) present a feature-based approach for integrating CAD and Computer-Aided Inspection Planning (CAIP) (Figure 3.12). The authors propose a method that uses features, which are geometric entities that describe the shape and size of a product. This is the basis for both the design and inspection planning process. The underlying concept of the approach is that by using product features, automatic matching to the most appropriate inspection step on the Coordinate Measuring Machine (CMM) can be achieved.

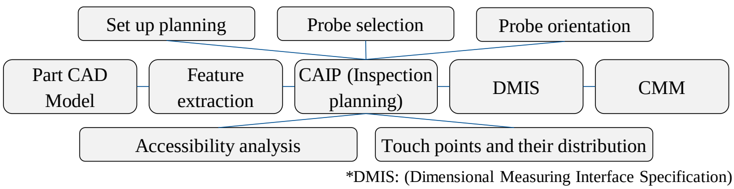


Figure 3.12: Method for the automated generation of inspection processes (KAMRANI et al. 2015).

The CAIP involves in this approach the setup planning, probe selection, accessibility analysis, and touchpoints of the CMM. The focus lies on CMM systems, which are especially suitable in inspection planning for manufacturing processes due to their accuracy and reduced inspection cost and time.

The authors do not assume sensorial skills as a prerequisite for the individual setup of CMMs but define all possibilities as sets of rules (i.e., numerical and graphical rules). This approach can be time-consuming and requires significant manual effort for various resources with sensorial skills. However, by using a rule-based approach to feature detection, inspection features can be efficiently detected using a predefined set of rules that can be applied to different products.

Romero Subirón et al. (2018) present a feature-based framework for inspection process planning. The framework integrates knowledge from both the product and the inspection system. The framework enables the specification, analysis, and validation of inspection assemblies. The inspection feature, proposed by the system, contains the necessary information to check compatibility between part and resource features and supports the design and selection of inspection solutions in collaborative manufacturing contexts. The ontological approach allows for automated reasoning and the capture of new knowledge by adding new rules.

Abouel Nasr et al. (2020) describe a planning system that automates machining plans, fixture setup, and inspection strategies (Figure 3.13). The system uses an approach to integrate the design process, including fixtures and inspection modules and uses STEP files of the product as input.

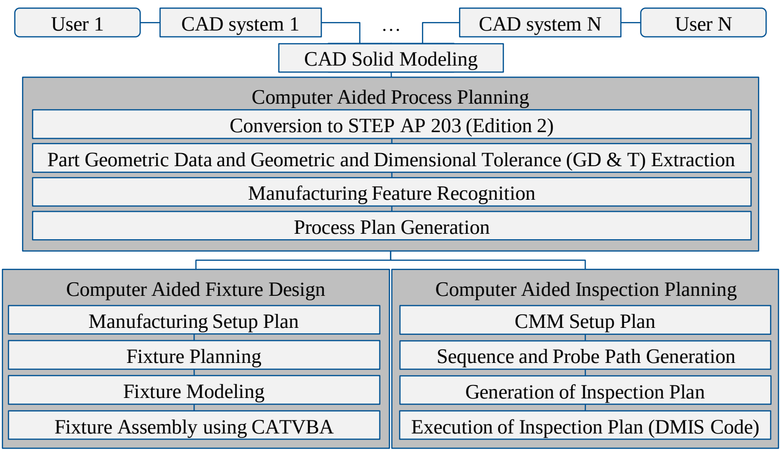


Figure 3.13: Approach for the automated planning of fixtures and inspection strategies developed by Abouel Nasr et al. (2020).

The CAPP module recognizes machining features and generates the required machining volumes, machine operations, machine tools, cutting tools, and feature locations. The modular fixture layout is developed in the computer-aided fixture design using a set of rules, search strategies, and a graphical database of various fixture components.

The CAIP module automatically generates an inspection plan for CMM. Here, the features to be inspected are allocated to the required functionalities of the CMM with a rule-based implementation. The focus lies on an accessibility analysis of the CMM (i.e., tactile functionality of the CMM). However, the approach is currently only focusing on generating inspection plans for manufactured parts and relies entirely on the functionality of CMMs.

Conclusion

All approaches focus on manufacturing and matching inspection requirements with inspection skills in the manufacturing domain. These approaches have not been applied for assembly planning, especially planning process monitoring in assembly.

3.3 Conclusion of the State of the Art and Need for Action

Chapter 3 outlines current approaches for the automated generation of virtual product representations and resource capabilities for production processes in different domains (i.e., assembly and inspection). These approaches aim to automate process planning in the areas of assembly and inspection with the aim of saving time, reducing costs, improving resource utilization, and minimizing the need for expert knowledge.

As can be seen in the approaches for feature recognition, only a few approaches focus on the detection of assembly features relevant for process planning (NEB 2019). In particular, there is very little research in the area of using features to inspect or monitor assembly processes. Existing approaches focus primarily on identifying geometric and technical features (i.e., those specific to the assembly process) and use rule-based or hybrid feature detection methods to ensure accurate classification within the appropriate domain. However, there is still no research or established methods for planning process monitoring in the field of assembly.

Furthermore, skill-based approaches have been developed with domain-specific purposes or more generic approaches on the setup and usage, as shown by HAMMERSTINGL & REINHART (2018) and JÄRVENPÄÄ et al. (2019). However, none of these have been applied to the use of monitoring processes in assembly and resources, including their sensorial skills.

Lastly, approaches for the automated generation of process plans have been sighted. Often, these approaches combine the generation of requirements through feature recognition and the usage of skills. MICHNIEWICZ (2019) pointed out that until now, process monitoring, and especially sensorial processes, have only been investigated very little. Due to the large number of possible assembly plans that can be generated with various selection criteria (process times, allocated resources), an automated approach to generating process monitoring plans is essential.

Chapter 4

Research Scope

This chapter presents the research framework for the dissertation. Following the comprehensive descriptive study of the state of knowledge already conducted, a more detailed clarification of the research according to the DRM model is provided here. The approach to address the challenges and the urgent need for action is outlined. In the remainder of the chapter, three research questions with associated scientific objectives are formulated. Four solution modules are then developed to address these objectives. Together, these modules form the methodology and serve as a framework for integrating the individual publications.

Production systems are constantly being adapted to improve their flexibility and reconfigurability in today's volatile environment. This adaptation is driven by the need to address challenges and trends arising from globalization, individualization, increased customer expectations, sustainability of resource utilization, and stricter quality guidelines and regulations (such as the MDR).

The complexity of planning assembly processes mainly depends on the large number of assembly sequences and the diverse combinations of resources that lead to many possible assembly plans. This increases by including multiple product variants in the planning process. In addition, complexity is further increased by the need to ensure process quality, as the planning of monitoring activities becomes increasingly difficult due to constant process changes with permanent re-planning of the assembly line. Manual planning of process monitoring involves considerable manual effort, resulting in longer planning times, higher costs, and reliance on expert knowledge.

Assertion:
Automation approaches and decision support systems in multi-variant assembly enable efficient and flexible planning of process monitoring, reducing planning time, costs, and the reliance on expert knowledge.

The introduction of assembly monitoring does not directly add value to the product but introduces non-value-adding processes. Consequently, the planning of assembly monitoring processes should be carefully strategized, parallelized, and implemented while considering different monitoring alternatives for each individual assembly plan.

There are two major considerations: first, identifying the required data, and second, determining an appropriate data modeling approach for creating multiple monitoring plan alternatives. These factors form the basis for the first two research questions. In addition, it is critical to examine the purpose of generating monitoring plan alternatives from the user's perspective. This involves the evaluation of various decision criteria, the support of each monitoring plan alternative in assembly process planning, and the selection of a suitable assembly plan by combining monitoring tasks. Consequently, this results in the third research question.

Research questions (RQ):

RQ1: How can *product- and process-specific* inspection features for process monitoring be identified *automatically from CAD models*?

RQ2: How must *information* in CPPS be modeled for process monitoring?

RQ3: How can various *demand-based process monitoring alternatives* be derived in an automated approach?

The research questions lead directly to the specification of three scientific objectives. The objectives are focused on three key areas. The first area involves the use of automated systems to analyze CAD product files and process specifications. The second area focuses on the development of production systems and resource models, with an emphasis on monitoring. Finally, the objectives aim to create an efficient and automated decision support system capable of developing process monitoring alternatives for multi-variant assembly.

Scientific Objectives (SO):

SO1: Computer-aided identification of *product- and process-specific* features for process monitoring

SO2: Utilization of the inherent flexibility of assembly systems for process monitoring by means of *skill modeling*

SO3: *Demand-driven generation of alternatives* for process monitoring in assembly systems based on the capabilities of the assembly systems

Chapter 5

Framework of the Decision Support System for Automated Planning of Process Monitoring in Multi-Variant Assembly

The following sub-chapters provide an overview of the decision support system, focusing on integrating individual publications into this system. These individual solution modules are designed to address specific research objectives. In addition, each publication is examined and presented in detail, highlighting the approach, solutions, and implementations used. It should be noted that the order of publications is based on logical coherence rather than chronological publication dates. In addition, each publication is subjected to extensive review and discussion.

5.1 Integration and Reviews of the Embedded Publications

The scientific objectives form the basis for the generation of solution modules, which are the framework of the system. Specific publications relate to modules or encompass the entire framework, as can be seen in Figure 5.1. The first scientific objective involves the development of two solution modules for identifying monitoring needs. The first module serves as a component that establishes boundary conditions for requirements and provides product-neutral knowledge on monitoring requirements in assembly. The second module focuses on product- and process-specific analysis and requires the development of methods for analyzing new product variants and processes.

The third module addresses the second scientific objective for modeling assembly systems and resources. This module provides information about the sensorial skills required for mapping resources to monitoring requirements. The fourth module addresses the third scientific objective. This module focuses on matchmaking, aiming to combine the domain of product and process requirements with that of the production system and resources.

1. Module 1: Structure of the knowledge database
2. Module 2: Identification of product-specific features
3. Module 3: Modeling the skills of the resources
4. Module 4: Generation of alternatives for process monitoring

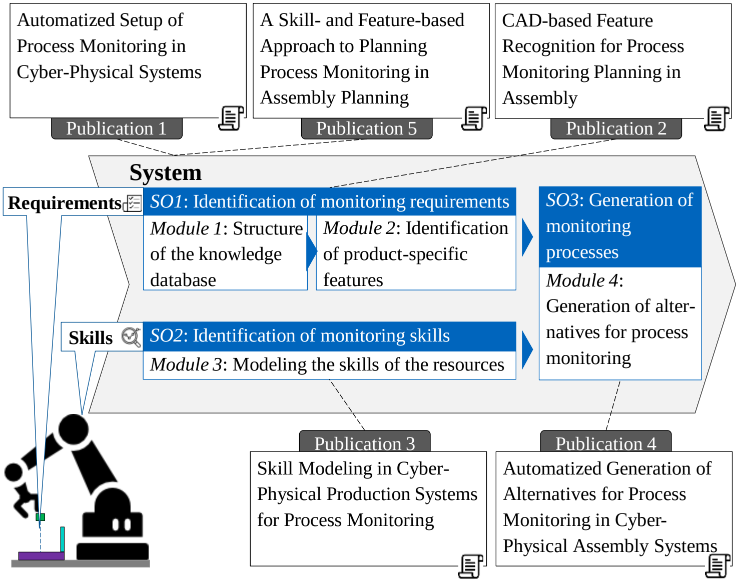


Figure 5.1: Approach for the automated generation of process monitoring plans, including the relevant publications of this thesis and their classification.

The first publication *Automated Setup of Process Monitoring in Cyber-Physical Systems* presents the concept of the decision support system and puts the framework into context. The second publication *CAD-based Feature Recognition for Process Monitoring Planning in Assembly* addresses the first and second modules.

The third module, which concentrates on skill modeling for monitoring processes, is covered in the third publication titled *Skill Modeling in Cyber-Physical Production Systems for Process Monitoring*. The fourth publication *Automated Generation of Alternatives for Process Monitoring in Cyber-Physical Assembly Systems* focuses on the last module for the generation of process monitoring alternatives.

The fifth publication *A Skill- and Feature-based Approach to Planning Process Monitoring in Assembly Planning* provides an overall implementation of the decision support system. It combines monitoring planning with the automated generation of assembly plans by providing additional criteria for optimization.

5.1.1 Publication 1: Automatized Setup of Process Monitoring in Cyber-Physical Systems (GONNERMANN & REINHART 2019)

The publication *Automated Setup of Process Monitoring in Cyber-Physical Systems* introduces a methodology to minimize the manual planning involved in implementing and initializing process monitoring in existing assembly lines. The primary objective is to reduce the manual planning effort for new product variants by automatically identifying the process monitoring requirements and available sensorial skills of individual resources and generating process monitoring plans. The automated process monitoring planning method consists of four steps, as depicted in Figure 5.2:

1. *Assembly Features*: Analysis of the virtual product to identify assembly characteristics and monitoring-related requirements.
2. *Skills*: Identify information about assembly line resources and automatically create a skill model based on their sensorial skills.
3. *Requirement-Skill Comparison*: Perform a matching process between monitoring requirements and sensorial skills of resources to generate monitoring resource combinations.
4. *Process Monitoring Planning*: Combine individual monitoring processes with monitoring plans and include user-specific criteria.

The first step of the approach is an analysis of the virtual product, particularly the CAD model and its additional features, such as PMIs, that specify the assembly process requirements. This enables the automated identification of specific assembly features about the correlating product parts and assembly processes, resulting in process monitoring requirements.

The second step is to identify the sensorial skills of resources (i.e., CPS). A skill model specifically for sensorial skills is required to match the process monitoring requirements with the existing resources on an assembly line. Based on its self-description, CPS can be used to automatically generate a skill model specifically for sensorial skills. Information about technical functions and dependencies needs to be taken into account to define resources and their ability to monitor critical parameters.

The third step is the comparison between process monitoring requirements and sensorial skills of the resources. The generated semantic descriptions of the requirements for monitoring the assembly processes and the sensorial skills of the resources are compared. The respective assembly plan already specifies the monitoring place since assembly processes and locations are predefined.

The matching process is divided into semantic matching and quantitative analysis. Semantic matching provides a general statement about whether the monitoring requirement can be met by the resource or a combination of resources. The requirement must semantically match the sensorial skill to verify the specific monitoring requirement. The quantitative analysis details whether the individual-specific actions can also be monitored on a parameter basis (e.g., necessary torque to be monitored). If the monitoring of a process is not possible with the resources available on the assembly line, a reconfiguration is suggested so that the correct data can be obtained.

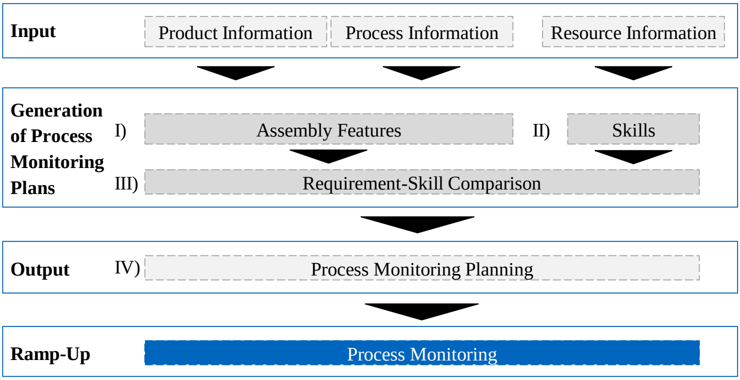


Figure 5.2: Concept of the system for the automated generation of process monitoring plans (Gonnermann & Reinhart 2019).

The fourth step involves the generation of alternative process monitoring plans from the potential matches of resource-process combinations of the third step. Different process monitoring plans can be systematically created by exploiting the corresponding assembly plan information. These plans can highlight discrepancies, such as variations in the number of reconfigurations required or the degree of accuracy of feature monitoring, which are then presented to the user.

Product, process, and assembly feature-specific process monitoring can thus be set up in an automated manner. Combined with intelligent data analysis tools, this method promises high potential for reducing the manual planning effort required to introduce and initialize process monitoring on existing assembly lines. It can also help to increase the flexibility of RMS by allowing process monitoring to be efficiently adapted to new product variants and assembly processes.

The key findings of the publication highlight several important aspects. First, it defines the scope and limitations of the approach and provides a clear understanding of what assembly system planning for CPS implies. In addition, the publication emphasizes the importance of variant assembly and examines related assembly planning approaches that have not yet been adapted to monitoring planning. The system primarily targets the value-added assembly processes and excludes secondary processes such as transportation and feeding. Finally, the approach introduces an interlinked assembly system that ensures a continuous flow of materials between the individual work steps, thereby increasing efficiency and productivity.

5.1.2 Publication 2: CAD-based Feature Recognition for Process Monitoring Planning in Assembly (GONNERMANN et al. 2023)

The concept presented in this publication describes the automated identification of process monitoring features and requirements in assembled products. The system exploits user interaction to facilitate the identification of monitoring functions and requirements. This enables customization to meet the specific monitoring requirements of a newly introduced product variant for assembly. The system's main objective is to identify and define monitoring requirements that must be considered when planning process monitoring.

The system uses product information derived from the CAD model of the assembled product. In addition, it takes process-specific information from the assembly plan as input. These inputs enable the system to determine the monitoring requirements for assembly processes. The extraction and recognition of the geometric and process-specific features rely on two sub-modules: one containing templates for monitoring requirements and one for parameterizing the process monitoring requirements.

The method consists of the following modules that lead to monitoring requirements with semantic descriptions and required parameters to be monitored (see Figure 5.3).

Modules:

1. *Extraction and recognition module*
2. *Monitoring requirements template module*
3. *Parametrization module*

Here, information about the product to be analyzed and the corresponding assembly plans containing process-specific information are required. The first module identifies geometric and topological features of the assembled product and individual parts, as well as process-specific information on the individual assembly processes. A rule-based approach identifies these features. In addition, the module requires the second module, which defines the process-specific monitoring requirements as templates.

Individual process-specific templates (e.g., joining processes, bolting processes) are stored in a database that contains process-specific, geometric, and topological monitoring requirements for each assembly process according to DIN-8593 (2003), independently of a product. As examples, templates of three assembly processes are presented in the publication, and an approach for creating these templates is given.

The filling of these templates is done in module three. These templates are filled and parameterized in combination with allocation rules and the results from the first module for a specific product. The user can interact with the system anytime and adjust individual monitoring templates or parameters if necessary.

The concept is implemented in a software system that uses OpenCascade's Python library (PyOCC) for feature extraction from STEP files, an SQL database for the monitoring templates, and PyQT for visualization. The system is tested using the use case of an assembled surround-view camera consisting of two housing parts, an electrical circuit board, and four screws.

The system is able to automatically identify the monitoring templates and populate them with the appropriate information from the process plans and CAD model. However, it should be noted that the system still requires some level of manual intervention, especially in the case of missing features or monitoring requirements. In addition, the initial setup of the system, especially the formulation of rules for the recognition of assembly features, initially requires expert knowledge and setup time.

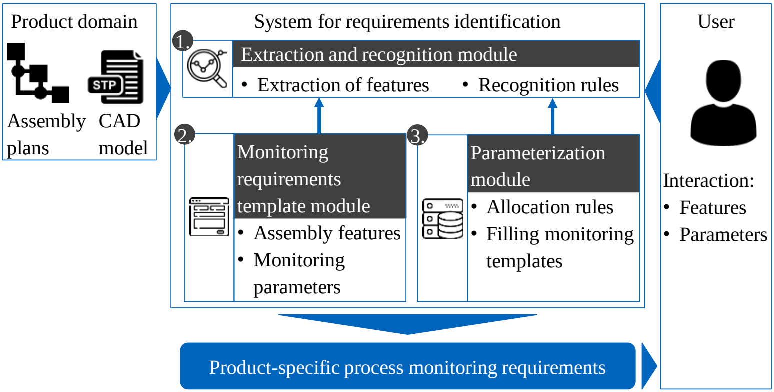


Figure 5.3: Method for the automated generation of process monitoring requirements from CAD models and assembly plan information (GONNERMANN et al. 2023).

The key findings of the publication show the potential to effortlessly and automatically generate product- and process-specific process monitoring features through rule-based feature extraction. The time required to identify critical process monitoring features for monitoring planning can be significantly reduced. In addition, the developed database of product-neutral monitoring features and the associated feature detection rules enable a seamless transition to new product variants with minimal manual intervention.

5.1.3 Publication 3: Skill Modeling in Cyber-Physical Production Systems for Process Monitoring (GONNERMANN et al. 2020)

The publication describes a method for automatically identifying skills of resources for planning process monitoring in an assembly system. This is intended to plan and deploy the use of RMS more efficiently by combining sensorial skills of different resources (i.e., composite skill), as can be seen in Figure 5.4. The approach includes the development of a skill taxonomy for sensorial skills implemented in an ontology and combination rules for sensorial skills using Semantic Web Rule Language (SWRL) and physical correlations between quantities in the taxonomy.

The skill taxonomy is a structure that classifies all sensorial skills according to determinable physical quantities, thus allowing the assignment of all sensorial skills to a group. Based on the literature review, 73 sensorial skills and their associated units were identified. The resulting skill taxonomy is applied identically for the two types of "testing" and "measuring" of the secondary assembly function "checking". When combined with a specific resource, this defines the skill ("Name of the Skill", Figure 5.4).

The skill structure for sensorial skills contains parameters and possible constraints that specify the properties of a resource in fulfilling the corresponding functionality. This skill structure describes the logical structure, sequence, and content of the data used to define a sensorial skill ("Skill Properties and Restrictions", Figure 5.4).

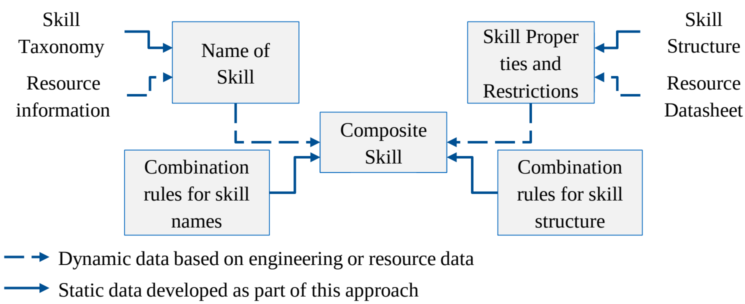


Figure 5.4: Structure of the skill taxonomy for the definition of a monitoring skill model of an assembly system (GONNERMANN et al. 2020).

To combine elementary skills (e.g., check presence) and form new composite skills (e.g., measure length of product), this publication presents combination rules for sensorial skills using the SWRL and physical correlations between quantities in the taxonomy. These rules can be used to express logical relationships and extend the sensorial skills taxonomy into an ontology.

To demonstrate the method, a use case is presented using the assembly system of the research project INTELLPROMO (2019). The assembly system consists of three combinable assembly stations that assemble the product, focusing on the second station consisting of two resources (R1 and R2) to assemble a camera housing. The identified elementary sensorial skills are automatically assigned based on the skill taxonomy for each resource of the assembly station, including the actorial skill "moving" to expand the scope of work of the sensorial skills.

By combining the identified skills, several composite skills are generated, illustrating the potential of this approach to improve the efficiency of a RMS. The User Interface (UI) is programmed in C# and WinForm. The skill taxonomy is implemented in Protegé with SWRL. The resource and production system information is imported through a text-based data format (i.e., XML and JSON).

The key findings of the publication are that different monitoring alternatives can be identified automatically by implementing a skill-based modeling approach. In particular, identifying similar monitoring processes performed by different resources is advantageous when planning process monitoring in production (i.e., brownfield scenario). Here, direct and indirect monitoring methods can be evaluated, and reconfiguration efforts can be weighed against monitoring accuracy or time. The initial setup of such a skill model can be used for other production systems with similar resources to decrease setup time and costs over time.

5.1.4 Publication 4: Automatized Generation of Alternatives for Process Monitoring in Cyber-Physical Assembly Systems (GONNERMANN et al. 2021)

The publication presents a decision support system for the automatic planning of different alternatives for process monitoring in the assembly of products in small batch sizes and high variant diversity. The system aims to reduce the time required for manual planning of process monitoring and the expert knowledge required to efficiently plan process monitoring. The system consists mainly of the matchmaking module and simulation-based validation, as can be seen in Figure 5.5.

The novelty of this approach is that it uses a decision support system that automates the process of planning process monitoring alternatives in RMS. This system consists of several extensible and interchangeable modules, including semantic matchmaking, analytical comparison, and simulation-based analysis. In interaction, monitoring requirements of individual assembly processes are assigned to singular or combined resources.

This approach helps assembly and quality planners to quickly and efficiently create process monitoring plans while supporting designers in the design process of new product variants or entirely new products through feasibility analysis of assembly process monitoring in an existing production system. The matchmaking module uses semantic comparison, an approximate string-matching approach, to automatically explore process resource combinations and alternatives for process monitoring plans. The search for semantic matches is defined by finding a minimum based on the Levenshtein distance metric.

Simulation-based validation tests the generated process monitoring alternatives for accessibility and visibility using a multi-body simulation. The monitoring task is considered successful if no objects interfere during the process or block visibility. Otherwise, it is classified as infeasible. The analytical comparison module then filters out allocations that are not feasible by comparing the monitoring requirements to the sensorial skills of the resources on a parameter level.

The system's input consists of product and production system-based data, such as assembly plans, process monitoring requirements, a resource library including their sensorial skills, and a production system layout. The system results are presented to the user as recommended actions based on specific criteria defined by the user (e.g., number of required reconfigurations, required monitoring quality due to sensor accuracy). The use case presented in the publication focuses on assembling a camera system. It shows the potential of generating alternatives for process monitoring (e.g., utilizing stored expert knowledge and generating multiple monitoring plans automatically).

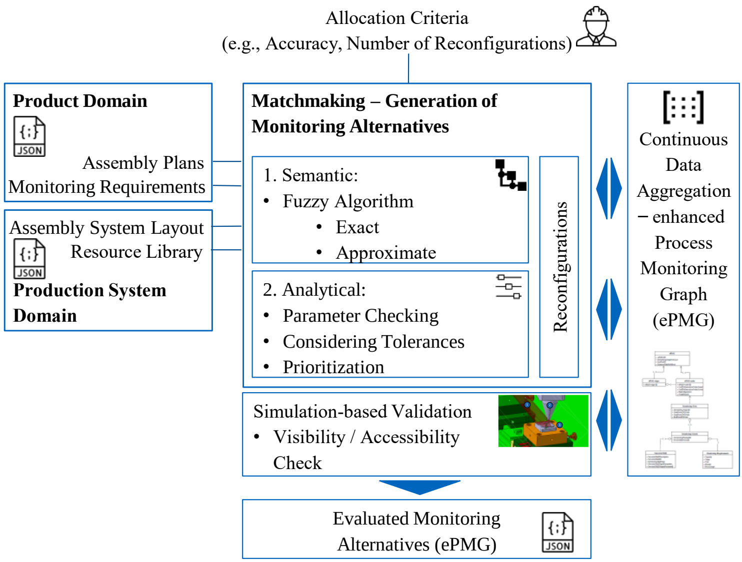


Figure 5.5: Method for the automated generation of process monitoring matches based on a semantical and parameter-based comparison (GONNERMANN et al. 2021).

The simulation-based validation module checks the feasibility of the alternatives by simulating the assembly process in a multi-body simulation environment. This step verifies the accessibility and trouble-free visibility of the assembly area by ensuring that the assembly feature or its immediate area is within the sensor's detection range and that no objects obstruct the view. Based on the generated alternatives, the enhanced process monitoring graph (ePMG) presents output data and recommendations to the user. This graph can be saved in a text-based format (i.e., JSON file). The user can then decide on the best alternative for process monitoring based on their specific needs (e.g., a minimum number of required reconfigurations).

The use case presented in this publication focuses on assembling a camera system consisting of two housing parts, four screws, and a printed circuit board. The assembly process includes three main steps: joining, screwing, and welding. Two assembly plans were defined in advance with different allocations of processes to resources and assembly stations. These assembly plans were imported into the system as JSON files, along with the resource library containing all the information models and sensorial skills of the system.

For the first assembly plan, the system generated 15 nodes (i.e., process resource combinations), resulting in various monitoring alternatives. For the second assembly plan, 31 nodes were generated. The comparison of the two assembly plans clearly shows the potential of generating alternatives automatically. The second assembly plan in the use case has a higher number of alternatives of possible process monitoring plans. The simulation-based validation in the system shows that alternatives are feasible, provided that the assembly area is accessible and interference-free.

The system's output (i.e., process monitoring matches and plan alternatives) is presented to the user. The generated ePMG can be searched according to specific user-defined criteria and output as recommendations for action. The publication shows the efficient generation of monitoring plans by automatically matching monitoring requirements with resource skills.

The key findings of the publication relate to the creation and integration of the modules for the generation of monitoring plans. In this context, existing methods have been modified and applied to process monitoring planning. Examples include the use of the Levenshtein distance metric, the mapping of parameters to monitoring parameters, and the validation of matches through visibility and accessibility checks. In addition to these modules, storing monitoring processes in a graph enables easy prioritization and selection of monitoring plans for the user.

5.1.5 Publication 5: A Skill- and Feature-based Approach to Planning Process Monitoring in Assembly Planning (GONNERMANN et al. 2022)

The publication presents a methodology for efficient and demand-driven assembly and process monitoring planning. The methodology consists of four modules: *Assembly Planning*, *Process Monitoring Planning*, *Optimization*, and *Validation*. The assembly planning module uses an assembly-by-disassembly approach to generate valid and collision-free assembly sequences for a given assembly product. The assembly processes are then matched with the actor resources of an existing production system. The resulting process resource combinations, the production system layout, and possible material flow enable the identification of different assembly plans.

The planning module for process monitoring builds on this and uses the assembly plans just generated. First, relevant product requirements for assembly process monitoring are identified and then assigned to sensory resources in the production system. This results in various possible process monitoring plans corresponding to a concretely specified assembly plan from the previous module (see Figure 5.6). The optimization module selects the best assembly plan, considering various criteria such as the number of reconfigurations, monitoring efficiency (i.e., identified monitoring plan with individual monitoring specifications such as possible sensor accuracy), and cost. The validation module checks the selected mounting and monitoring plan and identifies potential collisions and visual inaccessibility.

The methodology is demonstrated using two case studies: a simple LEGO® product and a more complex toy car product. In the first use case, the integration of the automatic generation of process monitoring alternatives into assembly planning was validated. The number of possible assembly sequences is limited to three. The existing production system and its resources consist of five manual or automated stations (i.e., workers or robots). The second use case focuses on a more complex scenario with multiple assembly sequences and, thus, assembly plans. Process monitoring plans increase compared to the first use case. Individual process monitoring matches (i.e., monitoring requirements and sensory resources) combined with the assembly process sequence provide additional criteria for selecting an assembly plan. This enables the optimization module to select a feasible assembly plan that is favorable according to user-specific criteria.

The results of the case studies show that the methodology can automatically generate assembly plans that include process monitoring alternatives. Consideration of process monitoring during assembly planning allows optimization for an appropriate assembly plan based on additional criteria, such as monitoring criteria, that lead to increased process quality. The semi-automatic generation of monitoring alternatives enables better utilization of the production system by reducing the manual planning effort to a minimum. The optimization module enables users to prioritize individual assembly and process monitoring plans by linking the information to multiple criteria.

The publication highlights the need for efficient and demand-driven assembly and process monitoring planning in modern production systems. The methodology presented in the publication addresses this need by providing an automated decision support system for assembly and process monitoring planning. The publication's novelty lies in integrating assembly and process monitoring planning and considering multiple criteria for selecting the best assembly plan. The methodology can be applied to a wide range of products and assembly systems and further developed to include more complex products and assembly systems.

The key findings of the publication highlight the rapid increase in possible monitoring plans. Manually, it is impossible to identify this amount of alternatives. The number may also become too large for the system once the use case reaches a certain complexity. The volume of monitoring schedules increases significantly depending on factors such as product design, the number of processes to be monitored, and the availability of various production resources and assembly schedules.

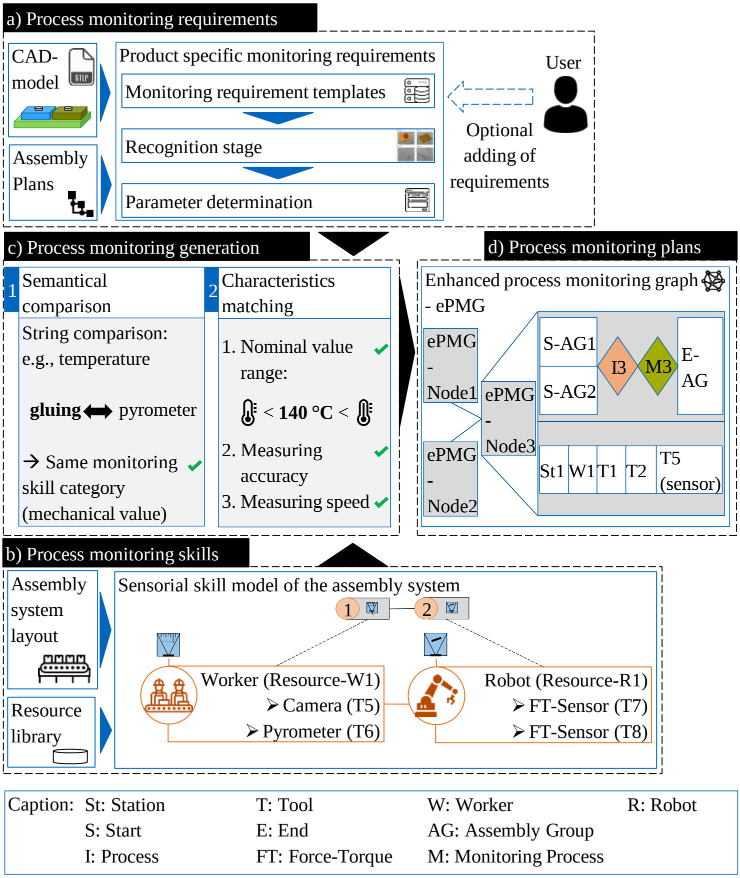


Figure 5.6: Entire system structure for the automated generation of monitoring matches and monitoring plans, including relevant decision criteria (Gonnermann et al. 2022).

However, the premature application of a termination criterion can lead to the exclusion of valid and necessary monitoring plans before they are adequately considered. This problem can be addressed by increasing the computational power or eliminating invalid, impractical, or less desirable monitoring plans earlier. On the other hand, the publication and associated use cases demonstrate the applicability of the approach and its adaptability to different scenarios.

5.2 Discussion of the Findings

The following chapter discusses the results of the decision support system for automated planning of process monitoring in assembly. The individual results and implementations of P1, P2, P3, P4, and P5 are presented concerning the scientific objectives of the chapter 4. In addition, transferability and application requirements are shown.

5.2.1 Scientific Contribution of the System

The main contributions, as well as the applicability of the system, are presented below. The research fields can be divided into three areas, which were also addressed in the state of the knowledge (see Chapter 3): *capability-based modeling*, *requirement identification through feature recognition*, and *process plan generation through matchmaking*. KOREN et al. (2018) reveals no sufficient approach to considering diagnosability in RMS. Individual approaches have been developed for assembly, manufacturing, or inspection planning that take into account different but similar research fields. In Figure 5.7, the publications and findings are categorized according to the research fields. Relevant to this thesis and similar approaches are also summarized in the figure.

The first publication (P1) deals with the overall concept of the decision support system for automated planning of process monitoring in assembly. In several approaches of JÄRVENPÄÄ et al. (2019), MICHNIEWICZ (2019) and ABOUEL NASR et al. (2020), the four domains of the PPRS model have been considered. The novelty of this publication lies in the application of process monitoring planning in assembly. The main idea is to integrate an automated approach to planning process monitoring in a high variety assembly with high-quality standards.

P1 motivates the topic of this thesis, provides a basic concept for the setup of the decision support system, and defines the boundaries of the system (e.g., value-adding processes in assembly, assembly line, station, and machine production level). This publication focuses on the assembly aspect and process monitoring in RMS. One critical aspect of this publication is that little attention is paid to the definition of sensorial skills and monitoring requirements. At this stage, the emergence and significance are discussed relatively briefly.

The second publication (P2) of this dissertation provides results on the generation of monitoring requirements using a rule-based feature recognition approach. The findings of this publication answer the first research question by providing a concept and implementation of the first scientific objective (*SO1: Computer-aided identification of product- and process-specific features for process monitoring*). The results in this publication show the feasibility and advantage regarding planning time and required expert knowledge of semi-automatically recognizing monitoring requirements. With regard to process monitoring planning, the results of this publication go beyond the research field of identifying process requirements (Figure 5.7).

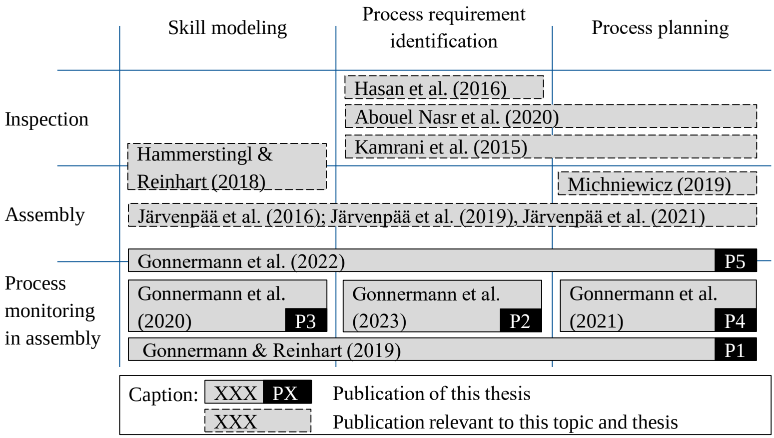


Figure 5.7: Categorization of the publications of this thesis according to the state of the knowledge.

In the field of manufacturing, and especially manufacturing feature inspection with CMM, there are approaches to feature recognition that focus on identifying process requirements, such as KAMRANI et al. (2015) and ABOUEL NASR et al. (2020). Thus, the first scientific objective (SO1) is fulfilled by introducing a computer-aided system for the identification of monitoring requirements semi-automatically by using product- and process-specific features. Since the main objective of this publication is to test the feasibility of automatically generating monitoring requests, limited consideration is given to the various aspects of feature recognition, especially machine learning approaches. This research topic should be addressed in further work.

The third publication (P3) contributes to a more detailed understanding and setup of sensorial skills relevant to monitoring planning. HAMMERSTINGL & REINHART (2018) and JÄRVENPÄÄ et al. (2016) present approaches to define sensorial skills that lack focus on monitoring planning. P3 also considers the classification of sensorial skills by physical units. This enables the generation of a sensorial skill model of an assembly system with different types of assembly processes (e.g., welding, joining). The publication fulfills the second scientific objective (SO2: *Utilization of the inherent flexibility of assembly systems for process monitoring by means of skill modeling*).

In addition to defining the elementary skills of individual resources, combined skills from one or more resources are also considered. This allows a wider consideration of an existing assembly system's functionalities and flexible usage. According to JÄRVENPÄÄ et al. (2018), the usage of SPARQL Inferencing Notation (SPIN) rules enables the efficient identification of combinatorial skills. This approach has been further implemented and applied for sensorial skills relevant to monitoring processes in assembly. This publication misses the transferability of the approach to multiple use cases. This publication's definition and generation of sensorial skills only show the concept and implementation, including one hybrid assembly system application scenario (i.e., manual and automatic resources).

The fourth publication (P4) represents an innovation by generating process monitoring plans based on a Levenshtein approach and a parameter-based fitting. Compared to MICHNIEWICZ (2019) and JÄRVENPÄÄ et al. (2021), this approach is considered more robust due to the Levenshtein distance algorithm. This provides rule-based matching of monitoring processes and resource skills by allowing errors due to human mistakes (e.g., incorrect descriptions or misspellings). In addition, the focus is on generating process monitoring graphs alongside assembly precedence graphs and assembly plans. Individual process monitoring plans can be generated and retracted for each assembly plan. With filtering the monitoring plans, the user can define individual, need-based alternative process monitoring plans (e.g., according to the minimum number of required reconfigurations).

The scientific objective three (SO3) is fulfilled by providing a concept and system for the *demand-driven generation of alternatives for process monitoring in assembly systems*. A shortcoming in this publication is the accuracy of semantic matchmaking. The Levenshtein distance algorithm must be configured precisely to obtain only valid matches between sensorial skills and monitoring requirements. An attempt was made to improve the system's robustness using a Levenshtein distance algorithm. This takes into account grammatical and spelling errors in skill and requirement descriptions and leads to success, especially when the sensitivity is set to a higher level. This approach is more robust than simple string matchmaking.

The fifth publication (P5) provides a new approach to automated assembly planning. Simultaneous planning of assembly and process monitoring allows additional criteria for process monitoring to influence the selection of suitable assembly plans. In this publication, constraint optimization algorithms were enriched with these criteria. The publication shows how all three scientific objectives are achieved in combination. Together, the main objective is achieved for efficient and demand-driven planning of process monitoring in a highly variable assembly. The flexibility of the assembly system can be used even more comprehensively by considering several criteria. The optimization approach, which is not part of this dissertation but can be considered an extension, shows how many monitoring plans can be efficiently handled (HASHEMI-PETROODI 2021). According to the author's knowledge, the parallel planning of assembly and process monitoring has not yet been considered. A feasible decision support system has been proven to be a valid solution when considering the key characteristic diagnosability according to KOREN et al. (2018). The contribution of this publication can be allocated to all three research fields (*skill modeling, process requirement identification, and process planning*) and applies to the assembly and process monitoring in the assembly domain.

P5 builds on previous publications (P1 - P4) by including the simultaneous planning of assembly and monitoring and demonstrating the modularity of the approach. Individual modules of the system have been shown in previous publications and are now combined in P5. Limitations of the main results arise from the limited use of small product and production system cases. In addition, the optimization module in this study could not analyze all generated data (i.e., assembly and monitoring alternatives) due to a lack of computational capacity. Thus, the criteria used to pre-select assembly and monitoring alternatives early on resulted in eliminating matches that may have also been valid. Therefore, further experiments on real use cases have to be conducted to verify the approach.

5.2.2 Transferability of the System

Implementing a decision support system for process monitoring planning involves an initial setup effort that can be time-consuming and costly. This can be reduced by defining the use case and boundary conditions. The implementation and usage of such a system must be evaluated intensely in each possible use case. This involves the following questions:

- How often changes the product or production system?
- Do the digital production systems and CPS already exist?
- Is the expert knowledge already documented regarding monitoring requirements or critical processes to be monitored?
- Do the processes have specific requirements that need a thorough monitoring process (e.g., product licensing, process regulations)?

The application field for this decision support system is designed for a multi-variant assembly. Products that have been mainly the focus of this research, and the research projects alongside it, are highly safety-relevant and mainly electro-technical products, such as surround view cameras, relevant for autonomous driving. The system configuration is intended to be reconfigurable (i.e., RMS). The system's versatility adds value in various production environments and can be easily adapted to different production scenarios. As highlighted by Koren et al. (2018), these systems should have the diagnostic capability to effectively deal with evolving changes in the layout and processes of the production system. By integrating process monitoring efficiently due to automated planning, the system achieves diagnostic capability by analyzing individual processes and drawing conclusions regarding the status of the RMS.

Additionally, to the condition of being a RMS, the system is designed to be set up for CPPS. The main intention is to use the self-description that each system provides. This simplifies the setup of a skill model for automated process monitoring planning. As described in the state of knowledge in Chapter 2.4, individual CPS enable a more efficient planning and reconfiguration of a production system, as shown in P3 and P4.

The system has been developed and validated in various use cases in industry and research projects (e.g., IntellProMo (2019) and Assistant (2020)). In addition to the product and assembly processes, the production system and equipment vary in these use cases. The system has been applied for assembly products that require joining, welding, and screwing processes. The production systems differ due to their automation degree (i.e., automated and hybrid production systems). Hence, transferability was demonstrated by applying the system for the automated generation of process monitoring plans to the individual use cases of these research projects. Further explanations and implementations of the system can be found in Appendix A.

Chapter 6

Conclusion

6.1 Summary

This thesis presents a decision support system for automated planning of process monitoring in assembly. The focus is on multi-variant production in a highly flexible and reconfigurable production system (i.e., RMS). More individualization leads to more frequent product and process changes that affect the robustness and quality of the production. In addition, the need for higher robustness and quality standards arises from the enforcement of stricter process and monitoring regulations (e.g., MDR) and the increasing importance of sustainability in production. This conflict increases the relevance and complexity of process monitoring in today's production (see Chapter 1). Planning process monitoring is time-consuming and costly, and additional expert knowledge is required to design the individual monitoring processes. In addition, there are constantly new product variants, changing processes, and means of production. This causes a dilemma for process monitoring in assembly. On the one hand, it is necessary to master new processes as quickly as possible, but on the other hand, the manual effort required for planning is too high.

Different assembly processes require various monitoring methods during execution due to variations in the physical quantities (e.g., thermal quantity, see Chapter 2.1.1 and Chapter 2.1.2). In addition, RMS can monitor a range of process types or adapt quickly by reconfiguring individual resources. The aspect of diagnosability in RMS has not been addressed recently (see Chapter 2.1.3). Still, it is becoming increasingly relevant, especially with regard to sustainable and resource-efficient production and less material waste (Koren et al. 2018). The reuse of production resources will be more relevant in the future and requires a better understanding of the individual processes and resource capabilities.

As shown in the state of the knowledge, various approaches encounter the problem of automatizing process planning, often focusing on assembly or inspection. Nevertheless, approaches from assembly and inspection planning can be taken into account. Individual aspects such as skill modeling and semantic- and parameter-based matchmaking have been identified as suitable methods for process planning. This thesis has extended these methods and implemented them in the context of process monitoring planning (see Chapter 3). The additional research clarification in Chapter 4 specifies the overall objective outlined in the introduction (Chapter 1.3), considering the existing state of knowledge.

This thesis shows how monitoring requirements can be identified automatically and described product-specific through a CAD-based feature recognition (Chapter 5.1.2). This is due to the input gained from the template database of product-independent monitoring requirements and the product-specific assembly plan. In addition, a method for modeling skills in cyber-physical production systems enables the identification and the use of elementary and combined sensorial skills (Chapter 5.1.3).

A matchmaking approach between monitoring requirements and skills allows the automated generation of process monitoring tasks and plans displayed in a monitoring graph (Chapter 5.1.4). This permits users to retract individual process monitoring plans according to user-specific demands (e.g., highest monitoring accuracy). The presented system has been integrated into an automated assembly planning process and combined with an optimization approach (Chapter 5.1.5). The validation process includes applying the system in research projects, focusing on assembling a new camera surround-view system. The benefits in these research fields can be listed as follows:

- Time and cost savings in the implementation of process monitoring
- Reduction of required expert knowledge due to a continuously increasing database (i.e., monitoring requirement and sensorial skill databases need to be maintained)
- User-specific generation of process monitoring alternatives
- Integration of quality aspects during the automated planning of assembly processes
- Simultaneous assembly and process monitoring planning with no additional planning time

The concept and implementations can be found in the dissertation's publications (P1 - P5). Automatizing monitoring planning processes reduces the required expert knowledge, planning time, and planning costs, as seen in the publications. The fifth publication demonstrates the large solution space an automated assembly planning approach provides. The number of possible monitoring plans can only be generated using the automated approaches presented in publications two, three, and four. The key findings of the publications support the assertion made in Chapter 4. Furthermore, a continuous use case has been applied to validate the decision support system in P2, P3, and P4. P5 gives a broader insight into the system by applying it to two different use cases and integrating it into an assembly planning and optimization framework. Finally, a discussion offers insights into the novelty of the individual results in the publications and the potential applicability of the approach to companies.

6.2 Outlook

This thesis addresses considerations related to dynamic and highly variable production environments with stringent quality requirements. As highlighted in the discussion, the initial setup of the decision support system requires an initial amount of work (i.e. time and cost). Therefore, the system is specifically designed for high variability production scenarios where design and process changes are not extensive but frequent. The current rule set for feature recognition is limited to individual processes (e.g., joining, screwing, welding). In future research, hybrid feature recognition approaches that can be easily extended should be considered. Neuronal networks with image recognition on two-dimensional images taken from different perspectives of a three-dimensional CAD model have been proven to be a fast and valid approach according to GUO et al. (2021).

In addition, skill-based approaches have demonstrated their effectiveness in automating process generation in manufacturing and transferring process plans to real-world manufacturing applications. Skill-based robot programming, as described in the work of HEUSS et al. (2022) and HEUSS & REINHART (2020)), is effective in automatically transferring process plans and tasks to real-world applications. However, this thesis has only partially explored these relationships between process plans and their transfer to real-world production systems.

In two prototype assembly systems (INTELLPROMO (2019) and a system at the *Iwb*), the transfer of process monitoring plans was tested using a Robot Operating System (ROS)(HEUSS et al. 2022; HEUSS & REINHART 2020) and a skill-based framework, as well as a hardware-independent communication architecture (i.e., OPC UA architecture). Further research is required in this area to use automatically generated process monitoring plans in existing production systems. Here, a consistent definition and database of skills are needed (KÖCHER et al. 2023; MALAKUTI et al. 2018).

In recent years, Large Language Model (LLM)s have gained increasing attention in various fields of research. These are advanced artificial intelligence models that are trained on large amounts of data to generate human-like responses. LLMs are currently a promising area of research, especially in combination with knowledge graphs (i.e. ontologies). Here, existing expert knowledge can be integrated into the models and retrieved individually with different restrictions. As an extension to this dissertation, LLMs thus represent an interesting further field of research in process monitoring planning.

Lastly, there is a great need for research to comprehensively analyze a broader product portfolio. Only individual new product variants are currently considered, while the simultaneous inclusion of all product variants is neglected. To achieve more efficient assembly scheduling, it is essential to closely examine and observe the assembly and monitoring processes of several different products. Considering this aspect enables a significant increase in the performance of the decision support system and the optimization of the entire production planning process.

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Appendix A

Visualizations of the individual Methods and Systems

The following additional figures in this appendix show the implementation of the decision support system of this thesis. The figures are chronologically based on how the individual steps are executed.
Figure A.1 shows the implementation of the generation and identification of monitoring skills for an existing production system. This Graphical User Interface (GUI) displays the realization of the sub-module developed in publication three (P3). Besides the allocation of individual skills to the resources and production system, further descriptions and parameters can be assigned to individual resources (e.g., hardware or information interfaces).

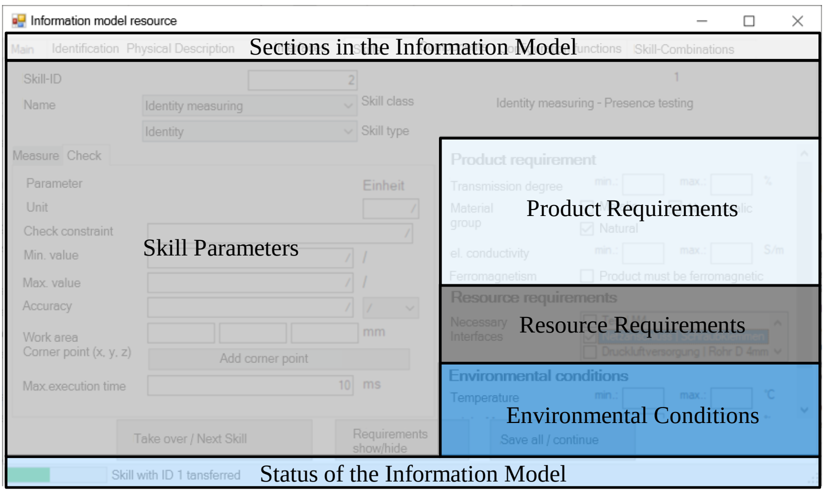

Figure A.1: Visualization for the identification of sensorial skills in a CPPS implemented in the form of a GUI (GONNERMANN et al. 2020).

Figure A.2 represents the combination of skills in an existing production system. The underlying production system reflects the assembly line of the research project INTELLPROMO (2019). By combining individual skills of the same resource or different resources, new skills can be identified (e.g., measuring the position using multiple "presence" skills at different positions).

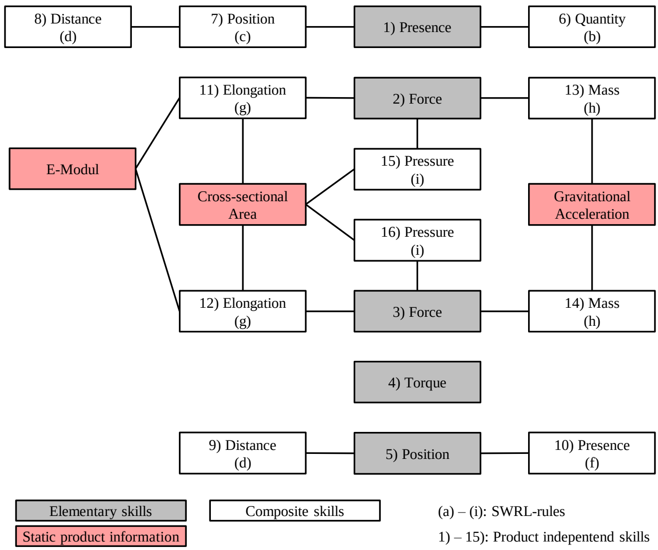

Figure A.2: Rule-based structure of the sensorial skills of the INTELLPROMO (2019) use case production system (GONNERMANN et al. 2020).

The process of generating multiple monitoring processes can be seen in Figure A.3. The production system, including assembly processes, is shown in combination with the processes required to generate different monitoring plans.

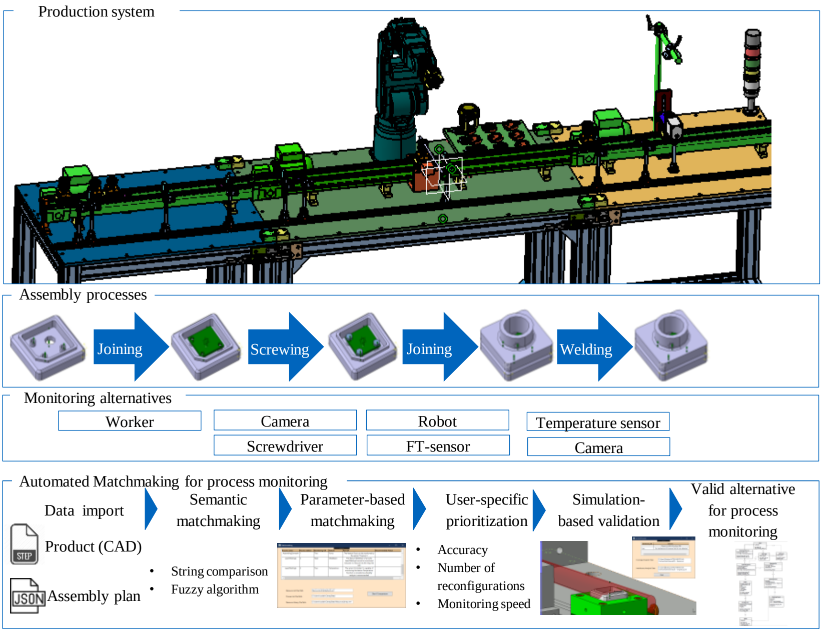

Figure A.3: Processes required to generate process monitoring plans implemented on the INTELL-PROMO (2019) use case production system (GONNERMANN et al. 2020).

Generating multiple process resource combinations for monitoring planning requires semantical matchmaking. The method of generating these matches is shown in Figure A.4

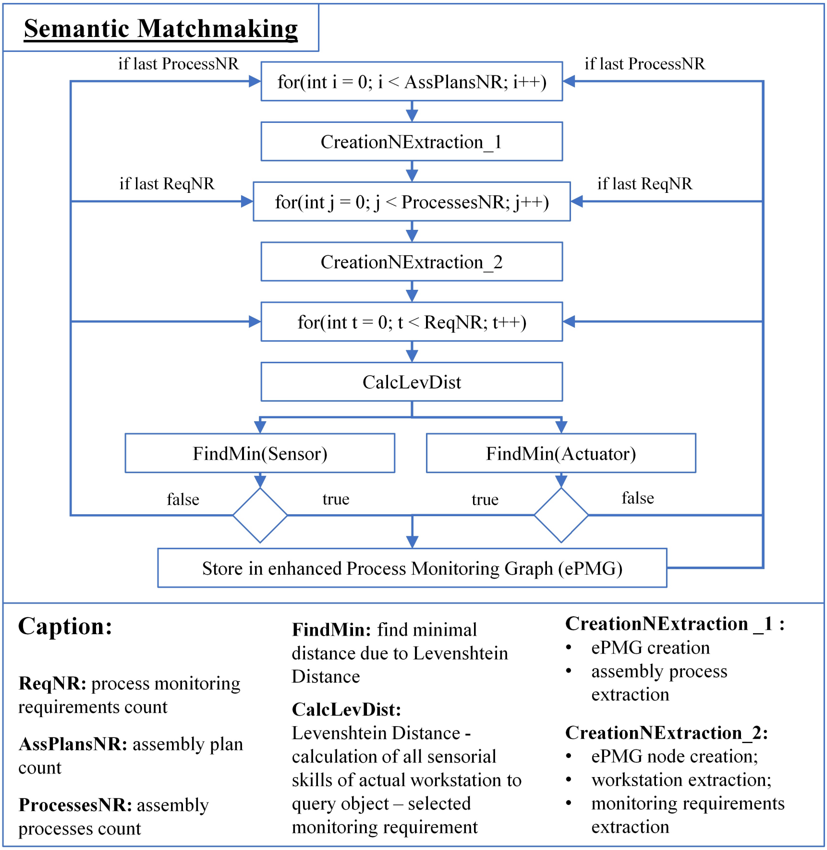

Figure A.4: Semantical matchmaking for the identification of process resource combination for process monitoring (GONNERMANN et al. 2021).

Similar to Figure A.3, this figure (Figure A.5) displays individual assembly processes required when mounting a surround-view camera. The production system resources and steps to generate monitoring plans are also shown.

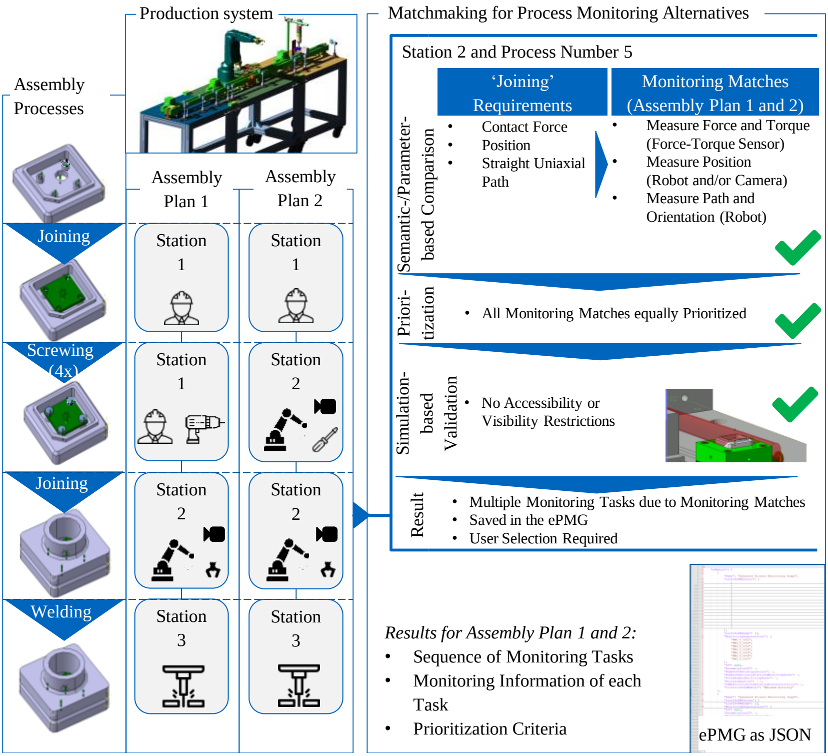

Figure A.5: Matchmaking processes implemented for the research project INTELLPROMO (2019) (GONNERMANN et al. 2021).

Figure A.6 shows the different steps for feature recognition in combination with a rule-based approach to detect assembly features relevant for monitoring (e.g., screws, holes).

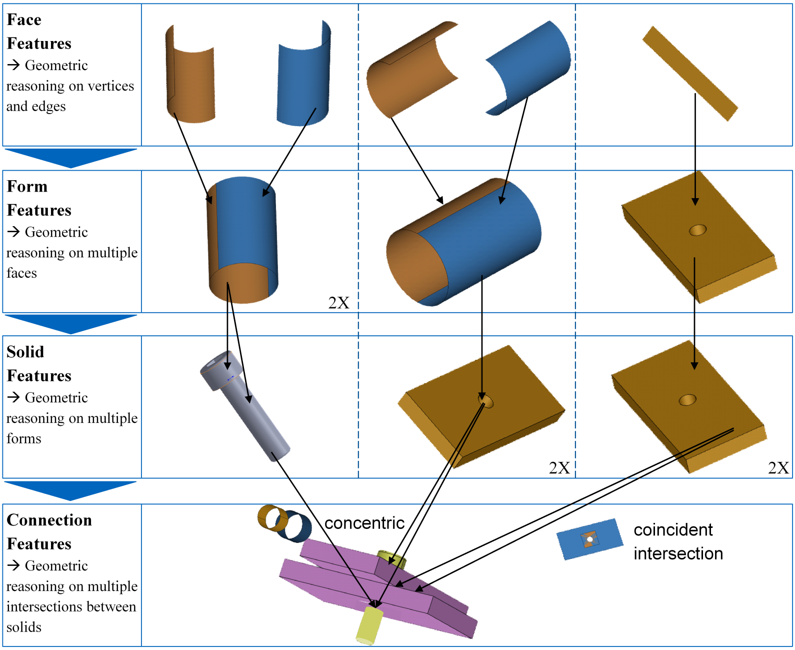

Figure A.6: Feature recognition method for the product-specific identification of monitoring requirements (GONNERMANN et al. 2023).

Figure A.7 displays the GUI designed to identify and generate monitoring requirements.

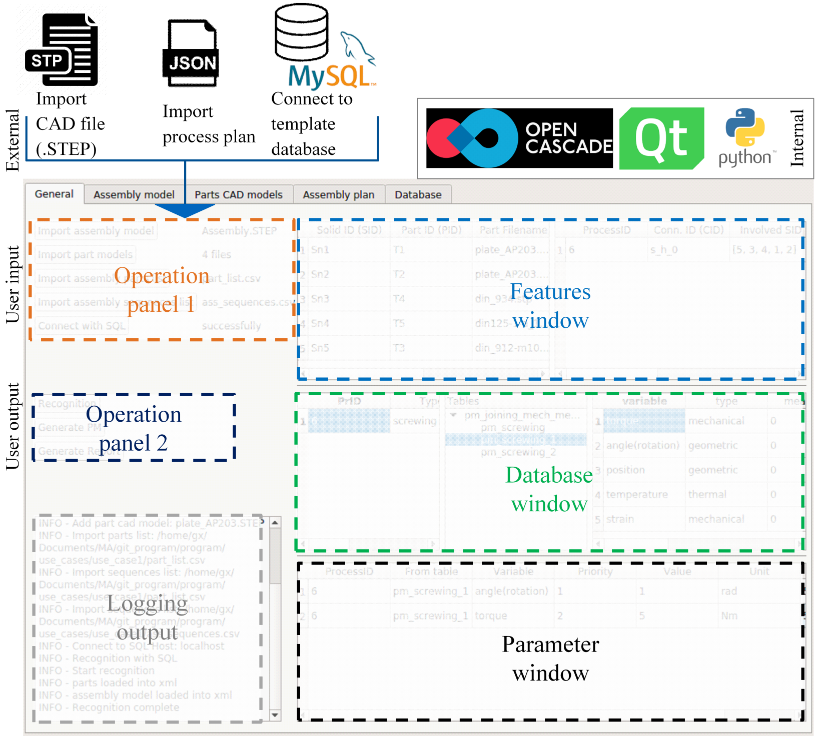

Figure A.7: GUI of the monitoring requirement generation system (GONNERMANN et al. 2022).

Figure A.8 displays the multi-body simulation to validate the monitoring processes that have been generated automatically. In this scenario, a camera is positioned above the robot. The yellow rays display the visible area of the camera whereas the red rays display the not visible area of the rays.

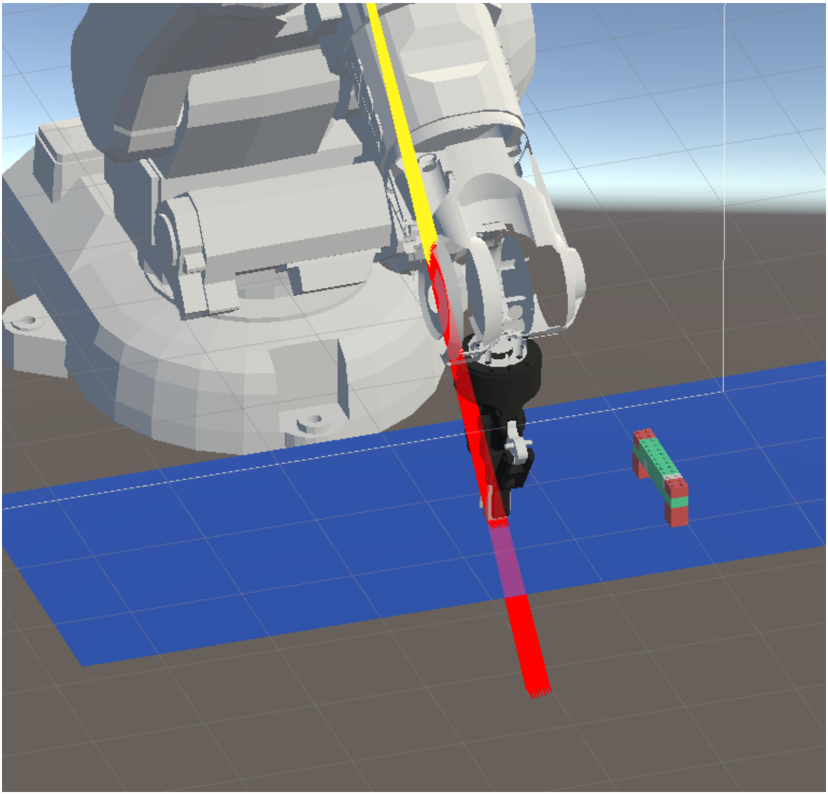

Figure A.8: Visualization of the accessibility and visibility simulation implemented in Unity (GONNERMANN et al. 2024)

Appendix B

Supervised Theses

The following Table B.1 shows all theses supervised at the TUM during the doctoral period. The results of the theses form the basis for this dissertation.

Table B.1: List of supervised dissertations on which this dissertation is based and which were supervised at the Technical University of Munich (TUM).

Students	Title	Thesis type
Marvin Lüdtke	Concept development of an ontology-based generation of product redesign suggestions in consideration of the manufacturing system	Bachelor thesis
Onur Kewazo	Development of a Gripping System for a Robotic Transport Platform	Bachelor thesis
Valentin Menrath	Development and Setup of a Cyber-Physical Production System with Decentralized Communication Architecture	Bachelor thesis
Wen Ziming	Development of a software architecture for the cyber-physical qualification of devices for process monitoring	Bachelor thesis
Benedikt Zels	Automated Generation of Recommendations for the Selection of Process Monitoring	Bachelor thesis

Students	Title	Thesis type
Luca Jansen	Visualization of assembly plan data for different roles in production	Bachelor thesis
Tao Ge	Automatic CAD-product design changes in Siemens NX	Semester thesis
Yao Zhang	Automated positioning of resources in a 3D simulation model	Semester thesis
David Steinbach	Development of a cyber-physical production system with simulation-based consideration of process uncertainties	Semester thesis
Svenja Rau-Meiswinkel	Development and construction of a cyber-physical demonstrator for task-oriented implementation of (dis-)assembly sequences using LEGO®	Semester thesis
Tim Wrede	Development and Database Connection of an OPC UA Communication Architecture for Process Monitoring of a reconfigurable Cyber-physical Assembly System	Semester thesis
Franz Hammerl	Development of a Benchmarking of VIBN Tools for the Concept Development of a Tool Independent Resource Description	Semester thesis
Philip Lang	Product-specific Configuration of Process Monitoring in Assembly using LEGO®as an Example	Semester thesis
Yifan Cao	Automated and CAD-based generation of assembly processes including inspection features with the example of Lego®	Semester thesis
Oguz Sarp	Inline Process Monitoring in Cyber Physical Assembly Systems	Semester thesis

Students	Title	Thesis type
Maximilian Kesy	Concept for Automated Generation of Requirements for Process Monitoring	Semester thesis
Gülex Yalim	Concept for automated initialization of process monitoring for reconfigurable assembly systems	Master thesis
Johannes Weth	Skill-based Resource Modeling for the Automated Initialization of a Process Monitoring in Assembly	Master thesis
Xiang Gao	Automated CAD-Feature Recognition for Process Monitoring in the Assembly	Master thesis
Stefan Nöhmer	Methodology for the automated configuration of process monitoring in cyber-physical assembly systems	Master thesis
Patrick Haslinger	Development of an Edge Layer for the automated Connection of Shopfloor Components to Public Clouds	Master thesis
Jenny Vytruchenko	Artificial intelligence for resource allocation in selforganizing, decentralized industrial systems	Master thesis
Bin Sun	Profitability Analysis for the Automated Planning of Process Monitoring	Master thesis
Sebastian Kurscheid	Development and evaluation of an automated planning of process monitoring in assembly	Master thesis

Appendix C

Publications of the Author

As part of the scientific work at *iwb*, the author contributed to the following publications:

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