Defining and Assessing Part Complexity: A Methodological and Applied Perspective in Sheet Metal Processing

Zur Erlangung des akademischen Grades eines
Dr.-Ing.

Von der Fakultät Maschinenbau
der Technischen Universität Dortmund

genehmigte Dissertation von

Greta Tjadea Tjaden, M. Sc.
aus
Mettingen, Deutschland

Tag der mündlichen Prüfung: 12.03.2026
1. Gutachter*in: Prof. Dr. Anne Meyer
2. Gutachter*in: Prof. Dr. Michael Henke

Dortmund, 2026

Abstract

Companies require information about their customers to maintain an attractive portfolio of products and services. This information is essential in different departments for a variety of tasks along the product life cycle. By providing this information based on data, decision-making processes can lead to more accurate outcomes and improved overall results. This thesis explores part complexity and its relevance in better understanding customer needs throughout the product lifecycle. The industry partner of and example used in this dissertation is TRUMPF, a German machinery and plant engineering company that builds machine tools for the sheet metal processing industry. Sheet metal processing contains process steps such as laser cutting, bending, and welding to manufacture sheet metal parts. The application possibilities are manifold, with use cases in industries such as automotive, construction, renewable energy, aerospace, and many more.

Many researchers agree that part complexity represents the manufacturability of a part. However, we identify three major research gaps in this field: (1), there is no consensus regarding the research method of assessing part complexity but co-existing methods differ in how they investigate part complexity. (2), the part complexity influencing part characteristics have not been thoroughly researched, even less for our field of research, sheet metal processing. (3), only two part complexity use cases have been identified in the literature, despite the increasing demand for data-based information along the product life cycle. This thesis addresses these three research gaps with these contributions:

(1), we develop a methodology for assessing part complexity and demonstrate its applicability by putting this research approach into practice. This methodology combines both qualitative and quantitative methods. (2), we conduct a computer-assisted self-assessment to let experts label the complexity of 80 parts. To facilitate this self-assessment, we develop a labeling tool that implements a visualization of the parts and provides additional part information. For complexity labeling, we implement a Likert scale ranging from 1 (least complex) to 5 (most complex), deliberately omitting the middle option “3” to encourage more definitive responses. Participants are also required to provide a written explanation for their chosen complexity rating. The participants of the computer-assisted self-interview are experts for the production unit that we chose as an example for our research endeavor. Furthermore, as an evaluation mechanism, we repeat a subset of 10 parts in each of the three weeks of the complexity labeling to assess the consistency of the participants' labeling over time. Second, we observe a consensus of the labeling participants in some of the repeating geometries and a clear correlation between distinct part characteristics and the reasons given for the assigned complexity ratings. (3), we identify part complexity influencing part characteristics based on the results of the aforementioned research approach. (4), by conducting a focus group, we explore the application possibilities of part complexity for the three main stakeholder groups: product and portfolio management, research and development, and sales and consulting. These results add to the two use cases of part complexity that have already been identified in the literature and demonstrate the usefulness of part complexity as a contributor to data-based customer information along the product life cycle.

Contents

List of Figures

List of Tables

List of Abbreviations and Acronyms

AHP Analytical hierarchy process
AI Artificial Intelligence

B2B Business-to-Business
BOL Beginning of Life

CaaS Calculate-as-a-Service
CASI Computer-Assisted Self-Interview

EOL End of Life
EU European Union

LOOCV Leave-One-Out Cross Validation

MOL Middle of Life

PC Part Complexity
PLM Product Life Cycle Management
PM Product and Portfolio Management

RFM Recency-Frequency-Monetary

SG SmartGate
SMS SortMaster Speed

Chapter 1
Introduction

Companies need to know their customers to provide attractive portfolios of products and services and remain competitive in the market. This is especially true in the field of mechanical and plant engineering. The machinery and plant engineering sector represents one of the biggest industrial sectors within the European Union (European Union (EU)), with approximately 80,000 companies employing 3.1 million people, and a total machine sales generating an estimated revenue of around 606 billion Euros [VDMA, 2022]. Within the EU, Germany, Italy and France are the largest machinery suppliers [VDMA, 2022]. Part of the machinery and plant engineering sector is the production of machine tools for sheet metal processing. TRUMPF Werkzeugmaschinen SE & Co. KG (TRUMPF, see Section 2.2) is such a manufacturer and serves as an example in this research.

Companies may gain a competitive advantage by utilizing data about their customers to map their portfolio to their customers' needs. The phrase "garbage in—garbage out" by Clark [1972] represents the principle that results can only be as good as the data they are based on, emphasizing the importance of data. Utilizing data about customers can lead to competitive advantages, such as tailoring the portfolio to meet the customers' needs.

This thesis identifies the research gap regarding data-driven customer information along the product life cycle and investigates part complexity as a contribution to closing this research gap. The research lacks an established definition of part complexity as well as an agreed-upon method to identify part characteristics that affect the part complexity. In addition, this thesis aims to uncover part complexity use cases not yet covered in the literature. In the following section, we present the motivation for this thesis (see Subsection 1.1). Afterward, we provide a detailed explanation of the research question in Subsection 1.2, and highlight the key contributions of this thesis in Subsection 1.3. Subsection 1.4 declares the use of generative AI and AI-assisted technologies in this thesis, while Subsection 1.5 gives an overview of the publications. Lastly, we give the outline of this thesis (see Subsection 1.6).

1.1 Motivation

In the recent past, machine tool manufacturers have been facing a rise in competitive pressure [McKinsey, 2016]. At the same time, the availability of manufacturing data from the shop floor has increased due to Industry 4.0 [Watanabe et al., 2020]. The global trend of increasing the individuality of the products and the demand for customized solutions makes staying competitive even more challenging. It underlines the demand for detailed information about the customers and their needs. To stay competitive and maximize revenues, companies increase their focus on their customers' needs [Aiyer et al., 2018]. For this shift, companies require data-driven information about their customers for customer-centric activities along the product life cycle [Tjaden et al., 2022].

In this thesis, we use the term *customer-centric activities* to summarize the activities related to the customers. The customer-centric activities include, but are not limited to (1) the management of the portfolio of products and services, (2) the development of new products and services, (3) refinement of already existing products and services, (4) activities related to sales and consulting, and (5) customer support in after-sales.

These customer-centric activities require information about the customers to help meet the goals mentioned above of competitiveness and customization. Experience has been a significant source of knowledge for tackling questions in customer-centric activities like portfolio decisions, product development, and sales activities. However, decision-making solely based on experience bears the risk of errors [Cooper et al., 2001], potentially leading to losing customers and not acquiring new customers. In contrast, data-driven decision-making processes offer more objectivity, reliability, and accuracy.

Especially in machine and plant engineering, e.g. for sheet metal processing, further information about the customers' production is required along the product life cycle to develop well-fitting portfolios of products and services as well as customized solutions. The internal stakeholders working on these tasks and requiring data-driven customer information are stemming from the areas of product and portfolio management, research and development, and sales and consulting [Tjaden et al., 2022].

To demonstrate the specific challenges associated with data-driven customer information inherent to machinery and plant engineering, we present a practical example from the domain of sheet metal processing, which deals with metal processing in the form of sheets.

1.2 Research Questions

The purpose of this thesis is to develop a methodology that allows the assessment of part complexity to provide data-driven customer information for the stakeholders within a mechanical and plant engineering company. Part complexity can contribute to understand the demands upon the customers' production. The research objective is to quantify the complexity of sheet metal parts as a foundation for the stakeholder groups of product and portfolio management, research and development, and sales and consulting to provide them with the data-driven information required for targeted customer-centric activities. After an explorative examination of different research questions, we extracted three research questions that have not yet been answered in the related work. These research questions guide the direction of this thesis:

Research Question 1: How can we determine part complexity in sheet metal processing?

So far, several approaches for determining part complexity exist in the literature. To the best of our knowledge, the literature does not agree on a definition of part complexity, despite its relevance across various domains. Moreover, a methodology that can be adapted to different use cases and industries is lacking. This thesis aims to address this gap by developing such a methodology. To validate our methodology, we aim to implement it exemplarily for one production unit from our industry partner.

Research Question 2: How do the part characteristics influence the part complexity in sheet metal processing?

Based on the results of the data collected during the application of our part complexity assessment methodology, we want to identify characteristics that contribute to the part complexity for the process steps of the chosen production unit. By closely analyzing these characteristics, we aim to uncover patterns and insights that can inform a deeper understanding of part complexity.

Research Question 3: How can part complexity contribute to the demand for data-driven information about the customers along the product life cycle?

We want to extend the applicability of the concept of part complexity by adding further use cases than those known in the literature. To the best of our knowledge, currently, only the two use cases "Production Technology Selection" and "Production Optimization" are researched in the literature.

We want to identify further use cases within the stakeholder groups and illustrate the benefits and limitations of part complexity with these use cases.

1.3 Contributions of this Thesis

The contributions of this thesis address the concept of part complexity as a key element for the demand for data-driven customer information along the product life cycle.

C1: Part Complexity Assessment Methodology for Sheet Metal Processing

The first contribution answers research question 1 and involves the development of the methodology for assessing part complexity. Although specifically designed for sheet metal processing, this methodology is adaptable to other domains. This methodology considers practices known in the literature regarding the assessment of part complexity and complements these practices with statistical elements. To ensure the quality of the assessment, several feedback loops are run, covering both the development of the methodology and the data collection for the part complexity assessment. In contrast to current practices of part complexity assessment, this methodology describes the whole process for part complexity assessment, from the creation of the data basis, selection of the participants, development of feedback loops as well as the development of a supporting online tool for the complexity labeling. In addition, this methodology is tested by implementing it for a production unit of sheet metal processing, ensuring its practical applicability.

C2: Identification of Part Characteristics Influencing the Part Complexity

The second contribution answers research question 2 by identifying part characteristics that influence the part complexity for an exemplary production unit from sheet metal processing, using the data collected with the supporting labeling tool as a basis. Section 2.4 explains this production unit in detail. For quality purposes, we only consider the labeling participants who pass a repetition test of re-occurring geometries in the labeling. By doing so, we introduce the part complexity concept in our running example. This thesis identifies the correlation between the geometrical characteristics, the chosen part complexity, and the explanation given for the part complexity. In addition, we created codebooks containing the categorized explanations of the labeling participants for the respective chosen part complexity. This identified correlation contributes to the part characteristics influencing part characteristics known in the literature for the domain of sheet metal processing. Moreover, we publish the geometries used for the labeling.

C3: Contribution of Part Complexity to the Need for Data-Driven Customer Information along the Product Life Cycle

The third contribution answers research question 3. Currently, the use cases of part complexity known in the literature are limited to the two use cases of production technology selection and production optimization. We add to these use cases in two different ways: Firstly, we add to these use cases from the industrial perspective, conducting a focus group with the previously identified stakeholder groups of product and portfolio management, research and development, and sales and consulting. The newly found use cases include portfolio optimization, comparison of customers with their peers, and production planning. Secondly, we compare the application possibilities of part complexity identified by the focus group to the demand for data-driven customer information known in the literature. This maps the contribution of part complexity to the demand for data-driven customer information along the product life cycle.

1.4 Declaration of Generative AI and AI-assisted technologies

Generative Artificial Intelligence (AI) and AI-assisted technologies were used during the thesis' work and writing process. We used Grammarly to increase the language and the readability of the writing. Connected papers helped during the literature research to identify papers that have been cited or cited analyzed publications. ChatGPT assisted in solving problems with coding the algorithm and the explorative data analysis as well as solving problems with LaTeX. After using these AI-assisted technologies, the author reviewed and edited the content as needed and takes full responsibility for this thesis.

1.5 Own publications

This section gives an overview of the publications and where they have been embedded in this thesis.

1. Greta Tjaden, Anne Meyer, and Alexandru Rinciog (2022), *Towards Adaptable Customer Segments and Reference Geometries*, Advances in Production Management Systems [Tjaden et al., 2022]
   Tjaden et al. [2022] published the pre-study on customer segments and reference geometries, presented in Subsection 2.3.

2. Greta Tjaden, Annika Baier, Maureen Strache, Cornelia Regelmann, and Anne Meyer (2023), *Maximizing Customer Satisfaction in Sheet Metal Processing: A Strategic Application of the Customer Health Score*, Advances in Production Management Systems [Tjaden et al., 2023a]
   Tjaden et al. [2023a] explores one further use case of data-driven customer information along the product life cycle and is incorporated in Section 3.

3. Greta Tjaden, Luis Feyhl, and Anne Meyer (2023), *Prototyping a data-driven customer segmentation utilizing machine usage data for product portfolio management*, Procedia CIRP [Tjaden et al., 2023b]
   Tjaden et al. [2023b] explores one further use case of data-driven customer information along the product life cycle and is incorporated in Section 3.

4. Greta Tjaden, Nick Große, and Anne Meyer (2024), *Understanding Part Complexity: A Novel Approach for the Identification of Complexity-Influencing Part Characteristics*, Advances in Production Management Systems
   Sections 4 and 5 extend [Tjaden et al., 2024]. This work also published the 80 geometries utilized for the labeling: Tjaden [2024]

5. Arthur Krause, Tobias Dannerbauer, Steffen Wagenmann, Greta Tjaden, Robin Ströbel, Jürgen Fleischer, Albert Albers, and Nikola Bursac (2024), *Enhancing efficiency and environmental performance of laser-cutting machine tools: An explainable machine learning approach*, Procedia CIRP [Krause et al., 2024]
   Krause et al. [2024] researched the optimization of machine tool operations, aiming at increasing their sustainability. While part complexity metrics have been considered in this work, it is not included in this thesis' content.

1.6 Outline of this Thesis

In Section 2, we give an overview of sheet metal processing and present TRUMPF, this thesis' industry partner. In addition, the problem is described, covering customer segmentation, exemplary sheets and geometries, and part complexity. Lastly, this thesis' running example, the laser cutting machine TruLaser Center 7030, is explained.

Section 3 presents the state of the art related to this dissertation. First, it provides an overview of the need for data-driven methods in the product life cycle management in Subsection 3.1, followed by the state of the art of part complexity in Subsection 3.2.

Section 4 refers to Contribution C1. After developing a definition of sheet metal part complexity based on the literature, we present the development of the research design. Subsequently, the methodology is implemented into practice. We explain the exemplary production unit in detail and provide the results of the explorative data analysis of the geometry data set. After selecting a representative material and sheet thickness, we present the tool supporting the complexity labeling. The section concludes with a discussion and summarizes the first contribution as the interim result.

Section 5 presents the results of implementing the first contribution into practice and refers to contribution C2. After evaluating the participants' labeling consistency, the codebooks are presented that analyze the explanations for the chosen complexity as well as an analysis of the overall complexity per process step and the chosen explanations. Then, we present ten geometries and their labeling results in detail, followed by the transfer of the complexity labeling results to new geometries using algorithms. After a discussion, this section concludes with an interim result section summarizing the second contribution to this thesis.

Afterwards, Section 6 deals with the third and last contribution of this thesis, C3. First, the research method of focus groups is explained, followed by presenting the preparation of this method for our field of research. Then, we give details about conducting the focus groups, followed by the presentation of their results stand-alone as well as in the context of the related work. After a discussion, this section is concluded with a summary of this contribution as an interim result.

Section 7 is the final section of this dissertation. After summarizing the main contributions, followed by their limitations, an outline of the future work closes this dissertation.

Chapter 2
Problem Description and Background

This section first describes the fundamentals of sheet metal processing in Section 2.1 and then this thesis' industry partner in Section 2.2. Subsequently, we present the challenges and the current work of data-driven customer information along the product life cycle (see Subsection 2.3), consisting of customer segmentation, exemplary sheets and geometries, and part complexity. Section 2.4 concludes this section and presents the TruLaser Center 7030 as this thesis' running example.

2.1 Sheet Metal Processing

The range of sheet metal processing application fields adds complexity to the transition to data-driven decision-making in customer-centric activities. Although the sheet metal processing domain covers two- and three-dimensional geometries, we only concentrate on two-dimensional geometries. We excluded three-dimensional geometries to maintain a focused investigation, as their inclusion, although valuable, would have deviated from the intended focus of this work. Sheet metal processing encompasses various production techniques, including laser cutting, bending, welding, and punching. In addition, it involves part-handling tasks such as loading and unloading sheet metals, finished parts, sheet skeletons, and scrap, all of which are integral to the overall sheet metal processing workflow.

These processes can be combined as required for the production of the sheet metal geometries. Mechanical engineering, automotive, electrical industry, and many other sectors utilize sheet metal products, and the variety of applications is reflected in the variety of sheet metal geometries. This variety also influences the development of machine tools for sheet metal processing.

We present three exemplary geometries to represent possible sheet metal processing products. These geometries are used during this research project; for clarification purposes, we do not rename them. As we manually altered these geometries, we do not know their application purposes but present possible explanations as to how they may be applied.

Figure 2.1 visualizes geometry B, which is a narrow rectangle that presents with an uneven outer contour. Possible application scenarios are in the construction sector, especially door frames.

Fig. 2.1: Geometry B. Own visualization

Geometry C, shown in Figure 2.2, is larger in height than geometry B, also has an uneven outer contour but additionally has many circular inner contours in different sizes. Possible application scenarios are in garden decoration or ventilation, as air may flow through the inner contours.

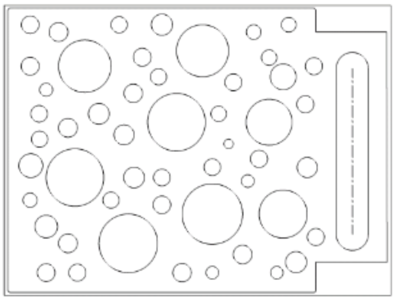


Fig. 2.2: Geometry C. Own visualization

The last exemplary geometry is geometry I, which is visualized in Figure 2.3 and has a circular shape and two circular inner contours. Geometry I may be used as a fixture in domains such as mechanical or electrical engineering.

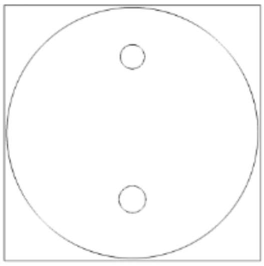


Fig. 2.3: Geometry I. Own visualization

2.2 The Industry Partner: TRUMPF

This thesis is a doctoral research project of the Technical University Dortmund in cooperation with TRUMPF Werkzeugmaschinen SE + Co. KG, hereafter referred to as TRUMPF. TRUMPF is a German machine tool manufacturer for sheet metal processing and offers solutions for bending, punching, combinations of laser cutting and bending processes, 2D and 3D laser cutting, laser welding, and additive manufacturing [TRUMPF, 2023].

2.3 Problem Description

The need for data-driven information about customers is present along the product life cycle, e.g. as stated in Li et al. [2015]; Tao et al. [2018]; Wang et al. [2021]. Along the product life cycle, companies make a series of decisions, such as "How should they design the product or service?", "Which customers do they want to address?", and many more. Decisions that rely on data are associated with a competitive advantage for the companies [Song and Kusiak, 2009] due to their higher accuracy and quality in comparison to their non-data-driven counterparts. For TRUMPF, we conducted a cross-departmental workshop and found the approaches of 1) customer segmentation, and 2) exemplary sheets and geometries as possible contributors to the foundation for data-driven customer information for the use cases along the product life cycle [Tjaden et al., 2022]. Furthermore, we identified 3) the concept of part complexity as a suitable candidate. We describe each of these three approaches and survey the related work in the following subsections: In Subsection 2.3.1 for customer segmentation, in Subsection 2.3.2 for exemplary sheets and geometries, and in Subsection 2.3.3 for part complexity. Where possible, we furthermore provide practical examples. Additionally, we evaluate each approach's applicability as a foundation for data-driven customer information along the product life cycle in the respective subsections. As we will see, the first two approaches customer segmentation and reference geometries are not suitable. Therefore, this thesis focuses on part complexity as its primary research subject.

2.3.1 Customer Segmentation

This subsection is mainly based on Tjaden et al. [2022]. Customer segmentation is a widely accepted approach to aggregate data about customers, as highlighted by several studies [Hosseini and Shabani, 2015; Kandeil et al., 2014; Maulina et al., 2019; Rivera-Castro et al., 2019; Simkin, 2008]. In the context of Business-to-Business (Business-to-Business (B2B)) segmentation, which applies to TRUMPF, common attributes identified in the literature include customer purchase behavior and customer value [Stormi et al., 2018; Kandeil et al., 2014], product preferences, frequency, and customer firmographics [Stormi et al., 2018]. Simkin et al. similarly identify typical traits of the agrichemical industry, namely product group, location, and business sector, but note that these are insufficient for creating meaningful customer segments. Additional attributes describing the customers, their needs, their buying behavior, and their decision-making reasoning are required [Simkin, 2008]. Other authors concentrate on the application of the Recency-Frequency-Monetary (Recency-Frequency-Monetary (RFM)) model [Stormi et al., 2018; Hosseini and Shabani, 2015; Maulina et al., 2019] or variations [Kandeil et al., 2014]

In our cross-departmental workshop conducted at TRUMPF, we identified a wide variety and range of attributes required by the stakeholders for the different use cases along the product life cycle. Many of these attributes cannot be obtained automatically but collected and updated manually, such as the cleanliness of the production site. To identify the most important data points and subsequently, minimize the required database for such a customer segmentation generator, we clustered the data points into groups such as "production data" or "data about the customer in general" and let the stakeholders vote on the importance of each data point.

However, since the stakeholders voted almost every data point as important, we could not reduce the required database for generating use case-specific customer segmentation models for sheet metal processing. Hence, one concludes that establishing and maintaining the eventually resulting database would be too cost-intensive, making the development of our customer segmentation generator unfeasible for this dissertation project.

2.3.2 Exemplary Sheets and Geometries

This subsection is mainly based on Tjaden et al. [2022]. Especially in machine tool manufacturing for sheet metal processing, companies need to know how their customers use the products and services. This is highly influenced by the products the customers produce. This makes having an overview of the products essential, e.g. for portfolio decisions, development, and customer interactions. In machine tool manufacturing for sheet metal processing, exemplary sheets—so-called benchmark sheets—have been employed for the purpose of exemplary customer products. For example, these benchmark sheets are used to compare the productivity of machines in regard to the customer's product portfolio. Table 2.1 exemplarily shows eight benchmark sheets that have been developed at TRUMPF to compare the productivity of 2D laser cutting machines. On sheets with sheet thicknesses between 1 and 4 mm, between 4 and 10 mm, and for sheet thicknesses greater than 10 mm, geometries that range in classes of low, medium, and high complexity have been placed. The process of placing geometries on sheets is called nesting.

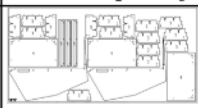
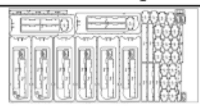
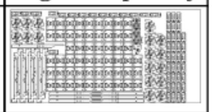
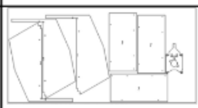
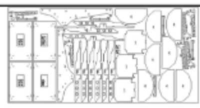
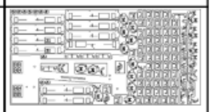
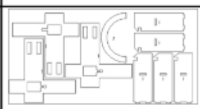
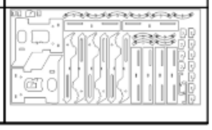
Sheet Thickness	Parts Complexity		
	Low complexity	Medium complexity	High complexity
1- <4 mm			
4 - 10 mm			
> 10 mm			

Table 2.1: Benchmark Sheets.

Exemplary sheets and geometries have also been employed in the literature [Deokar et al., 2016] as well as in the industry [Tjaden et al., 2022]. From a literature perspective, exemplary sheets and geometries have not been researched in detail, as we could find only one source employing such exemplary sheets [Deokar et al., 2016]. From a research and practice perspective, exemplary sheets are insufficient: They are time-consuming to establish and update, resulting in employees working with outdated information. Furthermore, we do not need exemplary sheets but exemplary geometries that can additionally support tasks like nesting optimization and production planning of orders, not of sheets. From a data governance perspective, the establishment of the database necessary for the creation of exemplary geometries inherits several risks:

1. Due to intellectual properties and non-disclosure agreements between machine tool manufacturer and customer as well as these customers and their customers, the geometries themselves may not be distributed or stored.
2. To overcome the intellectual property and non-disclosure agreement challenge, features describing the geometries may be collected that

contain sufficient information for the use cases of the stakeholders but insufficient information for the reconstruction of these geometries. Moreover, this information needs be stored for the time required for the justification of decisions that are taken upon this database to comply with transparency requirements towards the decisions of the stakeholders.

Due to the lack of research in the literature and the risks stemming from data governance, the approach of creating exemplary geometries to support the stakeholders with customer-based information seems infeasible at the moment.

2.3.3 Part Complexity

At the moment, both customer segmentation and exemplary sheets and geometries seem unfeasible. The underlying reasons for the unfeasibility are mainly due to missing geometrical databases that represent customer orders. The third approach that may contribute to data-driven information about the customers for the customer-centric activities in product and portfolio management, research and development, and sales and consulting is the concept of part complexity.

As we will see in Subsection 3.2, part complexity has been fairly researched in the literature. Based on this literature review, we can derive a definition of part complexity for the field of machinery and plant engineering for sheet metal processing. The use cases of part complexity known in the literature seem limited, and we want to extend the applicability of part complexity for the stakeholders' customer-centric activities during this dissertation.

Since part complexity seems to be the most promising approach in comparison to customer segmentation based on the data required by the stakeholders and exemplary sheets or geometries, the goal of this thesis is to develop and implement a methodology for the assessment of sheet metal part complexity and to extend the applicability of the part complexity concept.

2.4 Running Example: The TruLaser Center 7030

We chose the TruLaser Center 7030, depicted in Figure 2.4, as the example production unit since it is highly automated so we can neglect human activities, which bear more variance and variability than automated activities. The TruLaser Center 7030 covers these process steps:

1. Laser cutting: The geometries are cut out of the metal sheet using laser technology. The sheet thickness range varies from 1 mm to 12.7 mm, depending on the material.

2. Part Handling:

   a. Smart Gate: Small parts as well as scrap parts that are between 30 mm x 30 mm and 160 mm x 160 mm fall through this hole and are then transported to boxes for storage (see Figure 2.5).
   b. SortMaster Speed: Parts that do not fit in the SmartGate are transported with the SortMaster Speed, a roboter with many small suction cups. The SortMaster Speed can handle parts between 90 mm x 60 mm and 2000 mm x 1500 mm (see Figure 2.6).

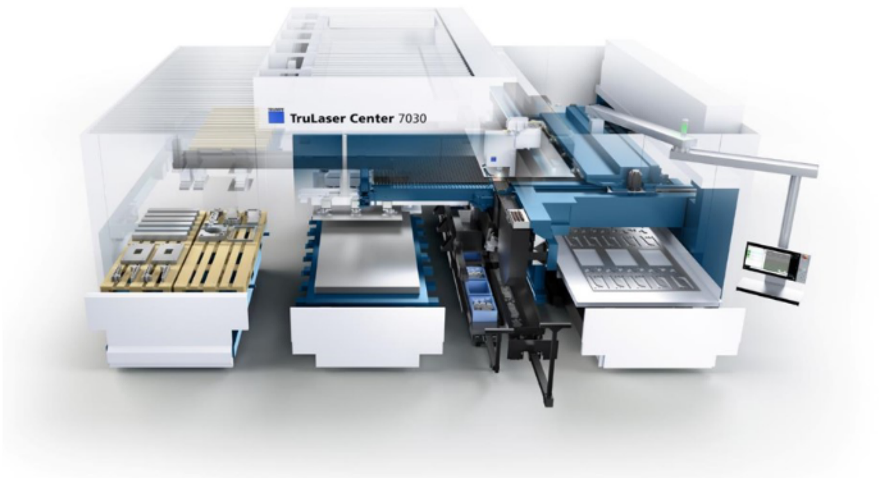


Fig. 2.4: The TruLaser Center 7030. Source: TRUMPF Group.

In the explanation of the TruLaser Center 7030's operation, we concentrate on the functionalities that are relevant to our case study. We assume that the TruLaser Center 7030 is connected to storage, making it autonomous. First, metal sheets are delivered to the TruLaser Center 7030 from the storage. After the machine or remote operator starts the machining program, the TruLaser Center 7030 will cut the metal sheet as previously defined in the machining program. During the laser cutting, the SmartGate is positioned under the laser beam, and scrap parts as well as finished parts with maximum dimensions of 160 mm x 160 mm fall through the SmartGate. The SmartGate is depicted in Figure 2.5. The scrap parts and finished parts are collected separately in storage boxes. The storage boxes are the blue boxes in the lower half of Figure 2.4. The finished parts that have dimensions bigger than 160 mm x 160 mm are sorted with the SortMaster Speed, which is a robotic arm with small suction cups. Figure 2.6 shows the underneath of a SortMaster Speed, holding a part with the black suction cups. Finally, the

SortMaster Speed stacks the finished parts on the palette, which can be seen on the left side of Figure 2.4. The completely laser-cut metal sheets are called scrap sceletons and are stored in the right part of Figure 2.4.

Fig. 2.5: Part Handling with the SmartGate. Source: TRUMPF.

Fig. 2.6: Part Handling with the SortMaster Speed. Source: TRUMPF.

Chapter 3
State of the Art

This section presents the related work resulting from our literature reviews and is twofold: Subsection 3.1 presents the need for data-driven methods along the product life cycle, while Subsection 3.2 presents our findings regarding the part complexity.

3.1 Need for Data-Driven Methods in Product Life Cycle Management

This subsection extends the literature research of Tjaden et al. [2022] and presents the need for data-driven methods in product life cycle management (Product Life Cycle Management (PLM)) in the literature. PLM covers the journey of its product, from its creation to its degradation. We searched for the terms "data-based information along the product life cycle", "need for data product life cycle", and "product life cycle data" in the research search engines ResearchGate and Google Scholar. Our literature review covers publications up until June 20th, 2024. In addition, we considered related papers as well as recommendations from peers. We screened the literature for data-driven use cases along the product life cycle: First, we filtered the relevance of the search results by their title. Subsequently, we scanned the abstracts regarding their match to the need for data-driven information along the product life cycle. We stopped the literature review when we no longer identified new use cases. One needs to keep in mind that the specific search for use cases along the product life cycle that would benefit from data-driven methods is challenging due to many use cases that are not linked to the product life cycle or PLM in the title, abstract, or keywords, making them hard to find. Moreover, we assume countless use cases could benefit from data-driven methods along the product life cycle. Hence, we do not claim our literature review to be complete. Instead, we want to motivate the investigation of solutions to this research gap by presenting a variety of potential applications of data-driven methods along the product life cycle.

Many authors emphasize the importance of data-driven methods along the product life cycle [Acerbi and Taisch, 2020; Marchetta et al., 2011; Pham et al., 2004; Rieger and Oleszek, 2023; Srinivasan, 2021; Terzi et al., 2010; Udroiu and Bere, 2018]. Figure 3.1 analyzes the year of publication of the 25 considered publications overall and for the three phases of PLM: The product life cycle is often divided into three categories Beginning of Life (Beginning of Life (BOL)), Middle of Life (Middle of Life (MOL)), and End of Life (End of Life (EOL)) [Terzi et al., 2010]. Since several publications covered use cases along the product life cycle from more than one phase, the number of publications per phase is greater than 25. We can observe a trend of increasing publications covering said topic. While EOL use cases have been covered more in recent years, we see stronger coverage of BOL and MOL use cases. Due to the trend of increasing number of publications and a stronger coverage of EOL use cases in the recent past, we expect more use cases along the product life cycle that could benefit from data-driven methods in the future.

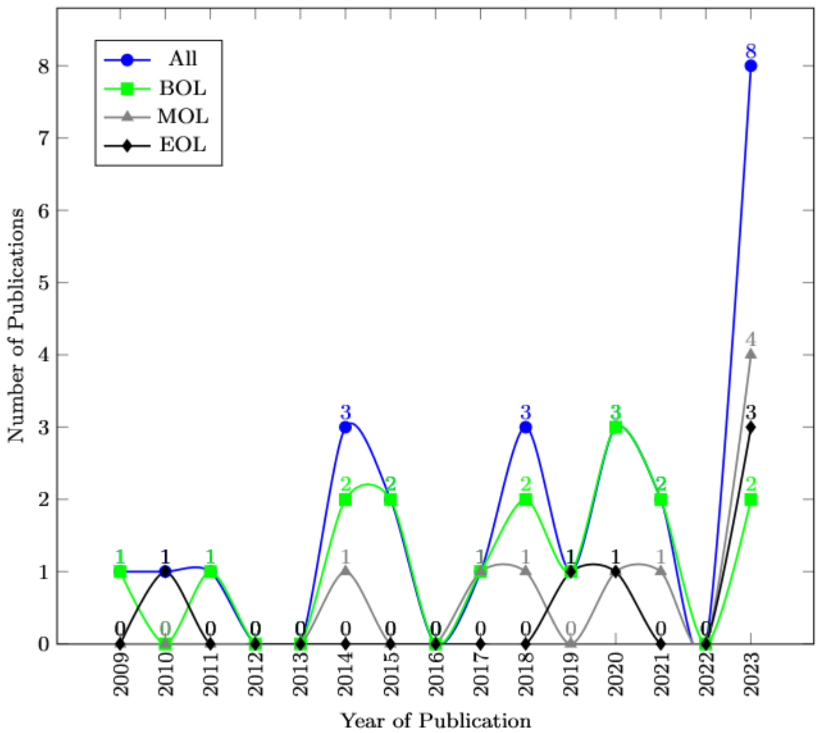


Fig. 3.1: Analysis of the Count of Publications per Year for the Topic of Data Need along the Product Life Cycle

Table 3.1 presents the use cases along the life cycle that we identified in our literature research and that could benefit from data-driven methods. We followed the three PLM phases according to Terzi et al. [2010] and structured our findings into Beginning of Life (see Subsection 3.1.1), Middle of Life (see Subsection 3.1.2), and End of Life (see Subsection 3.1.3). For better understanding, we only incorporated the phase categories for which we found part complexity use cases in the literature and do not claim the categories to be complete.

3.1.1 Beginning of Life

We found use cases needing data support for the first phase of the product life cycle, beginning of life, for the three categories market analysis, product development, and product manufacturing.

3.1.1.1 Market Analysis

The first use case during the market analysis phase that could benefit from data-driven methods is customer identification [Li et al., 2015; Tao et al., 2018; Wang et al., 2021]. The authors of Tjaden et al. [2023b] perform a data-driven customer segmentation by employing a K-means algorithm to build clusters of a customer database, using information such as the material and part size as input. The authors of Horvat et al. [2019] mention data-driven opportunity identification, using the utilization of customer data in the development of new food products as an example. They observed that 85 % of the responses to their survey utilize data about the three topics consumer involvement, food trends, and environmental factor data for the development of the new products. In addition, the authors of Horvat et al. [2019] see a high potential for product success if data would be involved in more phases throughout the product life cycle, such as opportunity identification, specifying customer requirements, and phasing-out decisions. Moreover, the authors of Horvat et al. [2019] observed a declining utilization of customer data once a product is launched. The specification of customer requirements using data seems to be the most relevant use case during the market analysis with a total of six mentions by Acerbi and Taisch [2020]; Feng et al. [2020]; Horvat et al. [2019]; Li et al. [2015]; Tao et al. [2018]; Wang et al. [2021]. The data-driven definition of product features has a total of five mentions by Acerbi and Taisch [2020]; Li et al. [2015]; MacCarthy and Pasley [2021]; Wang et al. [2021]; Zhang et al. [2017] and may be based on the results of the previously mentioned customer identification and specification of their requirements. Using data to define quality requirements is mentioned by MacCarthy and Pasley [2021]; Tao et al. [2018]. Both Terzi et al. [2010] and Zhang et al. [2017] suggest collecting data about the usage of the product or service to further improve the product or service's design. Furthermore, customer segments are useful to forecast demands and trends and to analyze historical data [Zhang et al., 2017].

Considered Aspect	[Acerbi and Taisch, 2020]	[Ahmadov and Helo, 2018]	[Blümke and Hof, 2023]	[Chakroun et al., 2023]	[Cheung et al., 2011]	[Dober et al., 2023]	[Feng et al., 2020]	[Horvat et al., 2019]	[Jensen et al., 2023]	[Kassner et al., 2015]	[Lachmayer et al., 2014]	[Leberruyer et al., 2023]	[Lee and Suh, 2009]	[Lee et al., 2014]	[Li et al., 2015]	[MacCarthy and Pasley, 2021]	[Rinciog et al., 2020]	[Sreenu and Gupta, 2014]	[Stoll et al., 2023]	[Stormi et al., 2018]	[Tao et al., 2018]	[Terzi et al., 2010]	[Tjaden et al., 2023a]	[Tjaden et al., 2023b]	[Wang et al., 2021]	[Zhang et al., 2017]	Count
	Sources																										
Beginning of Life (BOL)																											
Market Analysis																											
Customer identification															●						●				●		3
Customer segmentation																								●			1
Opportunity identification								●																			1
Specification of customer requirements	●						●	●							●						●				●		6
Definition of product features	●														●	●									●	●	5
Definition of quality requirements																●					●						2
Analysis of historical data																						●				●	2
Demand and trend mining algorithm for predictive life cycle design																										●	1
Product Development																											
Product design							●	●																			2
Customer-centric product development																					●						1
Research and understand customer behavior																					●						1
Research and understand customer preferences																					●						1
Improving future product generations											●		●														2
Definition of waste management practice	●																										1
Definition of circular product requirements	●																										1
Cost assessment					●																						1
Product Manufacturing																											
Selection of (sustainable) suppliers	●																										1
Optimization of supply chain network																										●	1
Simulate and test product								●							●												2
Training of a real-time scheduler		●															●				●						3
Smart production planning with the analysis of customer orders																					●						1
Feature extraction from step files for improving operation control																		●									1
Quality Assurance										●		●															2
Middle of Life (MOL)																											
Sales & Distribution																											
Client groups																									●		1
Sales prediction																				●							1
Sustainable procurement of product									●																		1
Product Usage																											
Ensure product performance																			●			●	●				3
Product Usage Monitoring																							●				1
Repair																											
Predictive maintenance				●					●					●												●	4
Automated anomaly detection, leading to new revenue streams, digitized servitization, and decrease prices for product services																										●	1
After-sales service	●																										1
End of Life (EOL)																											
Recycle activities	●		●						●													●					4
Dismissal activities	●								●													●					3
Data-driven phasing out decisions						●		●	●																		3

Table 3.1: Literature Review: Need for Data-Driven Methods along the Product Life Cycle.

3.1.1.2 Product Development

Product development is the second category of the beginning of life phase for which the literature provides use cases that would benefit from data-driven methods. Both Feng et al. [2020] and Horvat et al. [2019] identified product design as a use case that would benefit from data-driven methods. The authors of Feng et al. [2020] focused on the product design phase and identified the customer requirement analysis, conceptual design, and detailed design as tasks that could benefit from data support. We summarized the conceptual design and detailed design as product design in Table 3.1. In addition, Feng et al. [2020] believe that design knowledge support also could benefit from data support, e.g. to enable the collaborative design of product concepts between different team members. Tao et al. [2018] specify the product design slightly with customer-centric product development, underlining the importance of customer-centricity during this product development stage. Additionally, the authors of Tao et al. [2018] identified the research and understanding of both customer behavior and customer preferences as use cases that would benefit from enrichment with data-driven methods. The improvement of future product generations is mentioned by both Lachmayer et al. [2014] and Lee and Suh [2009]. In Lachmayer et al. [2014], they suggest collecting data during product usage and utilizing this data during the development of the product's next generation to further improve the product. In Lee and Suh [2009], the authors emphasize the importance of data and a data management system for stakeholders along the product life cycle. They mention specific tasks such as improving future product generations by utilizing data about the usage of previous product generations and maintenance activities. The use cases improving future product generations and product design are the only ones of the product development phase that have been mentioned twice in the literature. Acerbi and Taisch [2020] examine information management needs along the product life cycle. For product development, they identified the use cases definition of waste management practices as well as the definition of circular product requirements. The authors of Cheung et al. [2011] suggest enriching the cost assessment during the product development phase with product life cycle data from previous products for more accurate cost estimations.

3.1.1.3 Product Manufacturing

Product manufacturing is the last category of the BOL phase for which we identified use cases benefiting from data-driven methods in the literature. Both Acerbi and Taisch [2020] and Zhang et al. [2017] mention the topic of suppliers. While Acerbi and Taisch [2020] emphasize the selection of suppliers, especially sustainable ones, as a use case for data-driven methods, the authors of Zhang et al. [2017] mention optimization of the supply chain network as a whole. Another use case that would benefit from data-driven methods is product testing [Horvat et al., 2019; Li et al., 2015] as well as the simulation of products [Li et al., 2015]. Real-time schedulers mentioned by Ahmadov and Helo [2018]; Rinciog et al. [2020]; Tao et al. [2018] would allow for further optimization in the production planning but have sufficient databases as prerequisites. Another data-driven approach for optimizing production planning is analyzing customer orders [Tao et al., 2018], while the authors of Sreenu and Gupta [2014] view the feature extraction from step files as a suitable data-driven approach to improve the operation control. For the use case of quality assurance, we found two approaches in the literature: Kassner et al. [2015] use an application scenario as an example and analyze the benefit of data for quality assurance, using their product life cycle analytics approach that combines both unstructured and structured data stemming from different data sources. In Leberruyer et al. [2023], they employ artificial intelligence trained on data to improve the quality assurance of a company to enable zero-defect manufacturing. They analyze the influence of vibrations of an axle collected with sensors on the noise in the car, aiming to identify defective axles and reduce high noise levels.

3.1.2 Middle of Life

Middle of Life is the second phase of the product life cycle, for which we identified use cases of the three categories sales & distribution, product usage, and repair in the literature.

3.1.2.1 Sales & Distribution

Sales and distribution is the first category of the MOL phase for which we identified use cases. The authors of Wang et al. [2021] suggest using customer segmentation to identify client groups based on data. This appears to be similar to the BOL use case of Tjaden et al. [2023b], where they employed customer segmentation to group potential customers during the market analysis. Another use case for the method of customer segmentation is the sales prediction [Stormi et al., 2018] According to Jensen et al. [2023], a digital product passport containing product life cycle data would enable customers to procure their desired products more sustainably due to the increased transparency along the supply chain.

3.1.2.2 Product Usage

Product usage is the second category of MOL with the two use cases ensuring product performance and monitoring product usage. According to Stoll et al. [2023], data-driven methods could support maintaining the performance of products and services while collecting data from products in the field could enable monitoring the products' life status [Terzi et al., 2010]. The authors of Tjaden et al. [2023a] introduce a KPI system called customer health score that considers field data as well as information about the customer relationship, the products, and maintenance activities. This customer health score monitors the usage of the product and enables two use cases: First, it can be observed if the customer health parameters are within or not within the boundaries. If the parameters are not within the boundaries, the responsible product and for the product, the responsible category can be identified to investigate the reason for the deviation. Second, by observing the customer health score over time, specific measures for the customer success management can be derived to support the customer service.

3.1.2.3 Repair

For the last MOL category, we identified the three use cases of predictive maintenance, anomaly detection, and after-sales service in the literature. Predictive maintenance is the most popular use case, for which we found 4 mentions in the literature [Chakroun et al., 2023; Jensen et al., 2023; Lee et al., 2014; Zhang et al., 2017]. The authors of Chakroun et al. [2023] perform predictive maintenance, using both Discrete Bayesian Filter and Naïve Bayes Filter on a dataset generated with sensors of a packaging robot. By utilizing data for maintenance activities, e.g. with predictive maintenance, the products' life cycles can be elongated due to better repairs [Jensen et al., 2023]. In addition, such digital product passports could provide service manuals to make repairs easier for the customers [Jensen et al., 2023]. In their study, Zhang et al. [2017] view the automated detection of anomalies as an enabler for new revenue streams, digitized servitization, and reduced prices for products and services. After-sales service activities such as describing repair activities or the characteristics of spare parts could also benefit from data-driven methods, according to Acerbi and Taisch [2020].

3.1.3 End of Life

End of Life is the last phase of the product life cycle. Since we could only identify the three use cases of recycling, dismissal, and data-driven phasing out decisions, we do not provide distinction with further categories. Collecting data throughout the product life cycle in a product data pass may broaden the product's second life application possibilities on the example of batteries for electric vehicles [Blümke and Hof, 2023]. Tracing the product through its lifecycle and storing this data can enhance the trust in the quality of the used product, making it more suitable for recycling or other second-life activities [Blümke and Hof, 2023]. To prevent unallowed alteration of the product life cycle data, the authors of Blümke and Hof [2023] suggest physically connecting the data to its product. Jensen et al. [2023] also investigate the potential use cases of digital product passports, especially regarding the circular economy, and provide examples of what data should be stored in these digital product passports. They state that data stored in the digital product passport can be utilized to inform customers about end-of-life options like recycling or dismissal activities such as returning the product to its manufacturer. Another option is to simplify the disassembly of products by providing data about safe disassembly strategies [Jensen et al., 2023]. Information about the materials stored in the digital product passport allows for better recycling of the products' materials [Jensen et al., 2023]. Data collected during the product usage could assist in deciding about the products' second-life options, e.g. remanufacturing components of the product, and the remaining usage period of the product [Jensen et al., 2023]. Activities regarding both recycling and dismissal could benefit from information such as the material and components of the product [Terzi et al., 2010]. While Acerbi and Taisch [2020] also mention recycling as well as dismissal activities, Dober et al. [2023] suggest data-driven support for decisions of whether or not to phase out products or services.

3.2 State of the Art: Part Complexity

This section extends Tjaden et al. [2024] and presents our literature research on part complexity. To the best of our knowledge, no definition of sheet metal part complexity exists in practice. We want to fill this gap to enable the comparison of customers and their parts and hence, their requirements for sheet metal processing machine tools. For the literature review, we employed a mixed strategy. We systematically searched for the terms "part complexity" and "sheet metal part complexity" in SpringerLink, ResearchGate, and Google Scholar databases. We considered literature published until May 28th, 2024. Additionally, we considered previous literature cited by already identified literature and searched for literature citing the already found literature, using the database ConnectedPapers. We did not exclude literature based on the publication year. Our results regarding the importance of complexity in the context of manufacturing are followed by use cases of part complexity in the literature. Subsequently, we present definitions of part complexity and the influence of geometrical characteristics on the part complexity.

3.2.1 Use Cases for Part Complexity in Literature

We found engineering use cases for part complexity in literature for production technology selection and production optimization.

3.2.1.1 Production Technology Selection

In Greco et al. [2022], the authors aim to determine a part's complexity using an index to select the best suitable production technology: Traditional or additive manufacturing. The authors of Valentan et al. [2011], too, assess a part's complexity to compare its manufacturability for milling, turning, additive manufacturing with support, and additive manufacturing without support. They distribute the parts into eight cubes that they call octants. They consider part characteristics such as the vectors within the octants, the size of the part, the material, and the manufacturing time [Valentan et al., 2011]. Moreover, they consider experts' estimates of the part complexity without specifying how.

In their study, ElMaraghy et al. [2012] aim to develop a so-called "manufacturing index" "to enable a simple comparison of alternative designs" (p. 799). The overall complexity of a reconfigurable manufacturing system consists of the complexity of the machines, the complexity of the buffers, and the complexity of the material-handling system.

Lohtander et al. [2007] hint that sheet metal part complexity may be assessed based on geometrical features such as holes or bending and how difficult they are for the respective process steps. The bending equipment of choice highly depends on the geometrical characteristics of bending features. Small parts can be bent with punching machines, while large parts need to be bent with bending machines. Moreover, features usually are processed in a certain order: Cutting comes before bending, and surface treatment is usually the last production process step. Furthermore, the lot size of a geometry also influences the decision for a blank and hence how the features are produced. Hence, the geometry characteristics influence the production [Lohtander et al., 2007].

In Lohtander and Varis [2007], the authors analyze sheet metal parts according to their manufacturing features. These features cover common characteristics of sheet metal parts, such as threads, material, and size [Lohtander and Varis, 2007]. For the feature cutting, they created two sub-classes edge and hole, since these features differ significantly in the manufacturing process. Edges may be formed with punching techniques while being not suitable for the production of holes. Subsequently, they analyze how the manufacturing method can be selected based on the manufacturing features.

The authors of Greco et al. [2022] use both objective and subjective metrics to calculate the part complexity, but do not explain how they developed this equation. For the subjective assessments, they use the Likert scale ranging from 1 (very simple) to 5 (very complex). They demonstrate the usefulness of their combined complexity metric with a case study, analyzing 26 polymer components, and selecting either Selective Laser Sintering or Injection Molding as production technologies. To select the production technology, they also consider production volumes (part repetition) and cost per part.

3.2.1.2 Production Optimization

In their work, Lohtander and Varis [2008] concentrate on the manufacturability of large sheet metal parts, focusing on size and dimension. They aim to streamline the production processes of an assembly, making its production less time-consuming and costly.

The authors of Qamar et al. [2019] want to quantify the shape complexity in metal extrusion to determine the optimal set of production parameters, e.g. the extrusion pressure, to improve the production processes, minimize product defects, and maximize the production efficiency. They state that the complexity also influences the durability of the tools, energy consumption, production cost, and more [Qamar et al., 2019]. They state that they need a complexity definition considering both the prediction of tool durability and the determination of extrusion pressure. In addition, they research the domain metal extrusion, where the quality of metal extrusion is mainly affected by shape complexity, which influences the production process and parameter selection [Qamar et al., 2019]. They could not find a statement defining extrusion complexity, but that the complexity represents the production difficulty, depending on the geometrical features of the die profile.

Lam et al. [2007] state that material cost makes up the majority of overall production cost. They want to optimize the nesting of geometries on the metal sheet to maximize the use of material by using the Minkowski sum evaluation. The authors of Lam et al. [2007] discovered that parts having the Minkowski sum inner loop offer a great material use potential.

Joshi and Ravi [2010] agree that a high complexity implies quality defects, higher cost, and reduced productivity.

In Ben Amor et al. [2022], they state that similar to traditional manufacturing processes, the geometrical complexity also increases the manufacturing time and cost for additional manufacturing processes.

3.2.2 Importance of Complexity in the Context of Manufacturing

When dealing with the phenomenon of complexity, one quickly realizes that there is a lack of a universally valid definition of complexity that would be accepted across disciplines [Suh, 2005; ElMaraghy et al., 2012]. Nonetheless, many agree that the relevance of complexity, in general, is significant, and different perspectives on complexity and its role have been analyzed, as this section lays down. To the best of our knowledge, no widely accepted separation between the different perspectives on part complexity has been established.

Methodologies for the evaluation of technological complexity have been researched since the 1980s and have evolved from index complexities calculated by mathematical programs towards questionnaire-based subjective assessments of complexity as well as more objective assessments that rely on system data [Greco et al., 2022].

According to Suh [2005], the importance of complexity has increased in both science and engineering. While almost all disciplines—e.g. natural science, social science, and engineering—deal with complexity, each discipline defines complexity individually in lack of a universal definition [Suh, 2005; ElMaraghy et al., 2012], since different complexity definitions serve different purposes: While Qamar et al. [2019] aims to define complexity for the domain of metal extrusion to optimize the production process to increase both process efficiency and product quality, Suh [2005] see the aim of defining complexity in predicting the behavior of natural systems and enabling a complexity reduction, e.g. aiming to decrease development cost. The authors of Greco et al. [2022] believe that so far, no individual metric is suitable for the description of part complexity. They believe that "a weighted combination of these metrics could provide more comprehensive results than those provided by individual metrics" (p. 5). At the same time, the authors of Brinkhoff et al. [1995] suggest that using too many parameters may limit the intuitive understanding of the calculation. Specifically for engineered systems, Suh [2005] assumes that their complexity will increase in the future due to the rising number of requirements these engineered systems shall fulfill.

A complexity reduction is—in contrast to the assumed increase in complexity—associated with benefits such as more reliability and performance improvement [Suh, 2005] as well as less cost of development and operation [Suh, 2005; Valentan et al., 2011]. The authors of Suh [2005] compare complexity observing physical things—where the complexity increases with the number of parts involved—with a functional perspective. For Suh [2005], complexity represents how certain the achievement of a functional requirement is.

The authors of Suh [2005] further differentiate between time-independent real complexity, time-independent imaginary complexity, time-dependent combinatorial complexity, and time-dependent periodic complexity. Time-dependent complexity means complexity that has parameters that change over time, while parameters of time-independent complexity remain the same. Combinatorial complexity means an increasing complexity over time due to uncertainties regarding the future outcome. With periodical complexity, they mean the complexity of systems that renew themselves over periods of time.

The authors of Qamar et al. [2019] differentiate between three approaches to define part complexity for the domain of metal extrusion:

1. Group similarly complex parts together: E.g. differentiating between solid (least complex), hollow (maximum complex), and semi-hollow (medium complex) extrusion shapes, where the extrusion difficulty increases with complexity.
2. Develop an equation combining complexity with extrusion pressure, many researchers relate the extrusion pressure with complexity in metal extrusion.
3. Define complexity based on tool wear: The higher the complexity, the earlier the tool fails due to wear.

The authors of Greco et al. [2022] view the aspects of design, manufacturing, and assembly as fundamental for complexity in the context of engineering.

The authors of ElMaraghy et al. [2012] state that the complexity of manufacturing processes is influenced by the complexity of the parts to be manufactured, the assembly complexity, and product variety without detailing part complexity.

3.2.3 Part Complexity as Manufacturability Indicator

This subsection sheds light on part complexity when being understood as a manufacturability indicator, starting with part complexity definitions in the literature, feature-based assessment of part complexity known in the literature in general, and features used at our industry example TRUMPF to describe parts.

3.2.3.1 Definitions of Part Complexity in the Literature

	Sources												
	[Buff et al., 2013]	[Claus et al., 2021]	[Salunkhe et al., 2015]	[Kumar et al., 2017]	[Lam et al., 2007]	[Esener et al., 2021]	[Schuh et al., 2019]	[Lohtander et al., 2007]	[Lohtander and Varis, 2008]	[Lohtander and Varis, 2007]	[Qamar et al., 2019]	[Joshi and Ravi, 2010]	[Turco and Maggioni, 2020]
Mentioning PC	●	●	●	●	●								
Defining PC: "surfaces that do not represent a classical geometry"						●							
Defining PC: "rare geometries"													●
Manufacturability as Indicator for Complexity				●			●	●	●	●	●	●	

Table 3.2: Part Complexity (PC) in Literature.

The results of the research on the sheet metal part complexity in literature are visualized in Table 3.2. Sheet metal part complexity is mentioned without being explained any further in Buff et al. [2013]; Claus et al. [2021]; Salunkhe et al. [2015]; Kumar et al. [2017]; Lam et al. [2007]. The authors of Esener et al. [2021] provide a rough definition of complex surfaces as "surfaces that do not represent a classical geometry (circle, arc, etc.)" (p. 416), while the authors of Turco and Maggioni [2020] state that complex products are characterized by being rare. These definitions seem insufficient to assess the sheet metal part complexity.

The influence of the sheet metal part's manufacturability is brought up in Schuh et al. [2019] by stating that complex geometries are difficult for production with conventional stamping. Other authors seem to agree with the perspective of complexity as an indicator of manufacturability [Kumar et al., 2017; Lohtander et al., 2007; Lohtander and Varis, 2008, 2007; Schuh et al., 2019; Qamar et al., 2019; Joshi and Ravi, 2010]. One needs to remember that three of these eight papers stem from the same research group, namely Lohtander et al. [2007]; Lohtander and Varis [2007, 2008].

3.2.3.2 Feature-Based Assessment of Part Complexity Known in Literature

Other researchers go into more detail regarding the geometrical characteristics making certain parts hard to manufacture and hence, increasing their complexity, as summarized in Table 3.3. While the majority of the papers deal with (3D) CAD data, mainly with an industrial context, we also found one paper illustrating complexity characteristics on islands [Brinkhoff et al., 1995], and one construction use case [Liu et al., 2022].

In their study, Kumar et al. [2017] developed a system for automatic feature extraction of sheet metal CAD files since none of the approaches they identified in the literature provided the required level of detail. In Radvar-Esfahlan and Tahan [2014], they extract geometrical features, such as holes and edges, aiming to generate a triangle mesh of the geometries' surface.

According to Greco et al. [2022], the entrappedness of a polygon represents its shape complexity without further specifying how they define entrappedness. Brinkhoff et al. [1995] illustrate the complexity of shapes using map data in the form of differently shaped islands and use attributes such as the deviation from the convex hull, the number of notches, the so-called amplitude of the vibration, and the overall complexity. Their overall complexity is a combination of the weighted attributes above in one measure, aiming to enable the classification of the islands on a uniform scale.

The authors of Camba et al. [2019] elaborate on the complexity of CAD models instead of the geometries, e.g. further considering the internal structure of CAD files. They also state that the geometry complexity influences the CAD complexity. They analyze a database containing 370 CAD models and analyze them—among others—regarding their geometry features as indicated in Table 3.3.

As stated in Joshi and Ravi [2010], the "shape complexity of a part is usually described in qualitative terms like low, medium, high, and very high" (p. 685). They analyze the complexity of a casting process with the use case design for manufacturability. They want to identify drivers for high costs within the geometries to alter the responsible geometrical features as early in the design process as possible to lower the cost. First, they give an overview of complexity factors that combine geometrical characteristics and tooling or process design for casting. Following, they identified the features number of

Geometry Features	Domain	Sources									
		[Greco et al., 2022]	[Brinkhoff et al., 1995]	[Camba et al., 2019]	[Radvar-Esfahlan and Tahan, 2014]	[Joshi and Ravi, 2010]	[Lian et al., 2012]	[Chougule and Ravi*, 2005]	[Liu et al., 2022]	[Bodein et al., 2014]	[Valentan et al., 2011]
Polygon entrappedness	not defined	●									
Deviation from convex hull	map		●								
Number of notches	map		●								
Amplitude of the vibration	map		●								
Complexity	map		●								
No. of faces	Industry / 3D CAD			●						●	
No. of vertices	Industry / 3D CAD			●							
No. of edges	Industry / 3D CAD			●							
Volume	Industry / 3D CAD			●							●
Surface Area	Industry / 3D CAD			●							●
Volume/area ratio	Industry / 3D CAD			●							
Volume ratio	Industry / 3D CAD			●		●					
Cube ratio	Industry / 3D CAD			●							
Sphere ratio	Industry / 3D CAD			●		●					
Holes	CAD data				●						
Edges	CAD data				●						
Length	3D CAD data					●					
Width	3D CAD data					●					
Height	3D CAD data					●					
Volume of bounding box	3D CAD data					●					
Volume of part	3D CAD data					●					
Surface area of part	3D CAD data					●					
Radius of imag. sphere of equal vol.	3D CAD data					●					
Surface area of imag. sphere	3D CAD data					●					
Area ratio	3D CAD data					●		●			
Number of cores	3D CAD data					●		●			
Total core volume	3D CAD data					●					
Minimum thickness	3D CAD data					●	●				
Maximum thickness	3D CAD data					●	●				
Thickness ratio	3D CAD data					●					
Draw distance	3D CAD data					●					
Machining cost of tube	3D CAD data					●					
Actual tool machining cost	3D CAD data					●					
Convexity	3D CAD data						●				
Surface-to-volume ratio	construction								●		
Number of openings	construction								●		
Reinforcement ratio	construction								●		
Number of embedded parts	construction								●		
Amount of exposed rebar	construction								●		
Number of triangles	Industry / 3D CAD										●

Table 3.3: Geometry Characteristics Indicating Part Complexity in Literature.

cores, volume and surface area of the part, core volume, section thickness, and draw distance as the main contributors to the costs, all of which can be derived from the CAD model of the parts. Cores enable the molding of parts with hollow portions and represent the inner hollow space of molding parts. The more cores a part has, the more tooling is required, increasing production costs. The section thickness is the thickness of the section of a part that is being analyzed. The draw distance is the tooling's maximum depth. In the view of Joshi and Ravi [2010], equations for the calculations for each criterion for the complexity should be defined such that they return values between 0 (low complexity) and 1 (high complexity). Moreover, they define the actual complexity "as the ratio of the additional cost of machining [...] to the cost of machining a cube of differential volume" (p. 690). They put their approach into practice, using 40 CAD data files from a tooling manufacturing company. They accessed the cost data from the senior tool maker, covering a period of two years and ignoring inflation. To derive the weights for their six criteria, they perform a multiple regression analysis. In the evaluation of their equation, they calculate the complexity of not yet considered parts, reaching an accuracy of 97.7 %, satisfying their accuracy requirement of at least 95 %.

The authors of Chougule and Ravi* [2005] aim to assess the manufacturability of castings to optimize production planning. The shape complexity is important for process planning and is being quantified based on the geometrical parameters of the casting model: The area and the number of cores. They define shape complexity as the sum of the weighted area ratio and the weighted number of cores. For calculated shape complexity values below zero, they manually set negative values to zero. Furthermore, they consider other geometrical features like maximum casting size, casting weight, minimum and maximum section thickness, and minimum and maximum core size. In addition to the geometrical features, they further consider attributes regarding the quality like dimensional tolerance, surface finish, and maximum void size, and attributes regarding the production like order quantity, production rate, sample lead time, and production lead time. They derived these characteristics from interviews with casting engineers, product designers, and purchase managers. They determined the weights of the parameters of the calculation using the analytic hierarchy process (Analytical hierarchy process (AHP)). To do so, they created a hierarchical structure of the problem to assess the priorities of the attributes relative to each other, evaluated the consistency of the relative priorities, and calculated the weights based on the verified relative priorities of the attributes. Moreover, they demonstrate their framework on an industrial example.

The authors of Liu et al. [2022] analyze production efficiency—consisting of structural complexity comparable to part complexity, production complexity, and management complexity—on the example of China's offsite construction industry. The structural complexity covers surface-to-volume ratio, number of openings (holes), reinforcement ratio (hinting at production time), number of embedded parts, and weight of exposed rebar (hinting at the structural complexity of the products). In addition to the literature research, the authors of Liu et al. [2022] conduct a field search, visiting three factories to observe the production processes and to semi-structured interview experts. To verify the impact of the complexity features and the production efficiency, they let 182 experts from the factories and researchers rank their influence, using the Likert Scale from 1 (no influence) to 5 (significant influence). They verified the reliability and validity of the ranking results using Cronbach's alpha test, Kaiser-Meyer-Olkin test, and Bartlett's test. They could confirm their hypotheses of a negative effect of structural complexity on production efficiency with a p-test.

Bodein et al. [2014] assess the complexity of a part for CAD modeling by the number of surfaces. They let CAD trainers assess the complexity of ten parts, resulting in a part being considered complex when it has more than 250 surfaces. They state that their definition could be refined by taking further characteristics into account, such as the size of the surfaces or the ratio of planar and non-planar surfaces.

Valentan et al. [2011] work with experts to assess the part complexity and observe a relation between the number of triangles of a geometry and its complexity: The more triangles a geometry has, the more complex it is. They further define that when the geometry decreases in size, the complexity increases. They calculate complexity as the ratio of the product of the surface and the number of triangles, and the volume.

In Contero et al. [2023], they aim to rank CAD models according to their modeling complexity to quantify the quality of the modeling process. They asked five experts for a pair-wise comparison of 95 different CAD models that were randomly chosen from a database. They also provide a literature overview of previously used geometrical characteristics in the literature, similar to Table 3.3.

3.2.3.3 Features Used at TRUMPF

To describe our two-dimensional geometries, we calculate geometrical features, following the list from Table 3.3. We use the geometrical features already established at TRUMPF since they seem to be suitable for our domain of sheet metal processing. These features are presented in Table 3.4.

We calculated the dimension of the part in the x- and y-direction, the area of the part including the inner contours, called the part area, and the area of the part excluding the inner contours, called area outer contour. Furthermore, we calculate the circumference of the part. The cutting degree is the sum of all inner contour areas divided by the area of the outer contour. The antipodal distance is the longest distance within the part. The part's cutting length covers the inner and outer contours. We also calculated the number of inner contours, if the centroid of the part lies within the part or not, the convex hull area, and the circumference. Moreover, we calculated the area and circumference of a circle covering the geometry as well as the

Number	Feature
1	Area of the part including inner contours
2	Length of the outer contour of the part
3	Cutting degree: Sum of all inner contour areas divided by the area of the outer contour
4	Area of the part's convex hull
5	Length of the part's bounding box in x-dimension
6	Length of the part's bounding box in y-dimension
7	Antipodal distance: Maximum straight dimension of the part
8	Contour length of the part's convex hull
9	Circumference of an adapted circle
10	Area of an adapted circle
11	Ratio of contour length of the outer contour and the circumference of an adapted circle
12	Contour length of the part
13	Amount of inner contours
14	Part area ignoring inner contours
15	Area ignoring inner contours of the part normalized by the area of the bounding box
16	Ratio of the area of the convex hull and the part's area, including inner contours
17	Ratio of the part's circumference and the circumference of the convex hull
18	Information if the centroid of the part lies on its part area or not
19	Perimeter of part outer contour divided by perimeter of bounding box
20	Length of x-axis for the rotated part polygon´s minimum rectangle
21	Length of y-axis for the rotated part polygon´s minimum rectangle

Table 3.4: Geometry features used at TRUMPF.

bounding box, which is the area of a rectangle covering the part. Furthermore, we calculated the ratio of the area of the bounding box and the part's area, excluding inner contours, as well as the ratio of the area of the convex hull and the part's area, including inner contours. In addition, we calculated the ratio of the part's circumference and the circumference of the convex hull. We provided the ratio of the part's circumference and the circumference of the circle covering the geometry.

Compared to the literature, we used the features of the area [Camba et al., 2019; Valentan et al., 2011; Joshi and Ravi, 2010], the inner contours [Radvar-Esfahlan and Tahan, 2014; Liu et al., 2022], and the length and width [Joshi and Ravi, 2010]. The authors of Joshi and Ravi [2010]; Chougule and Ravi* [2005] also used area ratios.

3.2.4 Literature Evaluation: Part Complexity

The literature agrees that complexity, in general, plays an important role in the context of manufacturing and is utilized for use cases such as production technology selection [Greco et al., 2022; Valentan et al., 2011; ElMaraghy et al., 2012; Lohtander et al., 2007; Lohtander and Varis, 2007] or production optimization [Lohtander and Varis, 2008; Qamar et al., 2019; Lam et al., 2007; Joshi and Ravi, 2010], but is also associated as helpful for cost reduction [Suh, 2005; Valentan et al., 2011]. Since the use cases for complexity are manifold across the disciplines, so far, no universal complexity definition exists [Suh, 2005; ElMaraghy et al., 2012], and the (co-)existing complexity definitions [Qamar et al., 2019; ElMaraghy et al., 2012] are tailored for specific use cases. The definitions of part complexity in the literature seem rather vague and insufficient for the sheet metal part complexity. However, the literature agrees that part complexity reflects a part's manufacturability [Kumar et al., 2017; Schuh et al., 2019; Lohtander et al., 2007; Lohtander and Varis, 2007, 2008; Qamar et al., 2019; Joshi and Ravi, 2010]. Furthermore, we found papers going into more detail on which characteristics of a part influence its manufacturability and hence, its complexity [Greco et al., 2022; Brinkhoff et al., 1995; Camba et al., 2019; Radvar-Esfahlan and Tahan, 2014; Joshi and Ravi, 2010; Lian et al., 2012; Chougule and Ravi*, 2005; Liu et al., 2022; Bodein et al., 2014; Valentan et al., 2011]. These papers additionally consider expert knowledge collected via interviews or manual labeling.

The literature could not provide an approach for the assessment of part complexity specifically tailored to the needs of sheet metal processing that seems sophisticated enough for our endeavor. However, the literature provided examples of how other researchers assessed the part complexity that seems worth following, such as purpose-specific definitions, e.g. for the definition of production process parameters, the reflection of part complexity as its manufacturability, and the linkage between a part's manufacturability and its geometrical characteristics. In the following section, we want to fill this research gap and develop a methodology for the assessment of part complexity using the example of sheet metal processing.

Chapter 4
Assessing Sheet Metal Part Complexity

This Section extends Tjaden et al. [2024] and aims to answer the first research question of this thesis: "How can we determine part complexity in sheet metal processing?"

First, we derive a definition of part complexity in sheet metal processing from the literature in Subsection 4.1. Building on this definition, we develop a methodology for the assessment of sheet metal part complexity in Subsection 4.2, followed by its implementation in practice in Subsection 4.3, using an exemplary production unit of TRUMPF. Ths production unit manufactures 2D sheet metal parts. Subsection 4.4 presents the discussion and critical reflection of our research approach, while Subsection 4.5 concludes this section with the summary of the first interim result.

4.1 Deriving a Definition for Sheet Metal Part Complexity

For deriving our definition of sheet metal part complexity, we follow the results of the literature review in Table 3.2 from Subsection 3.2, especially the authors of Kumar et al. [2017]; Schuh et al. [2019]; Lohtander et al. [2007]; Lohtander and Varis [2007, 2008]; Qamar et al. [2019]; Joshi and Ravi [2010]. The authors named above agree that the part's manufacturability is an indicator of the part's complexity. We conclude that the more complex a geometry is, the harder it is to manufacture. Since the part complexity reflects the manufacturability, the part complexity will change when the manufacturing process is changed.

Based on part complexity as a manufacturability indicator that depends on the manufacturing process, we derive the following definition:

We define sheet metal part complexity as the degree of manufacturability for each geometry and corresponding process step. The harder a geometry is to manufacture, the more complex the geometry is. Moreover, the sheet metal part complexity will underly change, as the manufacturability may change over time, e.g. due to changes in the production process.

In the following, we develop a methodology to assess the Sheet Metal Part Complexity.

4.2 Developing the Methodology for Sheet Metal Part Complexity Assessment

In this section, we describe the development process of our methodology for assessing the complexity of sheet metal parts. First, we explain the general developmental process. Subsequently, we chose a survey as our research method to utilize domain specialists' expertise, determined the number of geometries, selected participants for our survey, explained the evaluation mechanism, distinguished our contributions, and compared them to the literature.

4.2.1 Developing the research design

According to Mackenzie and Knipe [2006], researchers use the terms method and methodology interchangeably, while most definitions view methodology as the overall research approach and method as procedures or tools utilized to collect and analyze data. In our understanding of the term methodology, we follow Mackenzie and Knipe [2006], and propose a methodology for the assessment of part complexity that combines several established research methods.

The development process of our sheet metal part complexity assessment methodology is visualized in Figure 4.1. First, we decided on a mixed-methods approach that combines both empirical and qualitative research elements. Subsequently, we conducted an individual depth interview, investigating geometry characteristics that influence complexity, and decided to collect the data through an online survey. Both the development of the online survey tool and the decisions on experiment parameters underwent feedback loops from both scientific and industry perspectives. Before the final data collection, we conducted a pilot test and incorporated the findings into the online survey tool and the decision on parameters.

Based on our definition of part complexity, which links the complexity of parts to their manufacturability, we want to explore which parts are more difficult to manufacture and why. The data for such an endeavor is missing today, as there is, to the best of our knowledge, no database consisting of both geometries and their characteristics as well as feedback from their manufacturing. Hence, we rely on asking experts.

4.2.2 A Survey for Assessing Sheet Metal Part Complexity

Surveys are highly structured interviews that aim to collect comparable data to identify similarities and dissimilarities [Cooper and Schindler, 2003]. The most important advantages of surveys are their versatility for

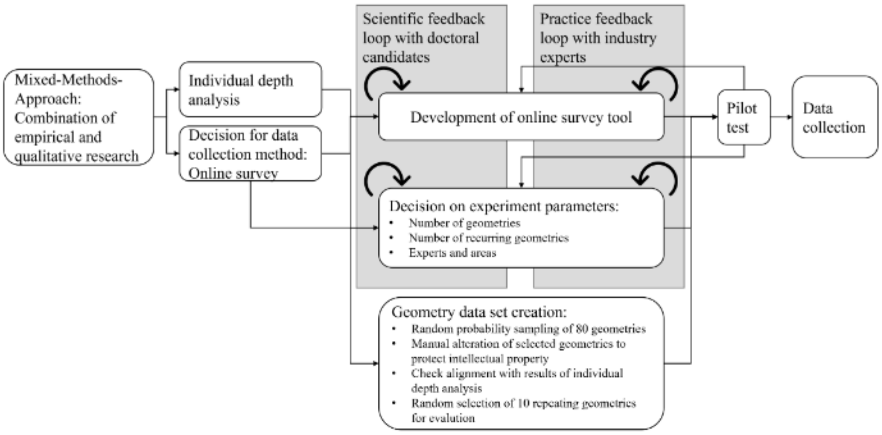


Fig. 4.1: Development of the part complexity assessment. Own visualization.

data collection and that by asking the right questions, conclusions can be drawn much faster than by making observations [Cooper and Schindler, 2003].

A sub-form of surveys are computer-delivered self-administered questionnaires, also called Computer-Assisted Self-Interview (CASI)s [Cooper and Schindler, 2003]. Computer-assisted self-interviews enable considering participants regardless of their geographic region [Cooper and Schindler, 2003]. CASIs offer advantages such as giving participants time for their answers, and using visualizations in the interview process [Cooper and Schindler, 2003]. Despite their versatility, surveys, in general, are prone to errors of (a) measurement questions and survey instruments, (b) interviewer with sampling, data entry, and process errors, and (c) participants Cooper and Schindler [2003]. Further disadvantages of CASIs include not being able to provide further information during the interview process or to directly clarify questions, and that they should be short in length [Cooper and Schindler, 2003]. The authors of Cooper and Schindler [2003] present a 10-minute maximum length as the rule of thumb for computer-delivered self-administered surveys.

We want to address the possible risks and disadvantages in our computer-delivered self-administered surveys for the labeling of geometry complexity—namely the risk of incompletion of the participants or misunderstanding of the task—by one-on-one meetings with each participant to educate them on the goal of the survey as well as their importance before the survey itself starts. To save time, we will not conduct these meetings with each participant individually, but organize meetings for teams, where possible. An example is a slot for the representation of the labeling in a regular meeting of the team, such as daily or weekly organizational meetings.

To conduct our surveys, we develop a labeling tool to be able to operate independently from the participants' schedule and their locations. Another advantage of this labeling tool is that errors stemming from the presence of the interviewer or other survey participants are highly unlikely to occur since there will be no interaction between the interviewer and the participants during the labeling, making our survey a self-administered survey in contrast to a telephone survey or a survey via a personal interview, according to [Cooper and Schindler, 2003]. Since we will distribute our labeling tool via the Internet, we can cover a larger geographic area, including employees on different sites. Furthermore, we will check for inconsistency in the participants' answers by repeating a subset of geometries, and the participants will be allowed to interrupt the survey after each geometry to cater to their roles in the organization. Ideally, approximately 40 experts participate in the labeling.

4.2.2.1 General considerations for our survey

We aim to determine part complexity in sheet metal processing and identify part characteristics that influence the part complexity. The material of the part is not directly relevant to the research question, but plays a vital role in evaluating the parts' complexity nonetheless. While the material indirectly influences a part's complexity due to differing properties like the materials' melting point, it provides no direct influence, which our research question concentrates on. However, if we—in addition to the complexity labeling of the geometries for each process step—ask the labeling participants to rate the complexity stemming from the material and the sheet thickness, the remaining answers may not be as precise as if we determine the material and sheet thickness before the labeling due to several reasons:

- Decision fatigue: The quality of each decision declines with the number of decisions to be made.
- Risk of dropping out: The more questions we ask, the longer it takes the participants to complete the labeling, increasing the risk of participants dropping out, and decreasing our expected database. Hence, it is likely to increase the data quality if we ask only the necessary questions.
- Alignment with the research question: We want to identify part characteristics influencing the part complexity. For a research question targeting the influence of sheet thickness and material, other research designs may be more suitable.
- Providing necessary information: If applicable, we want to provide information about the geometries within our survey.
- Risk of confusion: If we ask the participant for part complexity, complexity due to material, and complexity due to sheet thickness, it is possible that participants first select the material and sheet thickness, and then label the part complexity, while others may have a different approach. This would interfere with congruent data collection. If we ask

the participants in the first step for part complexity and in the second step for complexity stemming from material and sheet thickness, we increase the time required for the labeling and hence, the risk of dropping out.
- Risk of ambiguity: If we do not define the material and sheet thickness before the labeling and leave it up to the participants to decide which material and sheet thickness they are labeling, we put the quality of our collected data at risk.

Due to the reasons named above regarding decision fatigue, risk of dropping out, and risk of low data quality, we determined the material and sheet thickness before conducting the survey. By choosing the most used material for the exemplary production unit and the most used sheet thickness for this material, we broaden the applicability of our results.

4.2.2.2 Determining the Scale Design

In our survey, we want to ask our participants a rating question ("How complex do you think this geometry is?"), using a rating scale. According to Cooper and Schindler [2003], ordinal scales are used for rating and usually provide between 3 to 7 answer alternatives. Since we only want to measure the parts' complexity and no other characteristics, we will use a unidimensional scale instead of a multidimensional scale. We will use a balanced scale that provides an "equal number of categories above and below the midpoint" [Cooper and Schindler, 2003] (p. 272). Still, we want to exclude the possibility of the participants remaining neutral in their rating by excluding the average score, making our scale a forced-choice rating scale instead of an unforced-choice rating scale. Forced-choice rating scales inhibit the risk of producing a bias when many participants want to select medium complexity but are not given this opportunity [Cooper and Schindler, 2003]. However, we strongly assume that in our case, the majority if not all participants will have an opinion on a part's complexity, and from our point of view, the risk of producing a bias is smaller than the risk of indecisive participants. Hence, we decide between a Likert scale ranging from 1 to 5, as Liu et al. [2022] and Greco et al. [2022] did, and 1 to 7 to provide a more sophisticated distinction between different degrees of complexity. Since we assume that a distinction between not complex (1), a little bit complex (2), more complex (4), and highly complex (5), we choose a Likert scale ranging from 1 to 5 without the average response option to not give too many options to choose from and avoid participants choosing the middle option out of decision fatigue. The scale is depicted in Figure 4.2.

By only providing this scale as an answer option, we designed our survey to have structured responses, sometimes also named closed responses [Cooper and Schindler, 2003].

To conclude, our scale is a multiple-choice, single-response scale so that participants cannot answer with more than one value per question.

Fig. 4.2: Part complexity labeling scale. Own visualization.

In addition to the scale rating of a part's complexity for each production process step, we will ask the participants to explain the selection of a certain complexity. For their explanation, we could provide drop-down menus with an additional free comment section. By providing a drop-down menu, we might produce a bias in the participants' responses, since it is less time-consuming to select multiple answers in a drop-down menu than typing their answers. Hence, we decided not to provide such a drop-down menu and just asked the participants to explain each labeling in a mandatory text box.

4.2.2.3 Individual Depth Interview

Individual depth interview is the term for an interview with a person involved in the problem to be analyzed [Cooper and Schindler, 2003]. Individual depth interviews usually are rather conversational than structured and are held by one interviewer and one interviewee [Cooper and Schindler, 2003]. According to Cooper and Schindler [2003], individual depth interviews usually last a minimum of 20 minutes, while the total length depends on the topic of the interview. Individual depth interview participants may receive monetary compensation for their participation in the interview and may be provided with informative material as preparation for the interview [Cooper and Schindler, 2003]. A common use case for individual depth interviews is the area of business research [Cooper and Schindler, 2003].

We aim to gain more information about the exemplary production unit and geometrical characteristics that may influence the part complexity before conducting our survey to ensure coverage of the most important geometrical characteristics. The leading question of the individual depth interview is which geometrical characteristics are typically hard to manufacture with the exemplary production unit. The employees suitable for the individual depth interview also qualify for participation in the labeling due to their experience with the production unit. To avoid possible interference between the individual depth interview and our survey, we conduct the individual depth interview as early as possible to minimize the effects of the individual depth interview on the survey results. Moreover, we want to minimize possible interference between the individual depth interview and our survey results by minimizing the participants of the individual depth interview. In consequence, we start by conducting one individual depth interview with one employee.

Further individual depth interviews will be conducted if the information from the first individual depth interview is not sufficient to create the geometries for the survey.

4.2.3 Determining the Number of Geometries for the Survey

Ideally, we had ensured that the geometries selected for the labeling represent the majority of sheet metal geometries of TRUMPF customers for the exemplary production unit. Due to the large variety of sheet metal parts, this was highly difficult to impossible. The definition of the sample size was difficult since usual characteristics like the size of the target population or the population parameters [Cooper and Schindler, 2003] were unknown: Although we knew from how many geometries we drew our probability sampling, in reality, an infinite amount of different sheet metal parts existed. Hence, we used the previous research on the complexity from Section 3.2 as guidance: While Camba et al. [2019] used 370 geometries, Contero et al. [2023] used 95, Joshi and Ravi [2010] used 40, and Bodein et al. [2014] used 10. The two latter sample sizes seemed rather low, so we defined 80 as our sample size. One needs to remember that we aim to satisfy two opposing requirements with our geometry sampling size: On the one hand, the authors of [Cooper and Schindler, 2003] defined 10 minutes as the maximum length for a CASI, resulting in a limited number of geometries. On the other hand, we want to repeat a subset of our geometries to assess our participants' trustworthiness, increasing the number of geometries to be labeled and consequently, the time required for the labeling. Additionally, we wanted the number of geometries labeled to be sufficient to get statistically relevant results. Hence, we randomly selected the desired number of geometries from the database. For confidentiality reasons, we altered the geometries based on the geometries from the probability sampling to align with intellectual property and non-disclosure agreements by altering geometrical characteristics. These alterations included changing the size of the length in x- and y-direction, the number of inner contours, the size of the inner contours, the location of the inner contours, by adding or subtracting inner contours, by adding the general shape of the geometries, by adding geometrical characteristics identified in the individual depth interview like length and narrowness, and by deleting geometrical characteristics that seemed identifiable like a specific arrangement of inner contours. Afterward, we checked if the created data set abided by the minimum and maximum part dimensions of the chosen production unit. Lastly, we compared our geometries with the results from the individual depth interview to ensure that our probability sample contains sufficiently diverse geometries.

4.2.4 Part Complexity Labeling Participants

The labeling participants should be experts on the selected machine tool. Hence, we will perform purposive sampling [Cooper and Schindler, 2003] to select the labeling participants purposefully based on their expertise in the sheet metal processing production processes. To ensure that a variety of perspectives on complexity is covered, we want at least two people per area to label the geometries, covering product management, development, remote operation, and, if possible, customers:

1. The Product Management is responsible for the whole product. Hence, we assume that product managers have a profound understanding of the machine tool.
2. Since Development has developed the exemplary production unit TruLaser Center 7030, we believe that they know exactly what the strengths and weaknesses of the machine tool are.
3. The remote and machine operators work with the machine tool in their everyday lives and know how the exemplary production unit behaves in practice.

4.2.5 Evaluation Mechanisms in our Methodology

Before we implemented our labeling approach, we evaluated it with a pilot test. Although such a pilot test should have 25 to 100 people according to Cooper and Schindler [2003], we opt for a much smaller group size of one pilot tester due to the few experts. The results of the pilot test focused on having a drop-down menu for the sheet thickness, performance issues of the labeling tool that we did not detect in the tests prior, and formulation of questions.

We incorporate further mechanisms to evaluate the results of our data collection. To not only collect one point in time, but over a period of time, we perform a longitudinal study instead of a cross-sectional study [Cooper and Schindler, 2003] by choosing a period of three weeks for the labeling. For stability testing of our measurement, we perform a test-retest by repeating a subset of geometries over time to learn if the experts rate the geometries consistently, as discussed above. We want to repeat 10 geometries each week so that the labeling participants label 23 new geometries and 10 repeating geometries for their complexity.

4.2.6 Own Contributions and Comparison with Literature

Figure 4.3 presents the components of our methodology and their origin. The basis for our survey are the computer-assisted self-interviews, explained in Cooper and Schindler [2003]. To better understand the chosen production unit, we conducted an individual depth interview and used Cooper and Schindler [2003] as a guideline. [Cooper and Schindler, 2003] also provided information about scale types and characteristics, which we used to design the scale incorporated in our CASI interface. We incorporated the other features in our survey: We decided to use mandatory text boxes in addition to the scales to get more information about why the participants chose the complexity for the given part. Based on our individual depth interview results, we incorporated visualizations of the geometries and visualizations of the most important geometrical characteristics, namely the bounding box, the convex hull, and the centroid. Furthermore, we included further geometrical characteristics like material and sheet thickness, the part weight and area, the length and width of the bounding box, the ratios of the part area to the bounding box area, the part area to the area of the convex hull, and how the exemplary production unit can unload the part.

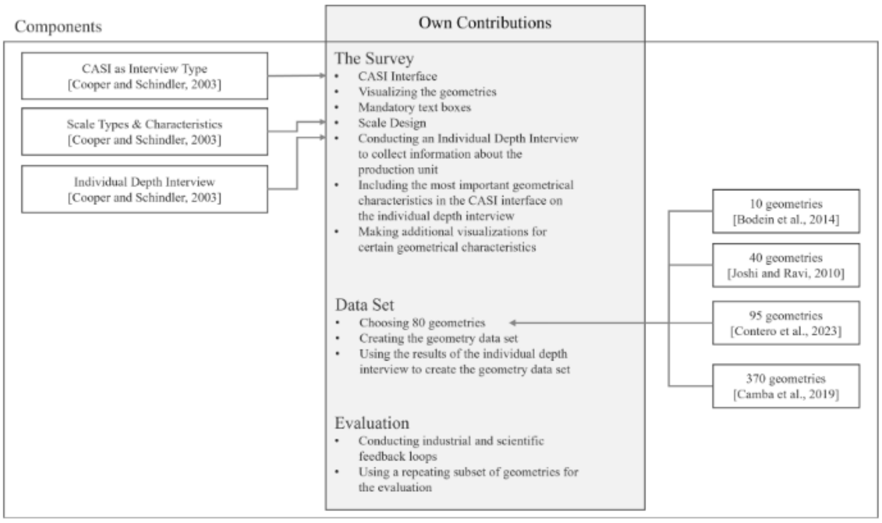


Fig. 4.3: Own contribution to the part complexity assessment methodology. Own visualization.

We used the literature as an orientation for the number of geometries used in the data set, in addition to the general considerations regarding decision fatigue and the risk of participants dropping out of the survey. While Bodein et al. [2014] and Joshi and Ravi [2010] used a rather little number of geometries with 10 and 40 geometries, respectively, Contero et al. [2023] and especially Camba et al. [2019] used a larger number of geometries with 95 and 370 geometries, respectively.

To evaluate our methodology, we employ industrial as well as scientific feedback loops prior to conducting the survey to improve our methodology further. In addition, we use a repeating subset of 10 geometries to be labeled each week to be labeled each time by the participants. This way, we can analyze the participants' labeling consistency over time and eliminate inconsistent process step labelings to improve the quality of our dataset.

As a next step, we compare our methodology to the approaches in the literature. The authors of Joshi and Ravi [2010] start their complexity assessment by asking part designers and tool makers and derive important features from this interaction, comparable to our individual depth interview. In contrast to our scale from 1 to 5 without the middle option, they use a scale from 0, indicating low complexity, to 5, indicating high complexity. Instead of a survey, they compute the complexity based on the features derived from their equivalent of the individual depth interview. For validation, they perform their equation on parts that were not used in the regression analysis they employed before.

In Contero et al. [2023], they aim to assess the complexity of CAD models rather than parts and do not perform an individual depth interview but rely on a literature review. They also perform a survey with five experts, visualizing the models in the survey. Instead of a scale rating, they let the experts chose which of two CAD models is more complex than the other.

The authors of Bodein et al. [2014] start with individual depth interviews of 20 people. They have 10 people in their survey and analyze ten parts. Their goal is to assess the complexity of CAD models based on design times.

In Camba et al. [2019], they also use an interface for users and analyze the complexity of 370 CAD models but do not state how many users participated.

Since we compare the methodologies, we did not focus on similarities and differences between the features used.

The differences between our methodology and the approaches from the literature are manifold: While previous work also employs computer-administered interviews [Camba et al., 2019; Contero et al., 2023] and visualizations [Contero et al., 2023] or scales [Joshi and Ravi, 2010], we did not find previous work utilizing mandatory text boxes to explore the reasoning behind the chosen complexity. In addition, we did not find previous work using a subset of repeating subset of geometries to analyze the consistency over time, aiming to exclude results with high deviations from further analysis.

4.3 Adapting the Methodology to the TruLaser Center 7030

Based on the preliminary considerations of the research design presented in Subsection 4.2, we developed a non-standardized qualitative-empirical research approach for the labeling of sheet metal parts' complexity, which is characterized by the combination of methods such as surveys and subsequent data analysis. We will employ this research approach in a case study at TRUMPF, using the highly automated laser cutting machine TruLaser Center 7030 as an example (see Subsection 2.4).

In this subsection, we first explain the chosen production unit in detail. Subsequently, we present our research approach, including the interface of our labeling tool.

4.3.1 Individual Depth Interview

As explained in Subsection 4.2.2.3, we conducted an individual depth interview to further explore the TruLaser Center 7030. We selected a remote operator of the TruLaser Center 7030 for our first individual depth interview to gain more information about which geometries to select for our labeling of the sheet metal part complexity. These are the geometry characteristics that influence the part complexity for the TruLaser Center 7030 resulting from our individual depth interview:

Laser Cutting:

- Small circular part
- Small circular inner contours
- Sheets thicker than 10 mm with many inner contours close together
- Sheets thinner than 2 mm and big parts
- Big inner contours

Part Handling with SortMaster Speed:

- Sheet thickness thinner than 2 mm and big parts
- Many inner contours
- Small web width, web width smaller than the circumference of the vacuum cups
- Narrow parts longer than 2 m
- ”Crazy parts”
- Coated sheets that decrease the electrical conductivity

Part Handling with SmartGate:

- Snowflake-like, frayed outer contour
- Bigger than 160 mm x 160 mm
- Sheet thicker than 10 mm
- Sheet thinner than 1 mm

We deem the results of the individual depth interview stated above sufficient for creating the geometry data set for the survey. We do not conduct a second individual depth interview.

4.3.2 Determining the Material and Sheet Thickness

We investigated the material of the sheets produced on machines of the type TruLaser Center 7030 over the course of twelve months, from July 2022 to August 2023, as presented in Table 4.1. Since mild steel is the most commonly used material with a share of 66.2 %, we selected mild steel as the material for the labeling.

Count	Percentage	Material
180355	66.2 %	Mild steel
35441	13 %	Aluminum
31135	11.4 %	Stainless steel
12498	4.59 %	Hot-dip galvanized mild steel
8434	3.1 %	Electrogalvanized mild steel
2735	1 %	Coated stainless steel
1068	0.39 %	Copper
452	0.17 %	Oxidized mild steel
132	0.05 %	Brass

Table 4.1: Material produced on TruLaser Center 7030 machines in the period of 07/2022 to 08/2023

This way, our labeling results will apply to the majority of the produced sheets. One needs to keep in mind that we can only analyze the material of machines that are connected to TRUMPF and not of the machines of the type TruLaser Center 7030 that do not send data. Moreover, we did not investigate the material of the parts, but of the sheets that have been produced on the connected TruLaser Center 7030. By doing so, we avoid a bias in the data produced by a possibly higher number of small parts nested on sheets in contrast to large parts. Moreover, the participants might answer the complexity questions for the material and sheet thickness they selected, making their answers non-comparable and would decrease the answers' usability to answer the research question.

In addition to the material, we pre-determine the sheet thickness. Like the material, the sheet thickness influences a part's complexity. Exemplarily, delicate inner contours are harder to cut in thicker material since the slag might solidify in the kerf, hindering the cutting of the part. Moreover, different materials may behave differently at the same sheet thicknesses. Although these phenomena may be relevant for future production decisions, we solely want to concentrate on geometrical features that influence the part complexity. If we incorporate additional questions targeting the influence of material and sheet thickness in our complexity assessment, we risk decision fatigue, diminished quality of the responses, and a higher dropout rate due to the increased time required for the labeling. Table 4.2 presents the sheet thicknesses used for mild steel from July 2022 to August 2023.

Sheet Thickness in mm	Share in %
1	10.1
1.3	0.7
1.5	14.66
2	12.68
2.5	5.31
3	17.9
3.5	2.94
4	14.08
4.5	7.28
5	4.48
6	2.1
6.35	3.68
7.87	2.67
8	0.76
10	0.49
12	0.12
12.7	0.02

Table 4.2: Sheet thicknesses of mild steel produced on TruLaser Center 7030 machines from 07/2022 to 08/2023.

The majority of the mild steel sheets have sheet thicknesses ranging from 1 mm to 5 mm. Furthermore, 5.78 % of the sheets have a thickness of 6 mm or 6.35 mm, while 3.43 % of the sheets have a sheet thickness of around 8 mm. Only 0.49 % of the sheets have a thickness of 10 mm, and 0.14 % of the sheets have a thickness of 12 mm or higher. The sheet thickness most common in mild steel sheets is 3 mm with a share of 17.9 %. Hence, we decided to use 3 mm mild steel sheets for our complexity labeling.

4.3.3 The Part Complexity Labeling Survey

In this subsection, we explain the structure of our labeling tool and present the final supporting labeling tool for our computer-assisted self-interviews.

4.3.3.1 Folder structure

The folder structure of our labeling tool is depicted in Figure 4.4. The labeling participants received the labeling tool, called GeoLabeler.exe, and the folder called geometries. The geometries folder contains 33 to 34 geometries, depending on the week of the labeling. Furthermore, this folder stores an

Excel file that contains the user names of the participants. Lastly, the geometries folder contains an Excel file with the pre-calculated geometrical characteristics. Pre-calculating the geometrical characteristics improves the performance of the labeling tool since less computational capacity is required. The file GeoLabeler.exe contains the Python code for the labeling tool.

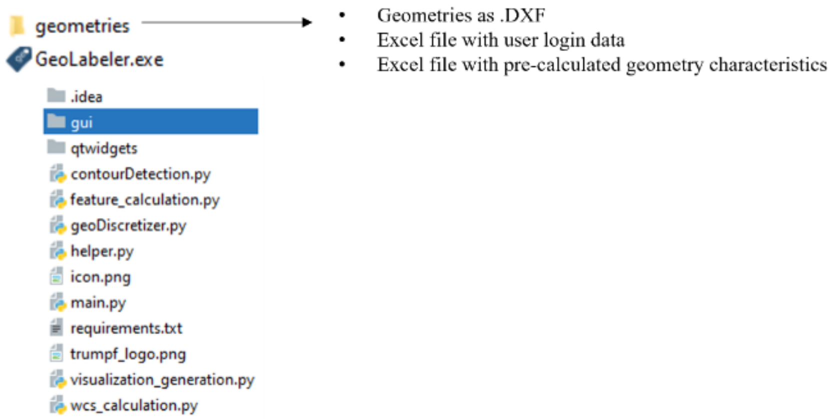


Fig. 4.4: Folder Structure of the Labeling Tool. Own visualization.

During the labeling, a log file is created and stored on the same level as the GeoLabeler.exe and the geometries folder. In case of malfunctions, we can use this log file to identify the root cause. Additionally, the resulting Excel file containing the users' labeling results is also stored here. After the users have completed the labeling, the users send it back to us via e-mail.

4.3.3.2 CASI interface

To support the labeling, we developed a computer-assisted self-interview (CASI) in the form of our labeling tool. We only show here the final version of the labeling tool, in which we considered all the adjustments from the industrial and scientific feedback loops as well as the recommendations from the participants.

Figure 4.5 shows the welcome log-in screen of the labeling tool, where the users log into the labeling tool with their user names.

The next figure, Figure 4.6, shows the labeling tool instructions the users see every time they start the labeling tool. First, we thank them for their participation and explain that they will label the geometry complexity in terms of their manufacturability on the TruLaser Center 7030 for the three process steps of laser cutting, part handling with the SortMaster Speed, and part handling with the SmartGate. We explained this production unit previously in Subsubsection 2.4. We explain that they will label 100

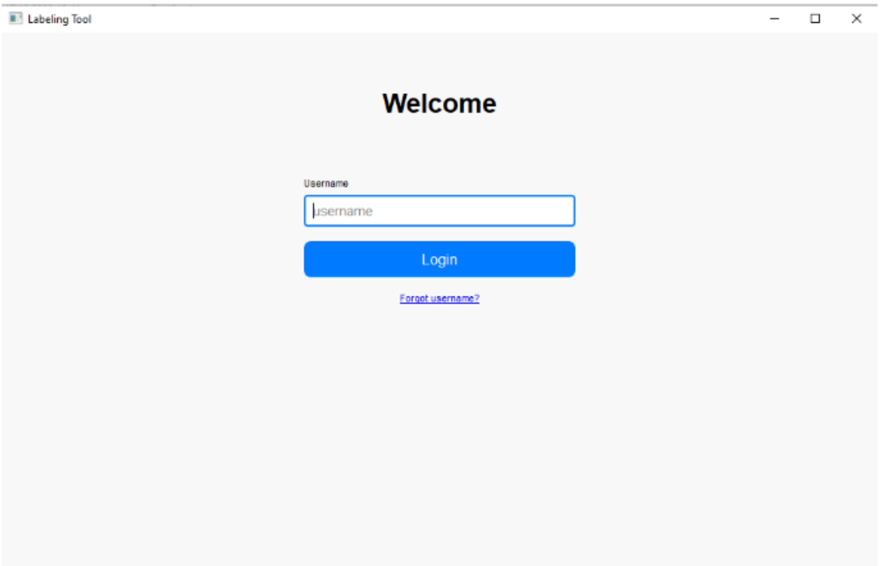


Fig. 4.5: Log-In Screen of the Labeling Tool. Own visualization.

geometries over three weeks with the material of mild steel and a sheet thickness of 3 mm, since this material and sheet thickness has been the most used in the past year. We tell them that we will provide additional geometric information in the labeling tool like the part area, width, and length, and ask them to provide us with an explanation of why they labeled the way they did. We remind them to contact us whenever they have further questions.

We gave the participants all this information previously in the meetings where we asked them to participate. Despite the redundancy, we decided to give them all this information again to minimize possible misunderstandings that could negatively impact the labeling results.

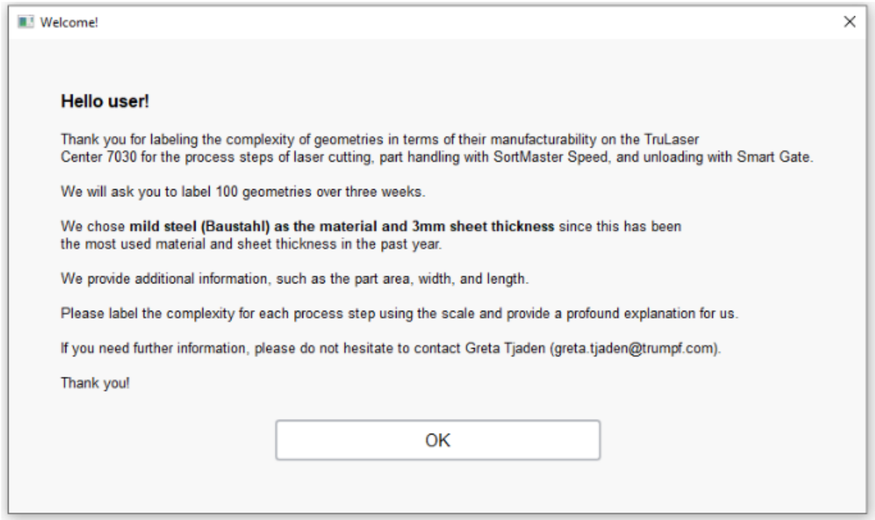


Fig. 4.6: Welcome Interface of the Labeling Tool. Own visualization.

Subsequently, the participants are at the labeling tool interface, which is depicted in Figure 4.7. The labeling participants label the complexity of each geometry for each process step of the TruLaser Center 7030: Laser cutting, part handling with the SortMaster Speed, and part handling with the Smart Gate. As an example, we chose a geometry that is suitable for both part handling with the SortMaster Speed and the Smart Gate. At the top, the participants see how many geometries they have labeled out of the total number of geometries. In this case, we see geometry number 26 of 33. Below, the geometry is visualized with scales in both x- and y-direction to give the participants the geometrical dimensions. The labeling participants can additionally choose to visualize the part's bounding box (red), its convex hull (blue), and its centroid (green) for further information in the lower right corner. These visualizations are also depicted in Figure 4.7. At the lower left corner are the scales for the labeling of the complexity of the three process steps. The scales from 1 (least complexity) to 5 (maximum complexity) without 3 as the middle option, as explained in Subsubsection 4.2.2.2. On the left side of the scales, the users document an explanation for their labeling. These explanations are mandatory. Next to the explanation boxes and left to the sliders for the visualization of the bounding box, the convex hull, and the centroid is the table with the additional geometrical information:

- Material mild steel
- Sheet thickness 3 mm
- Part weight in kg
- Part area in cm^2
- The dimensions of the bounding box (red) in x- and y-dimensions

- The ratio of the part area to the area of the bounding box (red)
- The ratio of the part area to the area of the convex hull (blue)
- The unload type: SortMaster Speed, Smart Gate, or both

When the participants have labeled each geometry and provided an explanation for their labeling choices, they can go to the next geometry using the Next button in the lower right corner. For practicality, we also included a Save and Exit button. If the participants have to go back to their jobs immediately, they can close the labeling tool this way and continue exactly where they left off when they start the labeling again.

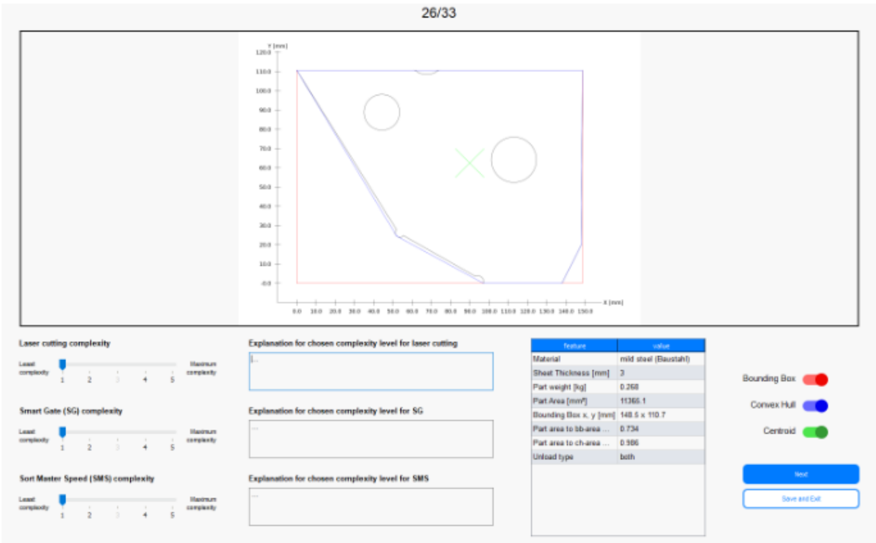


Fig. 4.7: Interface of the Labeling Tool. Own visualization.

When the participants have labeled each geometry for the week, the closing window from Figure 4.8 reminds them to send us the resulting Excel file.

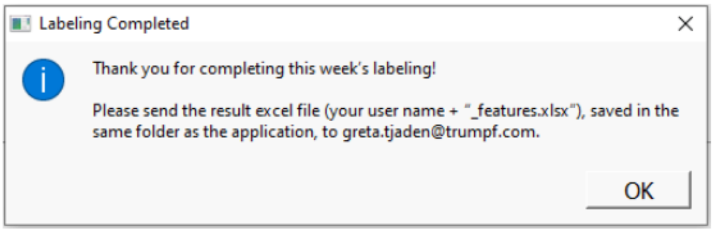


Fig. 4.8: The closing window of the labeling tool interface. Own visualization.

4.3.4 Geometries for the Survey

To create the geometry data set for the labeling, we followed the approach presented in Subsection 4.2.3.

4.3.4.1 Creating the Geometry Data Set for the Survey

We decided to use a geometry database of approximately 16,000 geometries of one customer that was transferred to TRUMPF almost a decade ago. While the timeliness and representativity of this database seem arguable, given that it is rather old and only stems from one customer, the benefits due to the lower risk of violation of non-disclosure agreement and intellectual property outweigh by far.

We randomly select 80 geometries for the complexity labeling from the selected database at TRUMPF, using random sampling. As mentioned previously, we alter these geometries to comply with intellectual property and non-disclosure agreements while distributing these geometries for labeling. The aim was to later calculate the necessary geometrical features for the labeling and to identify the linkage between geometrical features and part complexity if given. The features are shown in Table 3.4 in Subsection 3.2.3.3. We manually altered the geometries as described in Subsection 4.2.3

We randomly select the repeating subset of 10 geometries using the same approach as for the 80 geometries. To avoid participants finding out about the repeating subset, which may influence their labeling results, we checked the 10 randomly selected geometries for memorable geometries. As the last step, we switched out highly memorable geometries for less memorable ones. The geometry data set has been published in Tjaden et al. [2024] and in [Tjaden, 2024].

4.3.4.2 Explorative Data Analysis of Geometry Data Set

We want to give ourselves and the readers an overview of the resulting geometry dataset with an explorative data analysis. We do not aim for an exhaustive analysis but utilize features for this analysis that give a good overview of the geometry dataset. The features partially align with the features from Table 3.4 from Subsection 3.2.3.3 that are used later in the analysis and were complemented with features mentioned in talks with fellow researchers. As visualized in Figure 4.9, the majority of the geometries is handled exclusively with the SortMaster Speed, which is 63 geometries or 78.75 %. In contrast to this, 11 geometries or 13.75 % are exclusively unloaded with the SmartGate, and 6 geometries or 7.5 % apply to both unloading options. Figure 4.10 shows the length of the bounding boxes in the x- and y-direction. We can observe many geometries having smaller lengths and widths, while there are also some geometries having maximum lengths and widths for our exemplary production unit.

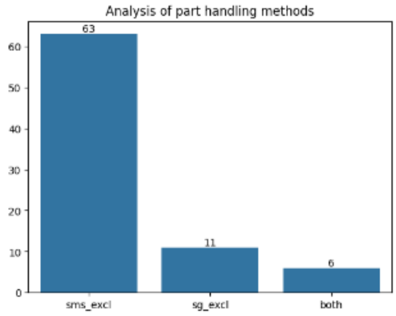


Fig. 4.9: Part handling methods. Own visualization.

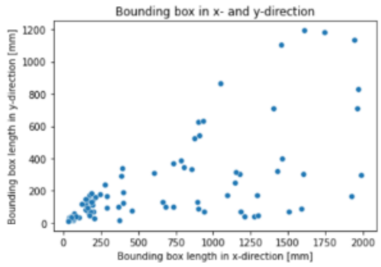


Fig. 4.10: Bounding box length in x- and y-direction. Own visualization.

Figure 4.11 shows that 59 geometries have inner contours, while 21 geometries do not. As we can see in Figure 4.12, the majority of the geometries having inner contours have between 1 and 15 inner contours. Some geometries have between 16 and 31 inner contours. In addition, two geometries have 52 and 219 inner contours, which makes them the geometries with an extraordinarily high amount of inner contours.

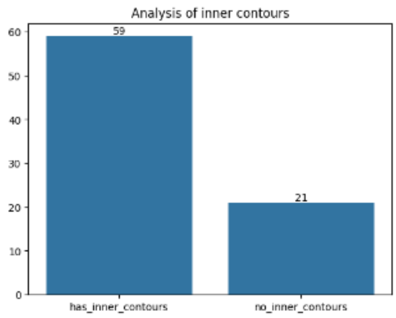


Fig. 4.11: Amount of geometries having inner contours. Own visualization.

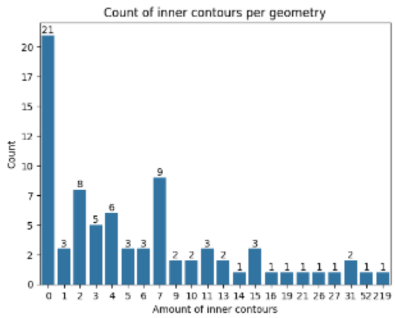


Fig. 4.12: Amount of inner contours per geometry. Own visualization.

In Figure 4.13, we see the boxplot of the area of the inner contours. Although the majority of the area of the inner contours is rather small, we have a significant number of outliers. Figure 4.14 visualizes the link between the amount of inner contours and the cutting degree, which we defined as the quotient of the sum of all inner contour areas and the area of the outer contour. As we can see, there is no direct relation between the amount of inner contours and the cutting degree.

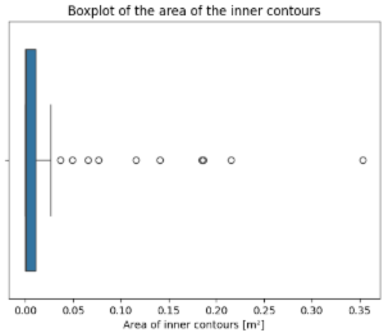


Fig. 4.13: Boxplot of the area of the inner contours. Own visualization.

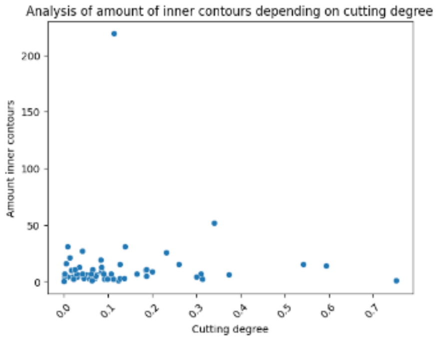


Fig. 4.14: Amount of inner contours and the cutting degree. Own visualization.

The geometry depicted in Figure 4.15 with 1 large inner contour has the highest cutting degree, while the geometry with 219 inner contours depicted in Figure 4.16 has small inner contours, which leads to a rather small cutting degree.

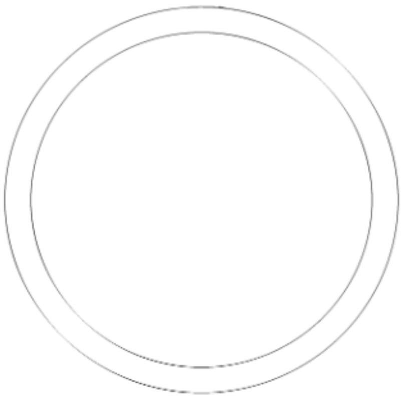


Fig. 4.15: Geometry with the highest cutting degree. Own visualization.

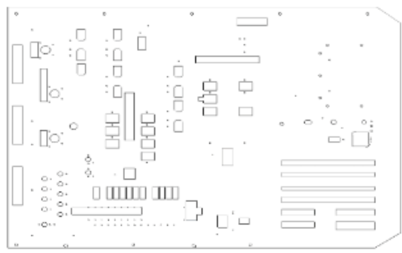


Fig. 4.16: Amount of inner contours per geometry. Own visualization.

As Figure 4.17 shows, the centroid lies on the geometry for the majority of the geometries, with 62 geometries in contrast to 18 geometries where the geometry does not lie on the part.

The next figure, Figure 4.18, shows the boxplot of the cutting length. We can see that the cutting length is unevenly distributed, with the median below 2,500 mm, the majority of the parts having a cutting length below 10,000 mm, and outliers having more than 25,000 mm cutting length.

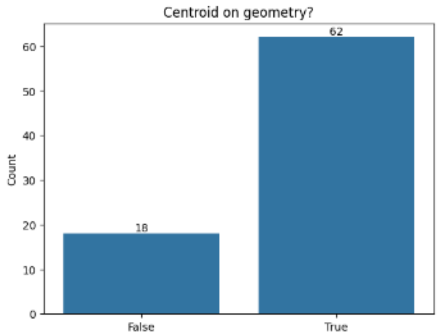


Fig. 4.17: Centroid on geometry. Own visualization.

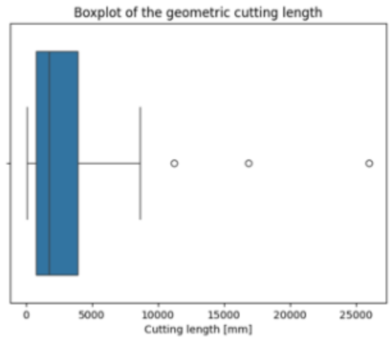


Fig. 4.18: Boxplot of the geometric cutting length. Own visualization.

In contrast to the cutting length, the geometric area depicted in Figure 4.19 has many outliers, although the huge majority of the parts have an area under 0.25 m^2. The smallest part has an area of 0.000314 m^2, while the biggest part has an area of 1.69 m^2. Figure 4.20 shows the link between the area of the geometries and the cutting length. As expected, the greater the area of the geometry is, the higher is also the cutting length. The majority of the parts have a cutting length of under 10,000 mm at an area of under 0.25 m^2. The part with the highest cutting length also has the greatest area. However, we cannot observe a proportional correlation between the area and the cutting length. It can be assumed that this is due to more complex outer contours or the presence of inner contours that impact the cutting length.

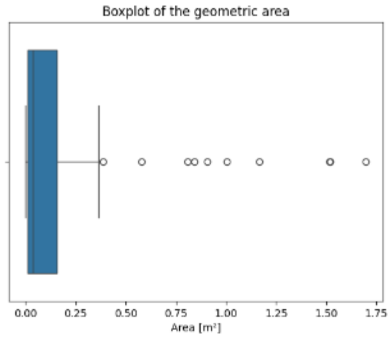


Fig. 4.19: Boxplot of the geometric area. Own visualization.

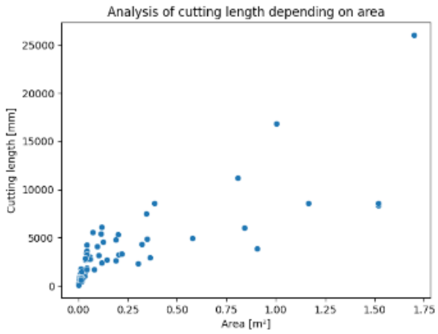


Fig. 4.20: Scatterplot of the cutting length depending on the area. Own visualization.

Figure 4.21 shows the rectangularity with a bin width of 0.1. We calculated the rectangularity as the ratio of the part area and the bounding box. Approximately half of the geometries have a rectangularity ratio of 0.8 or above.

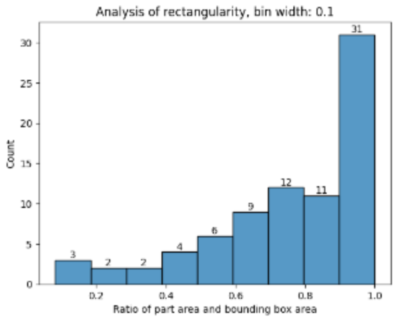


Fig. 4.21: Analysis of the rectangularity calculated as the ratio of part area and bounding box area. Own visualization.

Fig. 4.22: Geometry with a rectangularity ratio of 1. Own visualization.

As we can see in the Figures 4.22 and 4.23, these geometries are rectangular or similar. Figure 4.24 shows a geometry with a rectangularity ratio of 0.386, which does not resemble a similarity to a rectangular geometry.

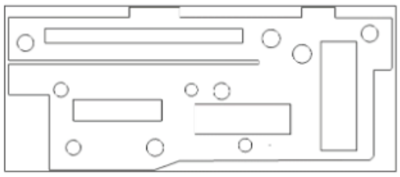


Fig. 4.23: Geometry with a rectangularity ratio of 0.827. Own visualization.

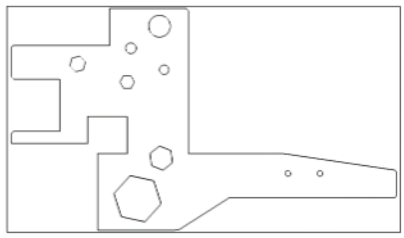


Fig. 4.24: Geometry with a rectangularity ratio of 0.386. Own visualization.

The minimum ratio of rectangularity is 0.082 and depicted in Figure 4.28. Figure 4.25 shows the distribution of the circularity with a bin width of 0.1. We calculated the circularity as the ratio of the part area and the area of a circle with the same circumference as the part. Figures 4.26 and 4.27 show geometries that resemble a perfect circle or a high similarity to a circle, respectively.

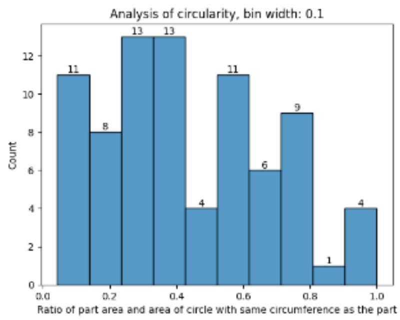


Fig. 4.25: Analysis of the circularity calculated as the ratio of the part area and the area of a circle with the same circumference as the part. Own visualization.

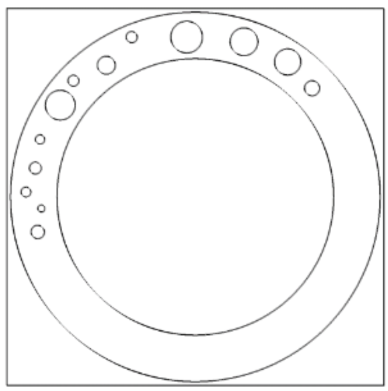


Fig. 4.26: Geometry with the maximum circularity ratio of 1. Own visualization.

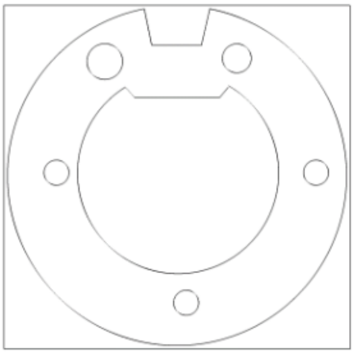


Fig. 4.27: Geometry with a circularity ratio of 0.877. Own visualization.

Fig. 4.28: Geometry with the minimum circularity ratio of 0.043. Own visualization.

Figure 4.29 shows the analysis of the undercuts for our dataset, which were calculated as the quotient of the circumference of the part and the convex hull. This calculation method is not free of flaws since it does not consider the criticality of the undercuts. For instance, a small undercut of a large length would have a low ratio of the part circumference and convex hull, although this undercut would make laser cutting more difficult due to its narrowness, and the part would become unstable due to its length. Since undercut caluclation is not the focus of our research, we decided to use this calculation method despite its flaws. The majority of the parts has little to no undercuts with a ratio of below 1.2. The maximum ratio of our dataset of 2.19 is achieved by the geometry shown in Figure 4.30. The lowest ratio of undercuts is 1 and depicted in Figure 4.22.

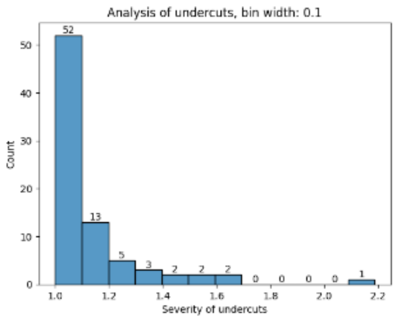


Fig. 4.29: Analysis of the undercuts calculated as the ratio of part circumference and convex hull. Own visualization.

Fig. 4.30: Geometry with the maximum undercut ratio of 2.19. Own visualization.

4.3.5 Selecting the Participants

To accelerate the process, we conducted the introduction meetings with the potential participants parallel to the development of the labeling tool. The introduction meetings always followed the same procedure: First, we presented ourselves and the dissertation project. Then, we presented the current status of the labeling tool and explained it in detail. We gave an overview of the labeling agenda with 100 geometries labeled in three sets over the course of three weeks. Lastly, we asked if anybody had questions for clarification, and who of the meeting members viewed him- or herself as suitable for the labeling. Some said they were not qualified enough regarding the chosen production unit to participate, and others said that they were not able to participate due to private leave from work, like parent leave. We considered suggestions made by the participants on how to improve the labeling tool, where possible.

We asked participants from the areas of product management, development, and remote and machine operation. In addition, we also considered recommendations from colleagues and potential participants to make the participants as diverse as possible to capture a holistic perspective on part complexity for our exemplary production unit.

Area of Origin	Number of Labeling Participants
Product Management	1
Development	3
Remote Operation	8
Machine Operation	13
Customer Center	9
Other	5
Sum	39

Table 4.3: Labeling Participants: Background and Results Analysis.

Table 4.3 indicates from which departments the participants stem: Product Management, Development, Remote Operation, Machine Operation, Customer Center, and Testing. Since the exemplary production unit has one product manager, one product manager participated in the labeling. Of the 39 participants in total, three employees from the area of development who developed our exemplary production units or parts of it volunteered for the labeling. Eight remote operators operate on the TruLaser Center 7030 unit remotely. The machine operators are the biggest group of volunteers, with 13 employees. The machine operators work with our exemplary production unit in the production facilities at TRUMPF and for the customers. Nine employees working in TRUMPF's customer center volunteered. The customer center is a showroom for the production units, and customers can experience the production units, ask questions, and produce exemplary parts on the production units. Two employees of the customer center preferred labeling the participants together. Five volunteers did not directly fit into any of the previous areas. Hence, we sorted them as "Other".

Due to confidentiality reasons, we semi-anonymized the participants by assigning a number to each participant, such as "P28". In Subsection 5.1, we analyze if the participants completed the labeling, and out of those, who passed the repetition test.

4.4 Discussion and Critical Reflection of the Research Approach

Despite our high efforts, our research approach is not flawless. To make our questions unambiguous, we predetermined the sheet thickness and the material, which limits the applicability of our labeling results. To evaluate the influence of both sheet thickness and material, further testing is required. Moreover, we manually altered geometries to comply with non-disclosure agreements and to protect intellectual property, which may influence our labeling results. This may limit the representativity of our labeling geometries, which are already limited by the fact that we chose 80 individual geometries for the labeling to balance the time bound by our survey and the knowledge research. In addition, the geometries are influenced by the results of the individual depth interview as a means to ensure a broad variety of complexity-influencing part characteristics in our geometry database for labeling. Moreover, we conducted the individual depth interview with an expert for the exemplary production unit, who also participated in the labeling. We tried to minimize this influence by scheduling the individual depth interview six months before the start of the labeling.

To evaluate the participants' labeling consistency and hence, the quality of our labeling results, we installed the repetition test by repeating ten geometries in each week of the labeling.

4.5 Interim Result: Assessing Sheet Metal Part Complexity

This thesis' first research question is **"How can we determine part complexity in sheet metal processing?"**. Until now, we have derived our definition of part complexity from the literature and adapted it to our domain of sheet metal processing. Furthermore, we developed a mixed-methods approach for the identification of part characteristics that influence part complexity, filling the research gap of a methodology for the assessment of part complexity that can be adapted to different use cases and industries. During the development of our methodology, we conducted several feedback loops of both scientific and industrial nature, and a pilot test to ensure a high quality. To allow for independent labeling and capture experts on different sites, we opted for computer-assisted self-interviews, a category of surveys. To further support these computer-assisted self-interviews, we built an online tool to assist in the labeling. The labeling tool presents a picture of the geometry as well as further information about its characteristics, such as the area. Furthermore, the labeling tool employs a multiple-choice, single-response, and forced-choice scale, similar to the Likert scales used in the literature, for the rating of the part complexity. In addition, the labeling tool provides a mandatory text box for the participants' explanation of the chosen complexity. To comply with non-disclosure agreements and protect intellectual property, we manually altered 80 geometries for our labeling database. To make our research design unambiguous, we pre-determined the material to be mild steel and the sheet thickness to be 3 mm, as this was the most produced material and of this material, the most produced sheet thickness of our exemplary production unit during the 12 months before the labeling. We asked experts for our exemplary production unit to participate in the labeling, stemming from the areas of product management, development, remote operation, machine operation, and the customer center. By adapting our methodology to our exemplary production unit, TRUMPF's TruLaser Center 7030, we demonstrated the methodology's transferability and applicability. To further evaluate our part complexity assessment methodology and fully answer our first research question, we will conduct it in Section 5.

Chapter 5

Part Characteristics Influencing Laser Cutting and Part Handling Complexity

This Section extends Tjaden et al. [2024]. First, we evaluate the dropout rate and the repetition test in Subsection 5.1, followed by analyzing the labeled complexities per process step in Subsection 5.2. Subsequently, we present the creation and evaluation of the codebooks as well as the final version in Subsection 5.3. In Subsection 5.4, we present the ten repeating geometries in detail, including the labelings and codebook categories. In Subsection 5.5, we try to transfer our labeling results to other geometries using regression and classification algorithms. Afterward, we discuss our research approach in Subsection 5.6, followed by the interim results in Subsection 5.7.

5.1 Labeling Completion and Repetition Test Results

As shown in Figure 5.1, we initially started with 40 participants in the labeling. Out of these 40 participants, half completed the first week. Subsequently, four more participants dropped out, while 16 participants completed the second week. 15 participants completed all three weeks of the labeling, making up 37.5 % of the starting group. The dropout rate is rather high with 62.5 % drop-outs and 37.5 % answers, despite the onboarding meetings, explanation of the Why, voluntary participation, inquiry coming from within the same organization, and reminders. However, the high dropout rate aligns with the experience of Cooper and Schindler [2003]. According to Wu et al. [2022], the average response rate for online surveys is 44.1 %, ranging from 34 % to 48.3 %. With our response rate of 37.5 %, we lie on the lower end of the expected response rate. The authors of Wu et al. [2022] further refer to Fosnacht et al. [2017], who observed that surveys with rather small sampling sizes need a response rate between 20 % and 25 % "to be fairly confident in their survey estimates" (p. 2). Our response rate lies far above this threshold. This indicates that the dropout rate does not diminish the quality of our survey results.

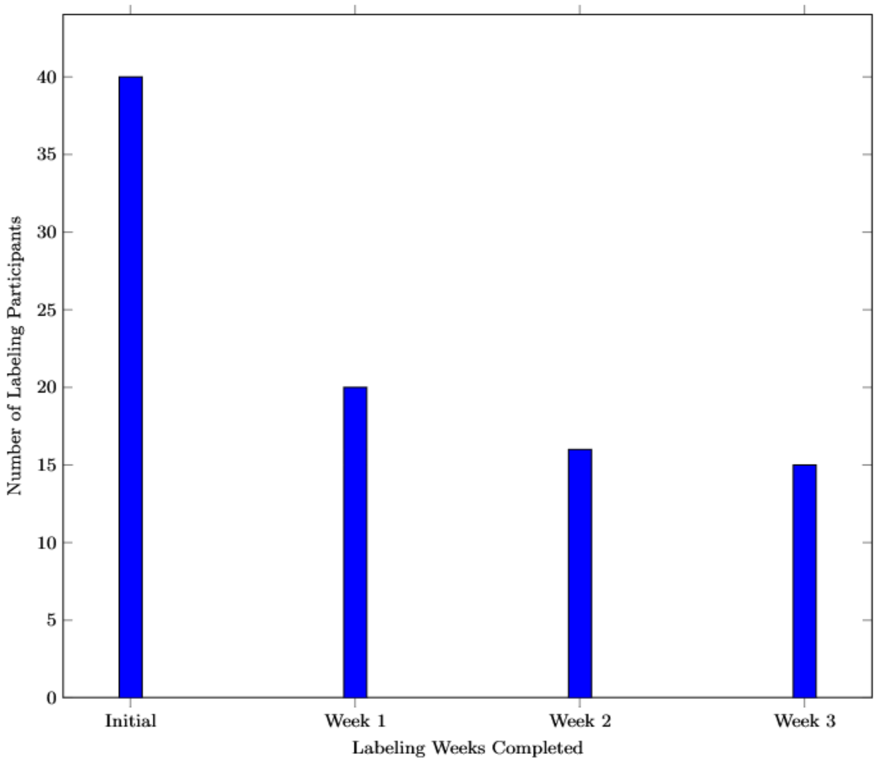


Fig. 5.1: Analysis of Completed Labeling Weeks

To allow for the evaluation of the consistency in the answers over time, we analyze the results of the repetition test of the 16 participants who completed a minimum of 2 weeks.

Ten geometries were randomly selected and repeatedly labeled each week, as described in Subsection 4.2.5, to analyze the consistency of the participants' answers. First, the repeating geometries are analyzed for each participant and process step. Unfortunately, we could not define limits of deviation in the literature that are suitable for our repetition test. This is why we defined the limits of deviation by ourselves: Deviation over time of 1 or no deviation is fine. This represents consistent labeling over the course of three weeks for this geometry. Critical are deviations greater than 1. Especially with our forced-choice scale design, where the middle value 3 is not an option, this means that the participant switched between low and high complexity. We defined 30 % as the critical limit of deviation: Below this limit, the participants are further considered; above this limit, the participants are excluded from further consideration for the affected process steps. The process steps of laser cutting and part handling with the SortMaster Speed were represented in the repeating geometries with 10 and 9 geometries, respectively. However, we only have two repeating geometries for the process step part handling with the SmartGate. Here, a critical deviation in one of the two parts already leads to more than 30 % deviation, excluding the participant from this process step. This results because the majority of the geometries are applicable for part handling with the SortMaster Speed and not with the SmartGate.

Figure 5.2 exemplarily shows the analysis of the repeating geometries for participant P1 and the process step laser cutting. The repeating geometries are named from A to J, while the numbers 0, 1, and 2 indicate the week of the labeling. Geometry A_1 is repeating geometry A from the second week of the labeling. For clearer visualization, each geometry has been assigned a color. Participant P1 has shown a high consistency in labeling: Eight of ten geometries have been labeled the same over the course of three weeks. Geometry B has a little deviation since it has been labeled with complexity 2 in the first week and complexity 1 in the two subsequent weeks. There is only one critical deviation for geometry C, which has been labeled with complexity 2 in the first week and complexity 4 in the two subsequent weeks. This results in a 10 % critical deviation for the process step laser cutting, which lies below the defined limit of 30 %. Hence, participant P1 passed the repetition test for laser cutting, and his or her labeling results for this process step will be considered in further analysis.

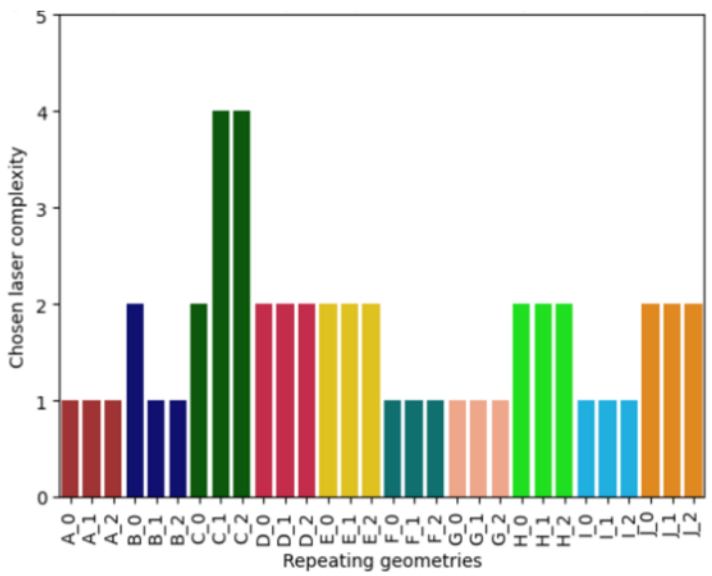


Fig. 5.2: Analysis of repetition test for participant P1 for the process step laser cutting. Own visualization.

We followed the same procedure for all participants and process steps. The resulting labeling deviations for all participants are visualized in Figure 5.3. On the x-axis, we see the participants, while the y-axis indicates the critical deviation. The process steps laser cutting, part handling with SortMaster Speed, and part handling with SmartGate are abbreviated in the legend with cutting, SortMaster Speed (SMS), and SmartGate (SG), respectively. The limit in critical deviation of 30 % is highlighted with the red dotted line. The three participants P4, P14, and P17 have labeled the geometries highly consistent and without any critical deviation. The five participants P19, P23, P27, P28, and P29 have labeled the geometries with critical deviation, but without reaching the limit for any of the process steps. P37 is the only participant who reached the limit of 30 % deviation for the process step laser cutting, while P1 and P16 reached the limit for the process step part handling with the SortMaster Speed. Participants P1 and P16 also reached the limit for part handling with the SmartGate, together with the six other participants P7, P12, P25, P30, P37, and P38. Concluding, one participant will not be considered for the process step laser cutting, and two participants will not be considered for the process step part handling with the SortMaster Speed. Eight and hence, half of the participants will not be considered for the process step part handling with the SmartGate. There is no participant which we fully excluded from the analysis.

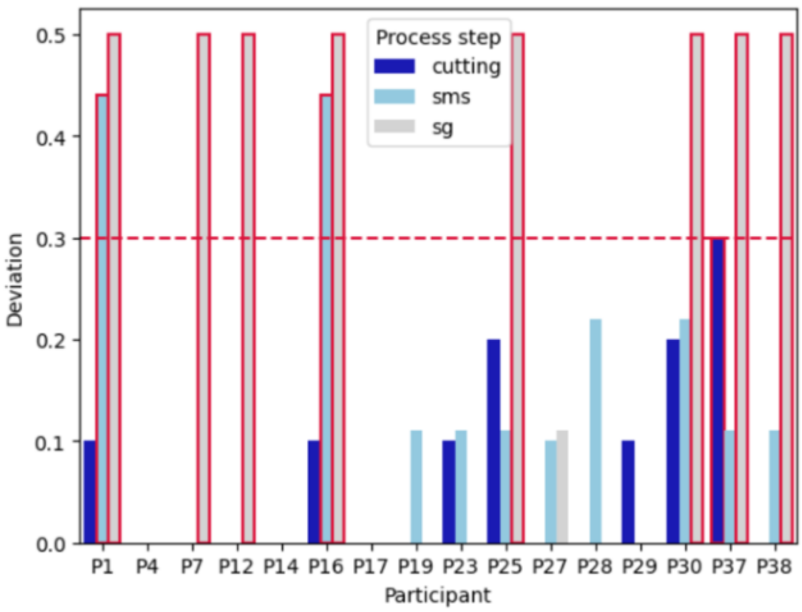


Fig. 5.3: Analysis of repeating geometries. Own visualization.

Due to the participants who dropped out, product management is not covered anymore in the labeling. This result could easily be expected since we only had one participant from this group. The area most participants cover is machine operation, with the five participants P12, P14, P16, P17, and P19 stemming from this area. Subsequent, we have the two areas remote operation and customer center, with each area having three participants: Participants P1, P4, and P7 belong to remote operation, while participants P25, P37, and P38 belong to the customer center. Two participants, P23 and P28, represent the area of development. It should be noted that participant P28 consists of two people who only wanted to participate as a group, not individually, as described in Subsection 4.3.5. For the three participants P27, P29, and P30, we could not identify their area, and they belong to the group "Other".

5.2 Analysis of Complexity

This subsection presents the chosen part complexities for the three process steps laser cutting, part handling with the SortMaster Speed, and part handling with the SmartGate. We only consider the participants who passed the repetition test for the respective process step. We analyze the participants' complexity labeling before the calculation of the average complexity of each geometry.

5.2.1 Laser Cutting

Figure 5.4 shows the chosen laser cutting complexity of the participants. With 1096 times, the majority of the complexity labelings were assigned with the complexity value 1. The second most chosen complexity class is complexity 2 with 344 labelings. Complexity class 4 was chosen 46 times, and complexity class 5 was chosen 7 times.

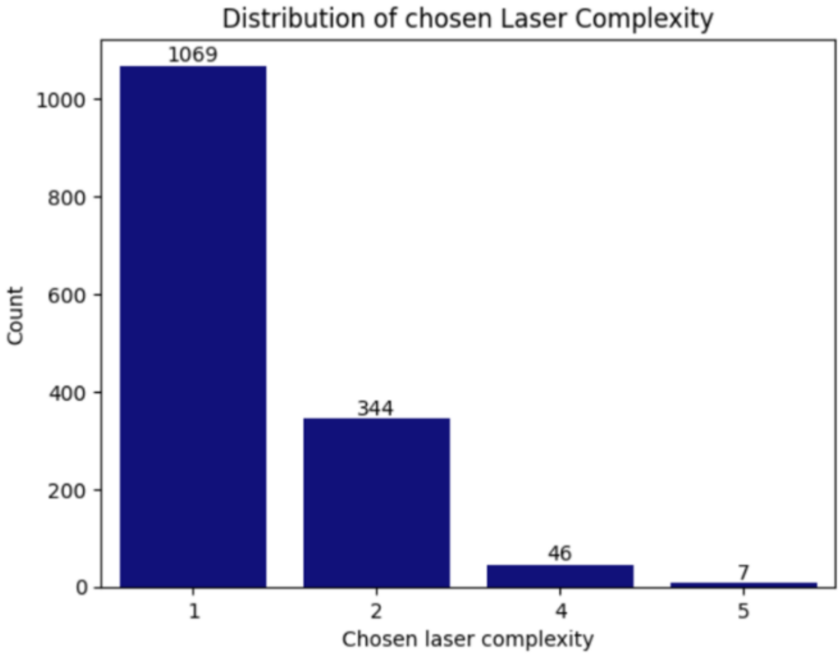


Fig. 5.4: Analysis of repetition test for participant P1 for the process step laser cutting. Own visualization.

Overall, the geometries in our labeling dataset were perceived as low complex with complexity values of 1 or 2, and only a few times, the participants chose the higher complexity classes of 4 or 5.

5.2.2 Part Handling with the SortMaster Speed

The chosen complexity for part handling with the SortMaster Speed is depicted in Figure 5.5. Since fewer participants passed the repetition test for part handling with the SortMaster Speed than for laser cutting and not every geometry was applicable for this part handling process, we see overall fewer labelings than for laser cutting. Complexity 1 was chosen 620 times, followed by complexity 2, which was chosen 314 times. Complexity 4 was chosen 132 times, while complexity 5 was chosen 35 times.

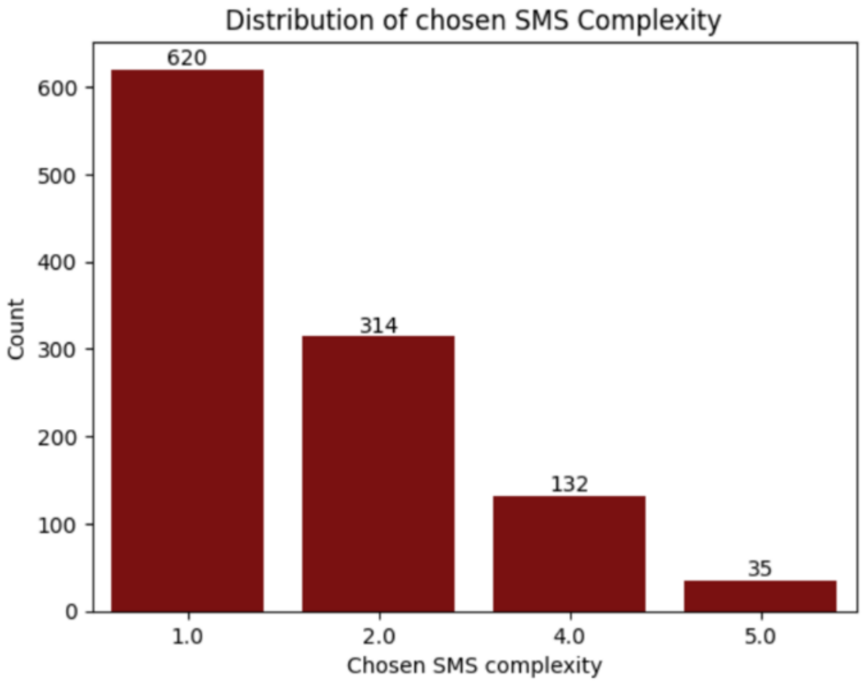


Fig. 5.5: Analysis of repetition test for participant P1 for the process step laser cutting. Own visualization.

The complexity labeling for the process step of part handling with the SortMaster Speed is imbalanced just like the complexity labeling for the process step laser cutting, although the gap between complexity 1 and 2 is not as severe as for laser cutting.

5.2.3 Part Handling with the SmartGate

Figure 5.6 presents the chosen complexities for the process step part handling with the SmartGate. Since the majority of the geometries in our dataset apply to this process step, we see the fewest labelings. While complexity 1 was chosen 135 times, complexity 2 was chosen 24 times. Complexity 4 was chosen 5 times, and complexity 5 was chosen 4 times. Again, we can observe an imbalance in the labeling, with a high gap between complexities 1 and 2.

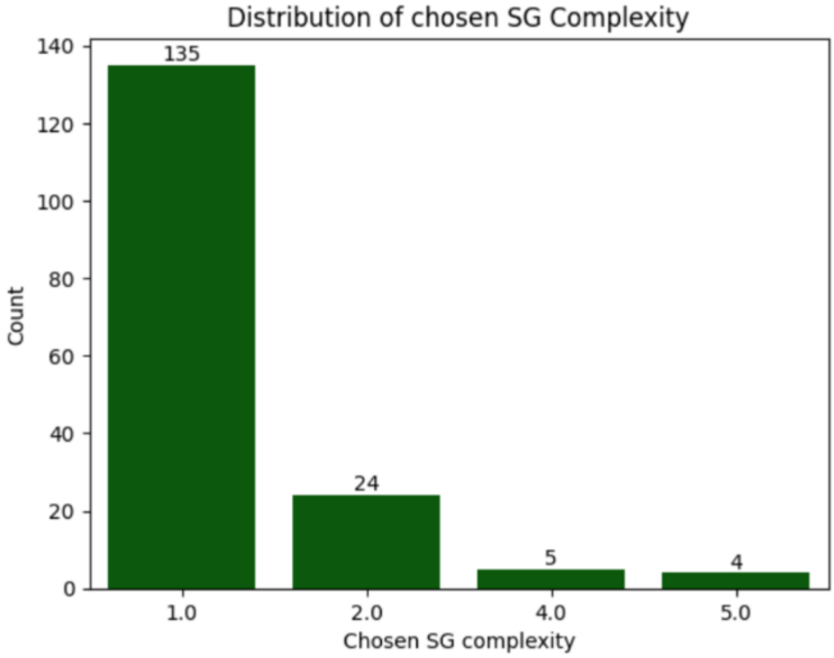


Fig. 5.6: Analysis of repetition test for participant P1 for the process step laser cutting. Own visualization.

5.2.4 Summary

We can see the most labelings for the process step laser cutting since each geometry applies to this process step, and almost all participants passed the repetition test for this process step. We can see an imbalance in the labelings with the most geometries being labeled with complexity class 1 or 2.

5.3 Categorizing the Complexity Explanations in a Codebook

This subsection presents the analysis of the explanations for the chosen complexities given by the participants. First, we create the codebooks containing the categorized explanations for each of the three process steps, presented in Subsection 5.3.1. Subsequently, we evaluate the codebooks, using both important characteristics of a codebook as well as a third-party evaluation adapted to our research, explained in Subsection 5.3.2. Concluding, Subsection 5.3.3 contains the resulting codebooks and analyzes the occurrence of each item in the codebook for the three process steps.

5.3.1 Creation of the Codebook

As described in Subsection 4.2, we provided text boxes in our online labeling tool for the participants' explanations of the chosen complexity. Both Döring and Bortz [2016] and Cooper and Schindler [2003] present codebooks for the analysis of text. Now, we analyze the participants' explanations in English and German. Naturally, the participants paraphrased the geometrical characteristics differently. Therefore, we create categories and assign fitting explanations to these categories. The categories used during coding are documented in a codebook. The codebooks contain the coding rules for assigning numbers or symbols to each variable used in the study and specify when to apply these variables to minimize data entry errors. [Cooper and Schindler, 2003].

We create the codebook's categories while categorizing the participants' explanations for the chosen part complexity for the process step. We define the categories inductive [Döring and Bortz, 2016] out of the data: When we encounter a reason for complexity, we assign it to a category. Then, we also group other reasons fitting into this category, regardless of the language or paraphrasing. To ensure the quality of our annotation, one researcher assigns the categories, and another evaluates the annotation. The final codebooks are shown in Table 5.4, Table 5.6, and Table 5.5.

To evaluate the codebooks, we follow the four requirements of Cooper and Schindler [2003] (p. 383): Appropriateness, exhaustiveness, mutual exclusivity, and single dimension. Appropriateness refers to data partitioning and the availability of data for comparison. Cooper and Schindler [2003] demonstrate the appropriateness with the example of age. Here, the data editors may create age ranges to allow for better pattern recognition and decide about the range size by using comparable age ranges, like the ones used by TV companies for advertisement selling. Exhaustiveness describes how researchers handle information received in an "other" option they provide in case they did not cover the entirety of answer possibilities in their answer design. The "other" responses can be handled by grouping the "other" options into existing categories, if applicable, creating new categories, ignoring "other" answers, or a combination. Mutual exclusivity means that answers fit into one category, and one category only. To clarify, Cooper and Schindler [2003] introduces the example of asking for a recipient's job, and this recipient has more than one job. A solution is to "add a second-occupation field to the data set" so that each of the recipients' jobs is categorized individually. Single dimension refers to the need for a definition for each category.

Appropriateness is hard to measure for our codebooks since we only have qualitative explanations like "inner contours" or "many inner contours" and not quantitative explanations like "four inner contours", for which we might have to introduce ranges as suggested by Cooper and Schindler [2003]. The categories' exhaustiveness is ensured during the creation of the codebooks: If an explanation did not fit into the already created categories, we created new ones. We further specified the codebooks' categories during the creations' evaluation loops. Mutual exclusivity is also ensured during the creation of the codebooks: We only created new categories if an explanation did not fit into the existing ones. The definitions in the codebook fulfill the single dimension.

Since the codebooks fulfill the requirements after Cooper and Schindler [2003], we continue with the third-party evaluation. The final codebooks will be presented in Subsection 5.3.3.

5.3.2 Evaluation of the Codebook

After we created the codebook, we evaluate it. This subsection first presents important characteristics of a codebook, followed by the third-party evaluation of the three codebooks for the process steps laser cutting, part handling with the SortMaster Speed, and part handling with the SmartGate.

To evaluate such a categorization, one usually checks the inter-coder-reliability and the intra-coder-reliability [Döring and Bortz, 2016] p. 558. The inter-coder-reliability is determined with two independently trained coders to evaluate a share of 10 % to 20 % of the data material, and the similarity of the results of the two coders is checked. Another reliability check is the intra-coder-reliability, where one coder codes the same documents twice within a time interval.

Since we analyze responses in text boxes and not interviews or other documents containing significantly more text, we adapted the codebook evaluation procedure to our research. For the evaluation, we selected the labeling results that had the most diverse categorized explanations. This was Participant P25 and the first week. A researcher not related to our research lab volunteered for our third-party evaluation. They did not have prior experience in the categorization of text results. We gave the volunteer the labeling results and the codebook. The volunteer categorized the first labeling results of participant P25 again. To grasp the similarity at first sight, we visualized the similarity using circles. A full circle means identical categorization, a half circle indicates at least one identical category and an empty circle means no similarity between the categorization. In the following, we present the evaluation of the codebooks for the process steps of laser cutting, part handling with the SortMaster Speed, and part handling with the SmartGate.

5.3.2.1 Laser Cutting

Table 5.1 presents the evaluation of the codebook for the process step laser cutting. The columns indicate the geometry, the categorization of the volunteer, our categorization, the similarity, the chosen laser cutting complexity abbreviated with LCC, and the explanation for the chosen complexity by participant P25.

File	**values ST**	**values P25**	**Sim.**	**LCC**	**Explanation**
1	inner contour problematic	inner contour problematic	●	2	Many inner contours that need to be unloaded.
2	inner contour problematic	inner contour problematic	●	2	Many cutouts.
3	inner contour problematic	inner contour problematic	●	2	Some cutouts but all in all normal contour
4	sheet thickness problematic, undercut	heat problematic, undercut	◐	2	Actually easy part with long, straight outer contours, but two undercuts are pretty narrow compared to sheet thickness - there might be some heat, but it's still very well feasible.
5	no issues	no issues	●	1	Large, straight outer contours.
6	no issues	no issues	●	1	Nice, straight outer contours, also with radius.This makes the cutting process easier as well.
7	no issues	no issues	●	1	Long, straight outer contours.
8	no issues	no issues	●	1	Easy small part
9	no issues	no issues	●	1	Easy to cut
10	no issues	no issues	●	1	Nothing complex
11	no issues	no issues	●	1	Easy to cut
12	no issues	no issues	●	1	Easy to cut
13	undercut, shape problematic	notches problematic, undercut	◐	4	Many undercuts, also with sharp edges.
14	shape problematic	notches problematic, heat problematic	○	2	Sharp edges, there may occur pearls in the turning point.

Continued on next page

File	values ST	values P25	Sim.	LCC	Explanation
15	no issues	no issues	●	1	Easy to cut, but oblong hole should be cut into pieces, so it can be ejected by SG.
16	no issues	no issues	●	1	Easy
17	no issues	no issues	●	1	not complex to cut, part is very large. It will take some time to finish the part, because some cutouts need to be ejected by SMS, because of their size.
18	no detailed explanation	heat problematic	○	2	easy to cut, long straight contour that is this thick enough, so not too much heat will occur here.
19	no issues	no issues	●	1	Easy to cut
20	shape problematic, undercut	notches problematic, undercut	◐	4	Complex to cut, due to undercuts with sharp and narrow edges
21	no detailed explanation	no detailed explanation	●	2	Good to cut
22	no issues	no issues	●	1	Good to cut
23	no issues	no issues	●	1	Easy to cut
24	no issues	no issues	●	1	Easy
25	no issues	no issues	●	1	Good to cut
26	no issues	no issues	●	1	Easy
27	no issues	no issues	●	1	Easy
28	no issues	no issues	●	1	Easy, long contours
29	no issues	no issues	●	1	Easy, big contours
30	shape problematic	notches problematic	○	2	Sharp, narrow edge
31	undercut	undercut	●	2	Undercut makes it a little harder
32	no issues	no issues	●	1	Easy
33	heat problematic, undercut	heat problematic, undercut	●	4	Very thin undercut, the beam might burn the material away

Table 5.1: Evaluation of the Codebook for Laser Cutting

The categorizations of 27 of the 33 geometries are identical, indicated by the full circle. The majority of these identical categorizations are "no issues" for complexity 1, and "no detailed explanation" for complexity 2 without a specific explanation for what makes this geometry complex. An example of this is the explanation for geometry 18, for which participant P25 chose complexity 2 and explained this by saying "Easy to cut, long straight contour that is this thick enough, so not too much heat will occur here". For this geometry, we see no similarity in the categorizations. Here, P25 explains what makes the geometry not complex. Three times, the categorizations slightly differed. This happened for the geometries 4, 13, and 20. For geometry 4, both parties agree on the undercut. The volunteer interpreted the rest of the explanation as a hint at the sheet thickness, while we interpreted a hint at the heat being the problem. Participant P25 mentions both, saying that the "undercuts are narrow compared to sheet thickness" and "there might be some heat". This example demonstrates the room for interpretation with free text explanations. All three categories are suitable for the explanation. For geometry 13, both parties agree on the undercut category. While the volunteer interpreted the mention of the "sharp edges" in the explanation as a hint at the geometrical shape, we categorized this as the notches being problematic. The same applies to geometry 14 and 30. For geometry 14, we additionally interpreted the mentioned "pearls in the turning point" as a hint at the heat. We see the same issue again for geometry 20. We meet the confusion if edges are to be categorized as shape or notch by incorporating the edges specifically in the definition of the category "notches problematic".

In summary, we have identical categorizations for 27 of 33 geometries. We have small differences in the categorizations of three geometries, and no similarities for another three geometries. With clear incorporation of edges to the category "notches problematic", we can reduce the dissimilarities to 2 small differences and 1 time no similarity.

5.3.2.2 Part Handling with the SortMaster Speed

Table 5.2 presents the results of the evaluation of the codebook for part handling with the SortMaster Speed. We have greyed out the geometries that do not apply to this process step.

File	values ST	values P25	Sim.	SMS C	Explanation
1	inner contour problematic	inner contour problematic, size problematic	◐	2	Big part but also big cutouts. But SMS has enough suction cups on the part.
2	inner contour problematic	inner contour problematic	●	2	Many cutouts, still enough suction cups on the part

Continued on next page

File	**values ST**	**values P25**	**Sim.**	**SMS C**	**Explanation**
3	no detailed explanation	no detailed explanation	●	2	there are more than enough suction cups on the part
4	no issues	no issues	●	1	Large part area to place suction cups. I don't expect problems with the undercuts.
5	no issues	no issues	●	1	Large area to place suction cups.
6	no issues	no issues	●	1	Large surface to place suction cups. No sticking in the skeleton, because of the radius.
7	no issues	no issues	●	1	Nothing special, thanks to the pins there will be no problems with the rectangular cutouts.
...					
9	detection pins placement problematic, suction cups placement problematic	suction cups placement problematic, pins placement problematic, shape problematic	◐	4	Contour is very thin, there fit only two pins on the whole part. Also, very few suction cups and needles to measure the current. It would take too much time to unload for such a small part - too expensive.
10	size problematic	size problematic	●	2	Big part, the distance between the two SMS is high, but due to the sheet thickness of 3 mm, I don't expect the parts to sag.
...					
13	undercut, scrap cutting required	undercut	◐	4	The undercuts might make it hard to get the part out. In this case, the undercuts need to be cut into pieces, then the part will get out easily.
14	no issues	no issues	●	1	Easy to get out

Continued on next page

File	**values ST**	**values P25**	**Sim.**	**SMS C**	**Explanation**
15	inner contour problematic	inner contour problematic	●	2	Many cutouts but enough suction cups are on the part
		...			
17	no issues	no issues	●	1	Big part, the two SMS have some space between them, but no sagging is expected due to the sheet thickness.
18	detection pins placement problematic, suction cups placement problematic	pins placement problematic, suction cups placement problematic	◐	5	Only one pin of each SMS fits the part, very few suction cups are on the part.
19	no issues	no issues	●	1	Enough cups on the part
20	undercut, scrap cutting required	undercut	◐	5	Complex to get out, because of undercuts –¿ cut undercuts into peaces before ejecting with SMS
21	no issues	no issues	●	1	Enough cups on the part
22	no detailed explanation	no detailed explanation	●	2	Enough cups, pins and needle pins are on the part
23	no issues	no issues	●	1	Enough cups on the part
24	detection pins placement problematic, suction cups placement problematic, size problematic	suction cups placement problematic, size problematic, pins placement problematic, shape problematic	◐	4	Very thin part. There can be one row of pins, suction cups, and needles on the part
25	no detailed explanation	no detailed explanation	●	2	Enough cups on the part
26	no issues	no issues	●	1	Easy

Continued on next page

File	values ST	values P25	Sim.	SMSC	Explanation
27	no detailed explanation	no detailed explanation	●	2	Enough cups on the part
28	size problematic	size problematic	●	2	Large part but enough cups on the part
29	no issues	no issues	●	1	Enough cups
30	no issues	no issues	●	1	Good to get the part out, no undercuts
...					
32	no issues	no issues	●	1	Easy, because there is no hole in the middle
...					

Table 5.2: Evaluation of the Codebook for Part Handling with the SortMaster Speed

Out of the 27 geometries applicable to part handling with the SortMaster Speed, we have 21 identical categorizations. For six geometries, we have slight differences in the categorization. We have no geometry with no similarities in the categorization. For geometry 1, both parties agree on "inner contour problematic", while we additionally used the categorization "size problematic", due to the participant mentioning the "big part". For geometry 9, both parties agree on the category "suction cups placement problematic". While the volunteer additionally categorized "detection pins problematic", we used the categories "pins placement problematic" and "shape problematic". The participant specifically mentions the pins as well as the suction cups. It is possible that the volunteer confused the regular pins of the SortMaster Speed with the detection pins. Instead of the shape being problematic due to the participant mentioning that the "contour is very thin", we also might have used the category "size problematic" due to the participant mentioning the "small part". This example further underlines the room for interpretation inherent to the complexity explanations. For geometries 13 and 20, both parties agreed on the undercut, while the volunteer also considered the category "scrap cutting required", which participant P25 has mentioned in the explanation. There is room for interpretation if one should only consider the underlying reason for the required scrap cutting, which is the undercut, or both. For geometry 18, the volunteer again confused the regular pins of the SortMaster Speed with the detection pins. The same also applies to geometry 24. For this geometry, both parties use the categories "suction cups placement problematic" and "size problematic". In contrast to the volunteer, we also used the category "shape problematic". A large amount of categories contained in the explanations seem to increase the difficulty in categorization.

In summary, we observe three reasons for disagreement in the categorization: First, confusing the regular pins with detection pins. Second, if one should only consider the geometrical characteristic or also the consequence of this characteristic. And third, the difficulty in categorizing a large number of aspects mentioned in the explanations. We meet these obstacles by refining the Codebook, and clarifying the differentiation between the regular pins and the detection pins of the SortMaster Speed. The other two obstacles have reasons regarding the interpretation and concentration, which are inherent to manual categorization by humans. however, all in all, we are satisfied with the evaluation results for the Codebook for part handling with the SortMaster Speed: First, we do not have categorizations without any similarity. By specifying the difference between the detection cups and the regular cups, we can minimize the difference in the categorizations to 5 different categorizations of geometries.

5.3.2.3 Part Handling with the SmartGate

The evaluation results for the codebook for part handling with the SmartGate are presented in Table 5.3. As in Table 5.2, we greyed out the geometries not applying to this process step.

File	values ST	values P25	Sim.	LCC	Explanation
...					
8	no issues	no issues	●	1	No problems expected, the part is not too small to be safely ejected.
9	pins placement problematic, inner contour problematic, tilting problematic	inner contour problematic, scrap skeleton problematic, tilting problematic, center of gravity problematic, clamping problematic, pins placement problematic	◐	2	The pin cannot be placed at the centroid, because of the hole in the middle. Therefore the part might turn and be stuck in the sceleton.
...					
11	no issues	no issues	●	1	Easy to eject.
12	no issues	no issues	●	1	No problems expected.
...					
16	no issues	no issues	●	1	Easy
...					

Continued on next page

File	values ST	values P25	Sim.	LCC	Explanation
31	undercut	undercut	●	2	Undercut makes the unloading process harder, but still no problem thanks to the pin
32	no issues	no issues	●	1	Easy, no undercuts or cutouts.
33	undercut, clamping problematic	material problematic, scrap skeleton problematic, clamping problematic, undercut	◐	4	If the undercut works, the part might be stuck in the sceleton at this material.

Table 5.3: Evaluation of the Codebook for Part Handling with the SmartGate

Out of the eight geometries applicable for part handling with the SortMaster Speed, we have six identical categorizations and two categorizations with small differences. There is no geometry without any similarity in the categorization. The two small differences in categorizing geometries 9 and 33 are due to the high amount of aspects mentioned in the explanations. In summary, this result is fine, since it does not hint at gaps in the codebook.

In the next Subsection, Subsection 5.3.3, we present the resulting codebooks for the process steps of laser cutting, part handling with the SortMaster Speed, and part handling with the SmartGate.

5.3.3 The resulting Codebooks

This subsection presents the resulting codebooks of the three process steps of our exemplary production unit, the TruLaser Center 7030. We present the codebook as well as the occurrences of each category for the process steps. We start with the process step laser cutting, followed by the part handling processes SortMaster Speed and SmartGate.

5.3.3.1 Laser Cutting

Table 5.4 contains the codebook for the process step laser cutting in alphabetical order. Since we want to identify the characteristics making a part more complex for laser cutting, we categorize the explanations given for parts labeled with complexity 1 as ”no issues”. For parts with a complexity higher than 1 and no explanation given, such as ”easy to cut” or ”...”, we categorize the explanation as ”no detailed explanation”.

Category	**Explanation**
bars_problematic	The bars are problematic, typically because they are too narrow (German: Steg)
bending_problematic	The part may bend
clamping_problematic	The part may clamp (German: verhaken)
contour_problematic	The contour may be problematic and it is not specified whether it is the inner or the outer contour
cutting_head_collision_problematic	A collision with the cutting head may occur
degree_of_cutting_problematic	The part may be cut very much
ejection_cylinder_placement_problematic	The placement of the ejection cylinder may be problematic
falling_detection_problematic	The falling detection may not work
heat_problematic	The heat may influence the part complexity
inner_contour_problematic	The inner contours are problematic
kerf_size_problematic	The participant sees a problem with the kerf (German: Schnittspalt)
laser_beam_interruption_possible	The laser beam may be interrupted during the cutting process
length_problematic	The length of the part is problematic
no_detailed_explanation	The participant did not choose part complexity 1 and did not provide any explanation
no_issues	The participant chose part complexity 1
notches_problematic	This category summarizes potential manufacturing problems due to part characteristics such as notches, edges, slots, taps, and flaps
outer_contour_problematic	The participant says that the outer contours led him to choose the complexity
pierced_hole_problematic	The participants see problems specifically with the pierced hole (German: Einstich)
possible_welding_problematic	During the laser cutting, an unwelcome welding may occur
scrap_cutting_required	The scrap produced by cutting the part might have to be cut to prevent manufacturing problems
scrap_skeleton_problematic	The scrap skeleton (German: Restgitter) may cause problems

Continued on next page

Category	**Explanation**
shape_problematic	The participants state that the shape of the part may cause problems
sheet_thickness_problematic	The sheet thickness may cause problems
size_problematic	The size is problematic for the process step
slugs_problematic	The slugs (German: Butzen, here: manufacturing waste) make the production more complicated
tension_problematic	Tension may occur in the part, hindering the process step
tilting_problematic	The part may tilt.
undercut	Problems due to the undercut, e.g. undercut is required or the undercut needs to be cut

Table 5.4: Codebook for Laser Cutting

Figure 5.7 shows the occurrences of the categorized explanations for the process step laser cutting.

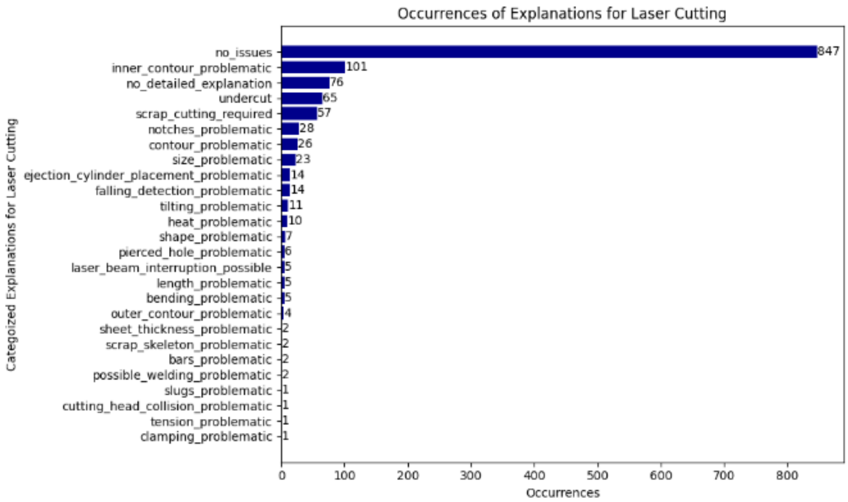


Fig. 5.7: Occurences of categorized explanations for the process step laser cutting. Own visualization

The categorized explanation with the most occurrences is "no issues" with 847 mentions, indicating that the complexity of laser cutting has a highly imbalanced distribution. The categorized explanation "inner contour problematic” has 101 mentions, making it the geometrical characteristics with the most mentions. This indicates that inner contours have the highest influence on the complexity of the process step laser cutting. The category ”no detailed explanation”, the collection of inaccurate complexity explanations, has 76 mentions. This means that 76 times, we could not identify which characteristic made the participant decide on a complexity higher than 1. The category ”undercut” has 65 mentions, followed by ”scrap cutting required” with 57 mentions. The category ”notches problematic” was mentioned 28 times, ”contour problematic” 26 times, and ”size problematic” 23 times. The categories ”ejection cylinder placement problematic” and ”falling detection problematic” each have 14 mentions. The category ”tilting problematic” was mentioned 11 times, and ”heat problematic” was mentioned 10 times. The categories ”shape problematic”, ”pierced hole problematic”, ”laser beam interruption possible”, ”length problematic”, ”bending problematic”, ”outer contour problematic”, ”sheet thickness problematic”, ”scrap skeleton problematic”, ”bars problematic”, ”possible welding problematic”, ”slugs problematic”, ”cutting head collision problematic”, ”tension problematic”, and ”clamping problematic” were each mentioned less than 10 times, suggesting the rather low significance of these categories.

5.3.3.2 Part Handling with the SortMaster Speed

Table 5.5 shows the codebook for the process step part handling with the SortMaster Speed in alphabetical order. We followed the same principles as for the codebook for laser cutting: Since we want to identify the characteristics making a part more complex for laser cutting, we categorize the explanations given for parts labeled with complexity 1 as "no issues". For parts with a complexity higher than 1 and no explanation given, such as "easy to cut" or "...", we categorize the explanation as "no detailed explanation".

Category	**Explanation**
bars_problematic	The bars are problematic, typically because they are too narrow (German: Steg)
bending_problematic	The part may bend
clamping_problematic	The part may clamp (German: verhaken)
contour_problematic	The participant sees the contour as problematic and does not specify whether it is the inner or the outer contour
detection_pins_placement_problematic	Placement of detection pins (German: Messspitzen) difficult. Not to confuse with the regular pins of the SortMaster Speed (see pins_placement_problematic)
ejection_cylinder_placement_problematic	The placement of the ejection cylinder may be problematic
falling_detection_problematic	The falling detection may not work
inner_contour_problematic	The participant says that the inner contours led him to choose the complexity
length_problematic	The participant sees problems due to the length of the part
narrowness_problematic	The narrowness of the part makes it difficult to manufacture
no_detailed_explanation	The participant chose a complexity higher than 1 and did not explain
no_issues	The participant chose part complexity 1
notches_problematic	This category summarizes potential manufacturing problems due to part characteristics such as notches, edges, slots, taps, and flaps
outer_contour_problematic	The participant says that the outer contour led him to choose the complexity
part_stability_problematic	The part's stability may be weakened

Continued on next page

Category	Explanation
pins_placement_problematic	The placement of the pins may be difficult
prefix_problematic	The prefix of the part before it is handled with the sortMaster Speed seems to be difficult
pressor_foot_placement_problematic	The placement of the pressor foot may be problematic
risk_of_part_falling	The part may fall
scrap_cutting_required	The scrap produced by cutting the part might have to be cut to prevent manufacturing problems
scrap_skeleton_problematic	The scrap skeleton may be difficult
shape_problematic	The shape of the part may be problematic
size_problematic	The size of the part may lead to manufacturing problems
suction_cups_placement_problematic	The placement of the suction cups may be problematic
tilting_problematic	Tilting (German: Verkippen) may occur, which may lead to manufacturing problems
undercut	An undercut may be required
weight_problematic	The weight may lead to manufacturing problems

Table 5.5: Codebook for Part Handling with the SortMasterSpeed

Figure 5.8 shows the occurrences of the categorized explanations for the process step part handling with the SortMaster Speed.

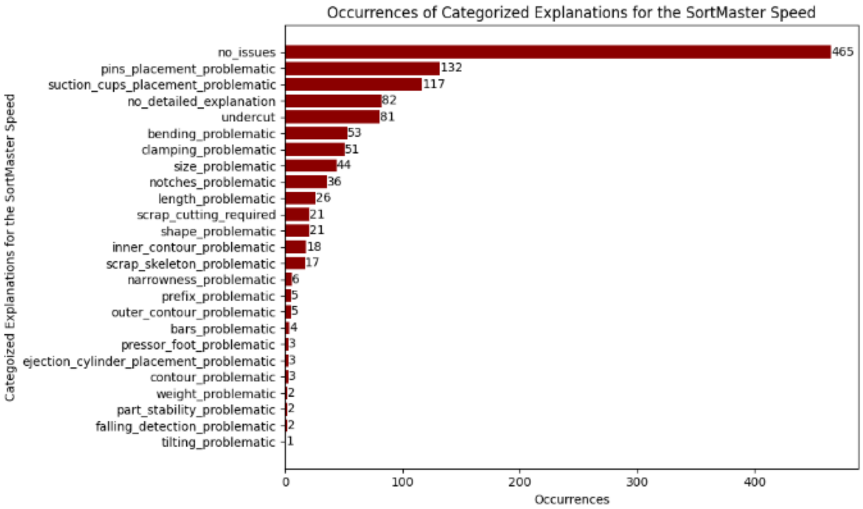


Fig. 5.8: Occurences of categorized explanations for the process step part handling with the SortMaster Speed. Own visualization

Similar to the occurrences of the categorized explanations of the process step laser cutting, the most used category was "no issues" with 465 mentions. The categories "pins placement problematic" and "suction cups placement problematic" were mentioned 132 times and 117 times, respectively. The category "no detailed explanation" was mentioned 82 times, closely followed by the category "undercut". The categories "bending problematic" and "clamping problematic" were mentioned 53 and 51 times, respectively. The category "size problematic" was mentioned 44 times, while "notches problematic" was mentioned 36 times. "Length problematic" was mentioned 26 times, while both "scrap cutting required" and "shape problematic" were each mentioned 21 times. "Inner contour problematic" was mentioned 18 times and "scrap skeleton problematic" once less with 17 mentions. The following categories were mentioned less than ten times: "Narrowness problematic" was mentioned six times, while "prefix problematic" and "outer contour problematic" were mentioned five times each. "Bars problematic" was mentioned four times, while "pressor foot problematic", "ejection cylinder placement problematic", and "contour problematic" were each mentioned three times. While "weight problematic", "part stability problematic" and falling detection problematic" were each mentioned twice, "tilting problematic" was only mentioned once. In summary, the most important characteristics influencing the complexity for part handling with the SortMaster Speed are the geometrical characteristics influencing the placement of the pins and the suction cups, undercuts, bending, and clamping.

5.3.3.3 Part Handling with the SmartGate

Table 5.6 presents the codebook for the process step part handling with the SmartGate in alphabetical order. We followed the same principles as for the codebooks for laser cutting and part handling with the SortMaster Speed: Since we want to identify the characteristics making a part more complex for laser cutting, we categorize the explanations given for parts labeled with complexity 1 as "no issues". For parts with a complexity higher than 1 and no explanation given, such as "easy to cut" or "...", we categorize the explanation as "no detailed explanation".

Category	**Explanation**
bending_problematic	The part may bend
center_of_gravity_problematic	The part's center of gravity may be problematic
clamping_problematic	The part may clamp (German: verhaken)
ejection_cylinder_placement_problematic	The placement of the ejection cylinder may be problematic
falling_detection_problematic	The falling detection may not work
inner_contour_problematic	The participant chose a complexity higher than 1 due to the inner contours
material_problematic	Problems due to the material may occur during production
no_detailed_explanation	The participant chose a part complexity higher than 1 and did not explain
no_issues	The participant chose part complexity 1
notches_problematic	This category summarizes potential manufacturing problems due to part characteristics such as notches, edges, slots, taps, and flaps
outer_contour_problematic	The participant says that the outer contour led him to choose the complexity
pins_placement_problematic	the participant sees a problem with the placement of the pins of the SortMaster Speed
scrap_cutting_required	The scrap produced by cutting the part might have to be cut to prevent manufacturing problems
scrap_skeleton_problematic	The scrap skeleton (German: Restgitter) may cause problems
shape_problematic	The participants state that the shape of the part may cause problems
size_problematic	The size is problematic for the process step

Continued on next page

Category	Explanation
slugs_problematic	The slugs (German: Butzen) make the production more complicated
tilting_problematic	The part may tilt
undercut	Problems due to the undercut, e.g. undercut is required or the undercut needs to be cut

Table 5.6: Codebook for Part Handling with the SmartGate

Figure 5.9 shows the occurrences of the categorized explanations for part handling with the SmartGate.

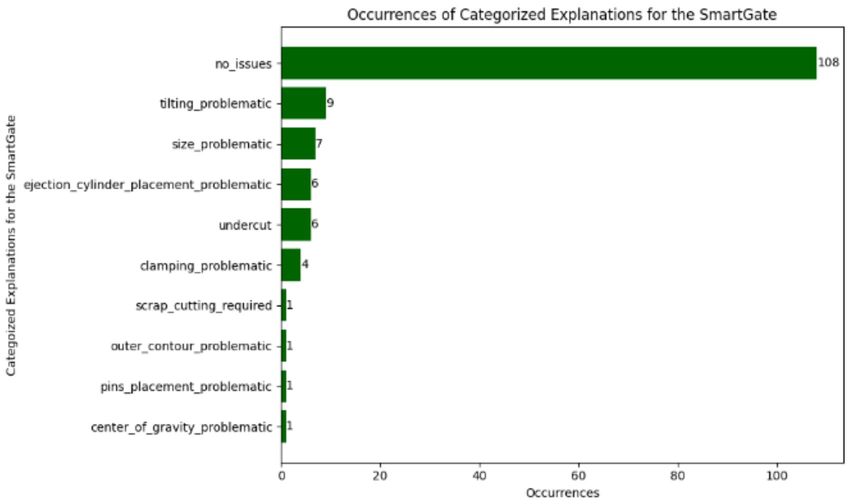


Fig. 5.9: Occurences of categorized explanations for the process step part handling with the SmartGate. Own visualization

By far the most important category is ”no issues”, with 108 mentions. With a huge gap, the category ”tilting problematic” follows with 9 mentions. While ”size problematic” was mentioned 7 times, both ”ejection cylinder placement problematic” and ”undercut” were each mentioned six times. ”Clamping problematic” was mentioned four times, while ”scrap cutting required”, ”outer contour problematic”, ”pins placement problematic”, and ”center of gravity problematic” were each mentioned once. In summary, the codebook for part handling with the SmartGate hints at low-complexity parts for this process step in the database.

5.4 Detailed Analysis of Geometries

This section presents a detailed analysis of a subset of geometries to gain more insight into the labeling results. We chose the repeating geometries for this detailed analysis. First, we give a short description of the geometry, covering the area, length, width, cutting degree, cutting length, and the amount of inner contours. Moreover, we depict the geometries. One needs to keep in mind that we oriented the size of these pictures to a pleasing appearance in the text and not the actual size of the geometries. Then, we present the complexity labeling for the applying process steps and calculate the mean complexity value for each process step. Here, we only consider the participants who passed the process step for the respective process step. This explains the missing bars of participants in the bar charts. Moreover, we present the categorized explanations of the respective process steps and chosen complexity values. After we present each repeating geometries, we give a conclusion at the end of this Subsection.

5.4.1 Repeating Geometries

This subsection presents the ten repeating geometries from A to J.

5.4.1.1 Geometry A

Figure 5.10 shows the repeating geometry A. Geometry A is a rectangle without inner contours or undercuts in the outer contour. It has an area of 3034.47 cm^2, with an expansion of 786.48 mm in the x-direction and 385.83 mm in the y-direction. Since it has no inner contours, the cutting degree is 0. The cutting length is 2344.62 mm. The centroid of geometry A lies on the part area.

Fig. 5.10: Repeating Geometry A. Own visualization

Figures 5.11 and 5.12 show the analysis of the labeling results for the process steps laser cutting and part handling with the SortMaster Speed, respectively. The experts agree that geometry A is overall easy to manufacture and has a low complexity. This results in categorized part characteristics of "no issues". Only participant P27 labeled the complexity once as "4", stating that the size of the geometry is problematic. We view this labeling as an outlier. We calculated mean complexities of 1 for laser cutting and 1.1 for the SortMaster Speed.

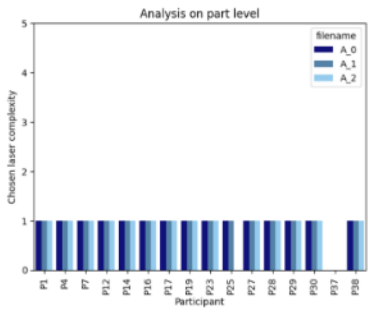


Fig. 5.11: Analysis of complexity labeling for laser cutting for repeating geometry A. Own visualization.

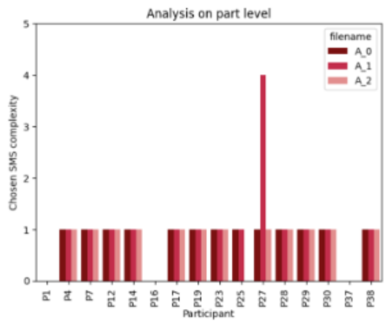


Fig. 5.12: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry A. Own visualization.

The categorized explanations are shown in Figure 5.13 for the process step laser cutting and in Figure 5.14 for the part handling with the SortMaster Speed. We only have the categorized explanation of "no_issues" for laser cutting since each participant labeled complexity 1 for each week. For the process step part handling with the SortMaster Speed, we have 37 explanations of "no_issues" and one time "size_problematic" from the outlier labeling.

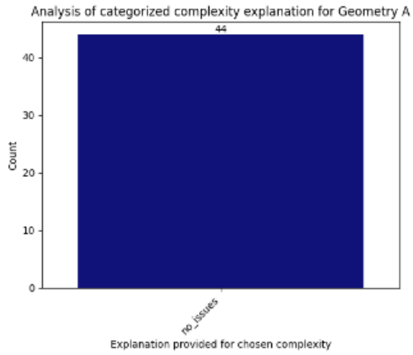


Fig. 5.13: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry A. Own visualization.

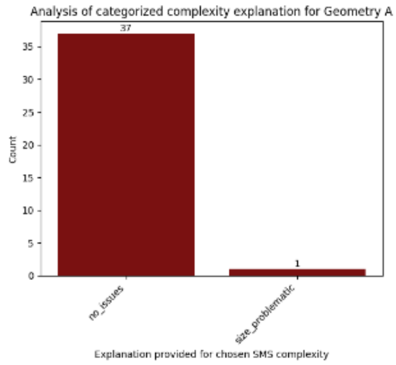


Fig. 5.14: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry A. Own visualization.

5.4.1.2 Geometry B

Geometry B is visualized in Figure 5.15. Similar to geometry A, geometry B has no inner contours, and the cutting degree is 0. In contrast to geometry A, geometry B is longer in the x-direction with 1991.02 mm, and shorter in the y-direction with 299.2 mm. Geometry B has indents in the outer contour, making a contour length of 4968.82 mm. The area of geometry B is significantly larger than the area of geometry A with 5787.65 cm^2. The cutting length is 4968.82 mm.

Fig. 5.15: Repeating Geometry B. Own visualization

Figures 5.16 and 5.17 show the labeling of the production processes laser cutting and part handling with the SortMaster Speed, respectively. In comparison to geometry A, we see a higher variance in the labeling, especially for part handling with the SortMaster Speed. We calculated an average laser cutting complexity of 1.2 and an average complexity for part handling with the SortMaster Speed of 1.6.

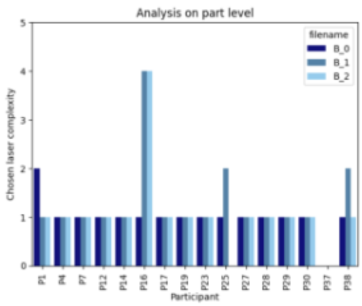


Fig. 5.16: Analysis of complexity labeling for laser cutting for repeating geometry B. Own visualization.

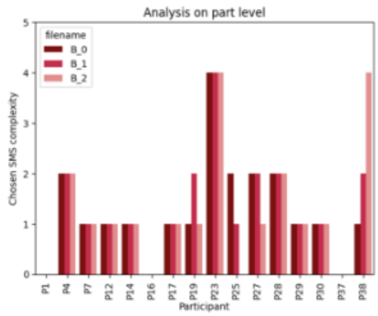


Fig. 5.17: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry B. Own visualization.

The categorized explanations for the chosen complexities for laser cutting are visualized in Figure 5.18. The explanations for the higher laser cutting complexity are the undercut with one mention and two mentions of the scrap skeleton being problematic. These explanations are related to the indents in the outer contour of the geometry.

The categorized explanations for part handling with the SortMaster Speed for geometry B are depicted in Figure 5.19. We have seven mentions that the bending may be problematic, followed by three mentions of the length. We have each two mentions of placement of the pins of the SortMaster Speed, the clamping being problematic, the size, and the undercuts. Furthermore, we have one mention that the placement of the suction cups of the SortMaster Speed may be problematic. Here, we can link the categorized answers to the indents in the outer contour of geometry B as well as the narrowness of the geometry. The bending, the size, and the length seen as problematic by the participants are related to the narrowness, while the clamping and the undercut are related to the indents in the outer contour. We do not see a link between the placement of both the suction cups and the pins of the SortMaster Speed and the geometry.

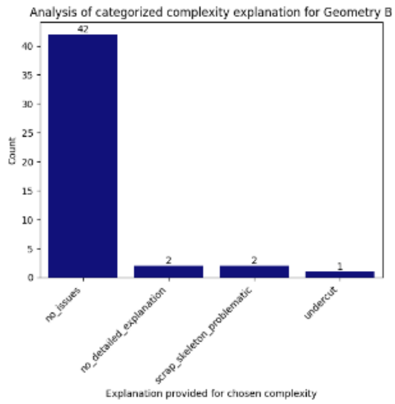


Fig. 5.18: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry B. Own visualization.

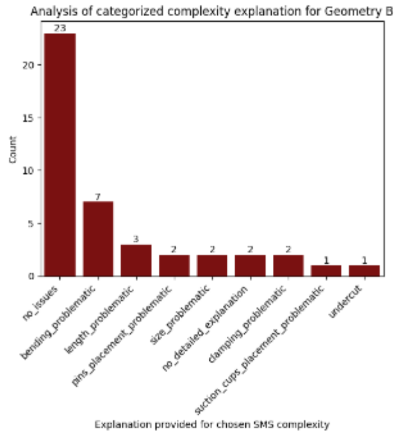


Fig. 5.19: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry B. Own visualization.

5.4.1.3 Geometry C

Figure 5.20 shows geometry C, a rectangular, almost quadratic geometry with 52 inner contours, consisting of circles of various sizes and one elongated hole. Geometry C has an area of 712.71 cm^2. It expands 386.36 mm in the x-direction and 290 mm in the y-direction. Geometry C has a cutting length of 5588.16 mm and a cutting degree of 0.34, due to the inner contours. The centroid is on the part area.

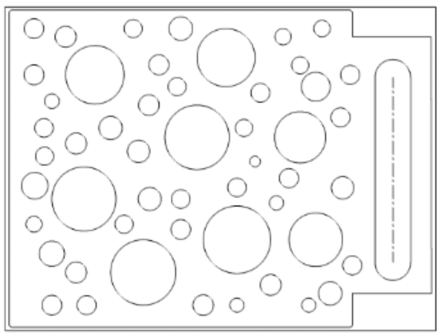


Fig. 5.20: Repeating Geometry C. Own visualization

We see the chosen complexities for laser cutting in Figure 5.21 and for part handling with the SortMaster Speed in Figure 5.22. We see a high variance in the labeling for the laser cutting, with complexity values ranging from 1 to 4. The calculated mean value for the laser cutting complexity is 1.5

We see a similar variance in the SortMaster Speed complexity, where the complexity values also range from 1 to 4. We calculated a mean complexity value for part handling with the SortMaster Speed of 1.8.

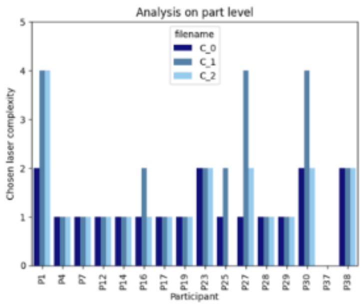


Fig. 5.21: Analysis of complexity labeling for laser cutting for repeating geometry C. Own visualization.

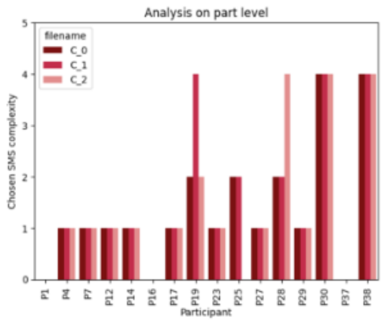


Fig. 5.22: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry C. Own visualization.

Figure 5.23 presents the categorized explanations for the process step laser cutting. The inner contour being problematic for the manufacturing process has been mentioned eleven times. The slugs being problematic was mentioned twice. The heat, degree of cutting, possible tilting, possible scrap cutting, falling detection, placement of the ejection cylinder, and size were all mentioned once. Here, we can see the link between the inner contours being the mostly mentioned characteristics making the part hard to manufacture and the geometry itself, having many inner contours and a rather large area of inner contours.

The categorized explanations for the part handling with the SortMaster Speed are shown in Figure 5.24. The placement of the suction cups being problematic was mentioned seven times, and the inner contours and the placement of the pins being problematic were mentioned five times each. Scrap cutting was mentioned once. Again, we can see the link between the categorized explanations and the geometry itself. The inner contours—both the amount and the combined inner contour area—provide less space for the placement of the suction cups and the pins of the SortMaster Speed shuttle. The mention of scrap cutting is also related to the inner contours since some of the inner contours are prone to clamping due to their size. This can be prevented by cutting the scrap produced by the inner contours.

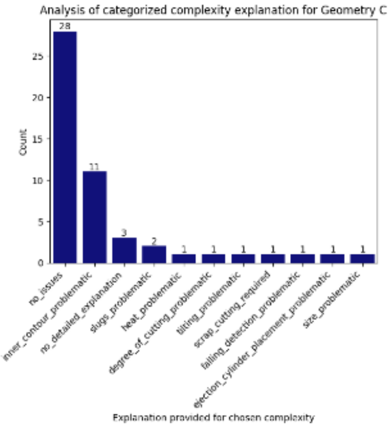


Fig. 5.23: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry C. Own visualization.

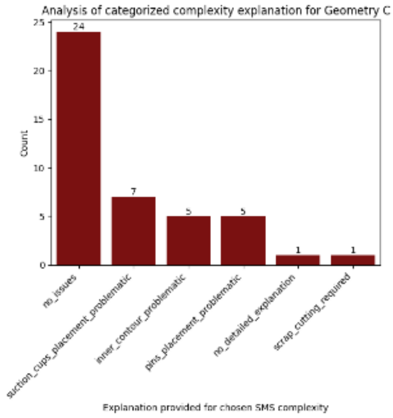


Fig. 5.24: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry C. Own visualization.

5.4.1.4 Geometry D

Geometry D is visualized in Figure 5.25 and is a rather long geometry with 10 circles of various sizes as inner contours and one big indent in the outer contour. The geometry expands 454.03 mm in the x-direction and 80.08 mm in the y-direction. It has an area of 323.57 cm^2 and a cutting degree of 0.016. The cutting length is 1341.62 mm.

Fig. 5.25: Repeating Geometry D. Own visualization

We see a slight dissonance in the participants' labeling for the process step laser cutting, with 12 participants consistently choosing complexity 1, and 3 participants choosing almost consistently complexity 2. This results in an average complexity value of 1.2.

We observe even more consistent labeling for the process step part handling with the SortMaster Speed, with the majority consistently choosing complexity 1 and three outliers with laser cutting complexity 2. We calculated a mean SortMaster Speed complexity of 1.1.

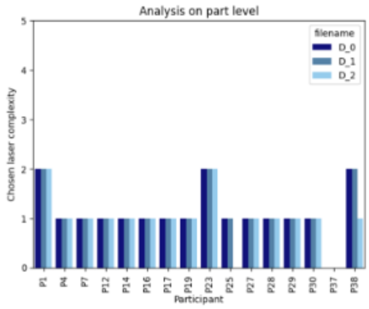


Fig. 5.26: Analysis of complexity labeling for laser cutting for repeating geometry D. Own visualization.

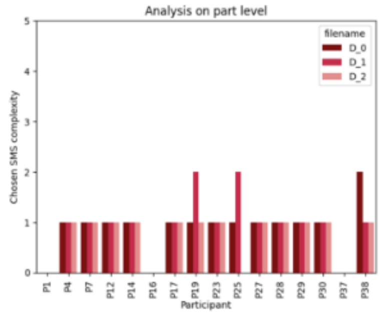


Fig. 5.27: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry D. Own visualization.

The categorized explanations for laser cutting and geometry D are visualized in Figure 5.28. We have five mentions of the inner contour being problematic and one mention each for the pierced hole and the contour in general. The mention of the pierced hole may be related to the fact that some of the inner contours of geometry D are small circles.

Figure 5.29 shows the categorized explanations for the part handling with the SortMaster Speed and geometry D. Each of the placement of the suction cups, the pins of the SortMaster Speed, and the narrowness of the geometry were mentioned once. Again, we can see the link between the explanations and the geometry: Narrow geometries are prone to bending during part handling with the SortMaster Speed, and inner contours make placing the suction cups and pins on the surface of the geometry more difficult.

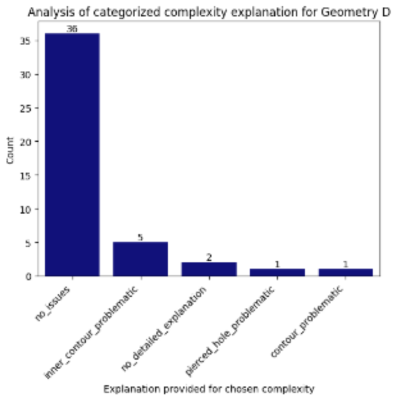


Fig. 5.28: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry D. Own visualization.

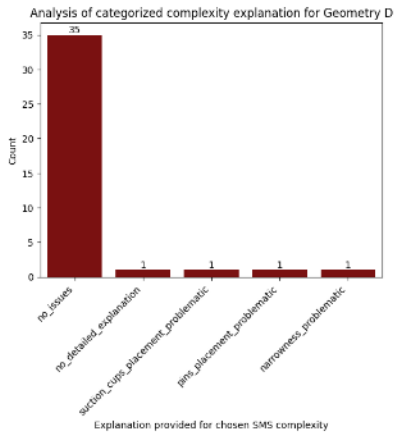


Fig. 5.29: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry D. Own visualization.

5.4.1.5 Geometry E

Geometry E, depicted in Figure 5.30, is a narrow geometry with two bigger rectangular inner contours and seven circles of various sizes as inner contours. In addition, it presents with a notch in the upper left outer contour. The geometry expands 735.17 mm in the x-direction and 98.71 mm in the y-direction. It has an area of 571.35 cm^2 and a cutting degree of 0.199. The cutting length is 3011.77 mm and the centroid lies on the part.

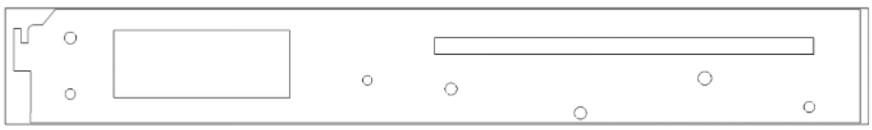


Fig. 5.30: Repeating Geometry E. Own visualization

The laser cutting complexity labeling for geometry E, shown in Figure 5.31, shows consistent labeling of complexity 1 or 2, resulting in an average laser cutting complexity of 1.4.

For the process step part handling with the SortMaster Speed, presented in Figure 5.32, we mostly see complexities of 1 and 2. Furthermore, participant P30 twice labeled the complexity as 4. This results in an average SortMaster Speed complexity for geometry E of 1.6.

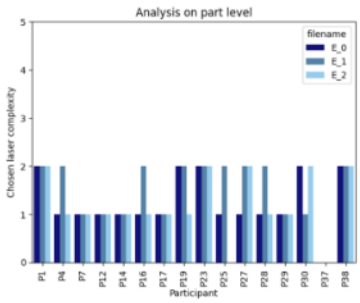


Fig. 5.31: Analysis of complexity labeling for laser cutting for repeating geometry C. Own visualization.

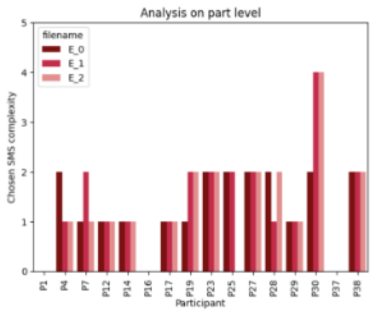


Fig. 5.32: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry E. Own visualization.

Figure 5.33 shows the categorized explanations for geometry E. Scrap cutting being required was mentioned ten times, followed by the inner contours and the undercut with 6 and 5 mentions. The contour in general, the falling detection, the placement of the ejection cylinder, and the size being problematic were each mentioned twice. The notch being problematic was mentioned once. We can assume that both the mentions of the undercut and the notch refer to the notch and the undercut on the left side of the geometry. The scrap cutting is probably directed at the two large inner contours. The mentions of the inner contours themselves also hint at the scrap produced by these inner contours. For this geometry, the link between the categorized explanations and the geometry is visible, although sometimes ambiguous.

The categorized explanations for geometry E and part handling with the SortMaster Speed is depicted in Figure 5.34. The undercut being problematic was mentioned ten times, followed by possible clamping with five mentions. These categorized explanations probably target the notch and the undercut on the left side of the geometry. The placement of the suction cups and the pins being problematic were each mentioned four times. The two large inner contours in combination with the smaller inner contours leave less space for the placement of the pins and suction cups of the SortMaster Speed. Scrap cutting being required was mentioned three times, the inner contours themselves were mentioned twice, and the shape being problematic was mentioned once. The scrap cutting is probably targeted at the two large inner contours. The shape being problematic can mean the notch on the left side of the geometry or the inner contours. For geometry E and the process step part handling with the SortMaster Speed, the link between the categorized explanations and the geometry is visible, although the geometrical characteristic of the inner contours was less mentioned than its consequences, the clamping, scrap cutting being required, and the difficult placement of the pins and the suction cups.

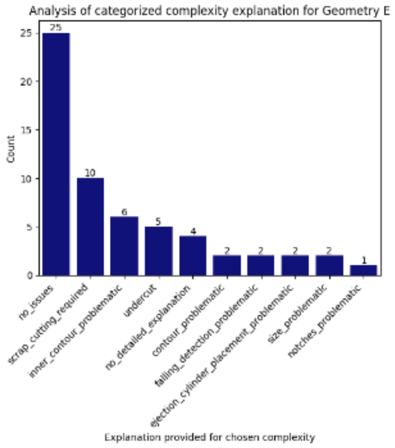


Fig. 5.33: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry E. Own visualization.

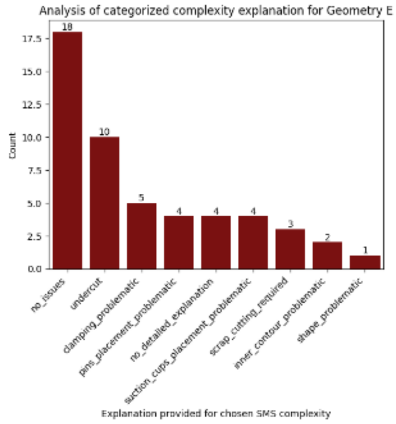


Fig. 5.34: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry E. Own visualization.

5.4.1.6 Geometry F

Figure 5.35 shows repeating geometry F, an almost rectangular shape with a notch in the upper right corner and small circles as inner contours. Geometry F has 31 inner contours in total, resulting in a cutting degree of 0.008 and a cutting length of 8330.44 mm. It expands 1947.2 mm in the x-direction and 1134.77 mm in the y-direction. With an area of 15171.61 cm^2, it is the largest of the repeating geometries.

Fig. 5.35: Repeating Geometry F. Own visualization

The labeled laser cutting complexity is presented in Figure 5.36 and shows low variance with mostly laser cutting complexity 1 and partly laser cutting complexity 2. The average laser cutting complexity of geometry F is 1.1.

The labeled complexity for part handling with the SortMaster Speed depicted in Figure 5.37 shows a similar pattern for geometry F as the laser cutting complexity, with one outlier labeling with complexity 4 from participant P23. The average SortMaster Speed complexity for geometry F is 1.4.

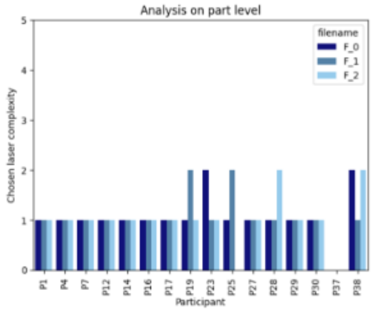


Fig. 5.36: Analysis of complexity labeling for laser cutting for repeating geometry F. Own visualization.

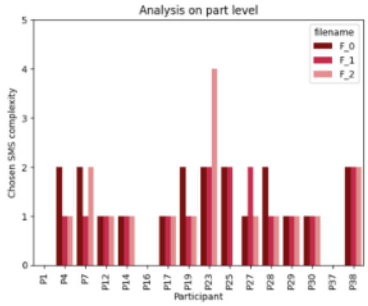


Fig. 5.37: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry F. Own visualization.

The categorized explanations for the chosen complexity for the process step laser cutting and geometry F are shown in Figure 5.38. The inner contours being problematic was mentioned twice. The size and the notches being problematic were each mentioned once. The categorized explanations reflect the low laser cutting complexity as well as the characteristics of geometry F with the many inner contours.

Figure 5.39 visualizes the categorized explanations for geometry F and the process step part handling with the SortMaster Speed. The size being problematic was mentioned four times, followed by the placement of the pins being problematic with three mentions and the placement of the suction cups being problematic with two mentions. The notches being problematic was mentioned once. While the notch on the upper right side of the geometry may inhibit manufacturing risks like clamping, the placement of the circles as inner contours through the geometry makes the placement of the pins and suction cups difficult, Again, we can see the link between the categorized explanations for the process steps and the labeled geometry.

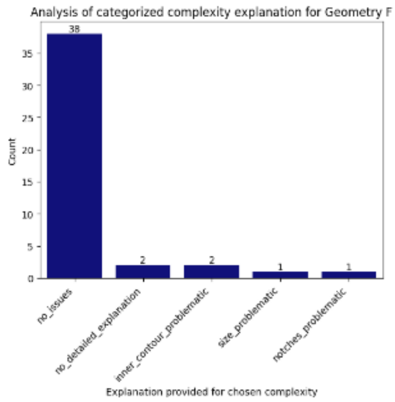


Fig. 5.38: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry F. Own visualization.

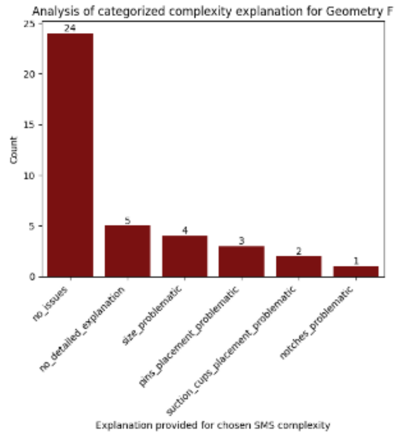


Fig. 5.39: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry F. Own visualization.

5.4.1.7 Geometry G

Repeating Geometry G, shown in Figure 5.40, is similar to geometry F, a rectangular geometry with a notch in the upper left corner. Geometry G has 5 circles as inner contours, although these are fewer and bigger than the inner contours of geometry F. It has an area of 172.85 cm^2 and expands 195 mm in the x-direction and 113.11 mm in the y-direction. The cutting degree is 0.072, and the cutting length is 897.76 mm.

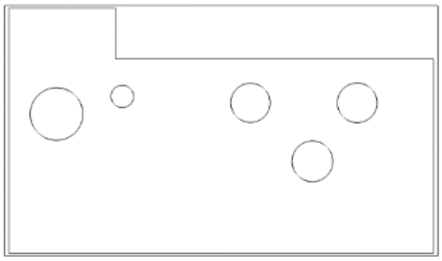


Fig. 5.40: Repeating Geometry G. Own visualization

The labeled complexities for laser cutting and part handling with the SortMaser Speed are depicted in Figures 5.41 and 5.42, respectively. Both process steps show consistent labeling with low variance and complexities ranging from 1 to 2. For both process steps, the average complexity is 1.1.

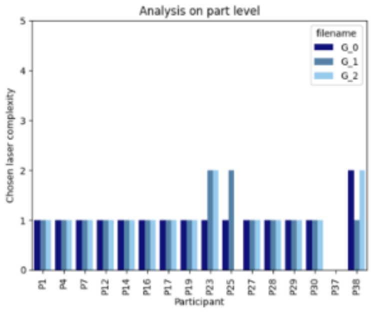


Fig. 5.41: Analysis of complexity labeling for laser cutting for repeating geometry G. Own visualization.

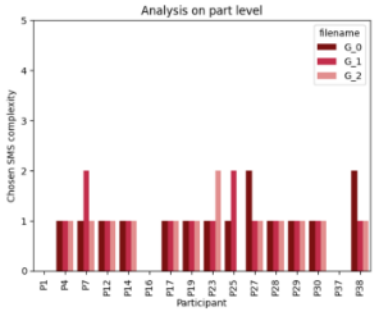


Fig. 5.42: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry G. Own visualization.

The categorized explanations for geometry G and the process step are depicted in Figure 5.43. The inner contour being problematic and the contour being problematic were each mentioned once. Geometry G has five inner contours, so we can see the link between the categorized explanations and the geometry itself. The little explanation of what characteristics make this geometry hard to manufacture is reflected in the low complexity of laser cutting.

Figure 5.44 shows the categorized explanations for geometry G and part handling with the SortMaster Speed. Again, the low complexity is reflected in the absence of explanations: No issues were mentioned 33 times and 3 times were not detailed explanations given. Only the inner contour being problematic and the size being problematic were each mentioned once.

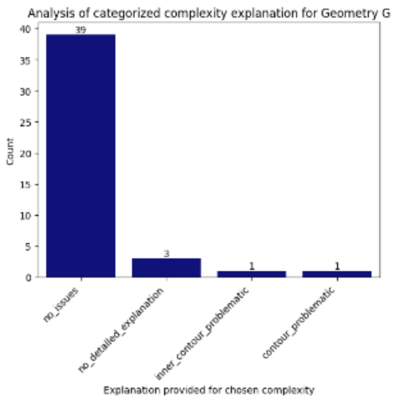


Fig. 5.43: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry G. Own visualization.

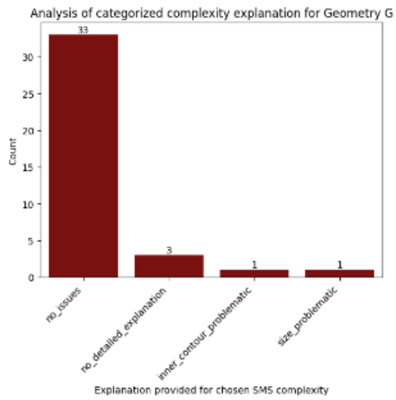


Fig. 5.44: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry G. Own visualization.

5.4.1.8 Geometry H

Geometry H, a rectangle with step-wise corners of the outer contour as well as 1 bigger and 30 smaller, circular inner contours, is depicted in Figure 5.45. Geometry H has the longest cutting length with a value of 8555.05 mm. It expands 1960.77 mm in the x-direction and 708.27 mm in the y-direction and has an area of 11641.86 cm^2. The cutting degree is 0.14.

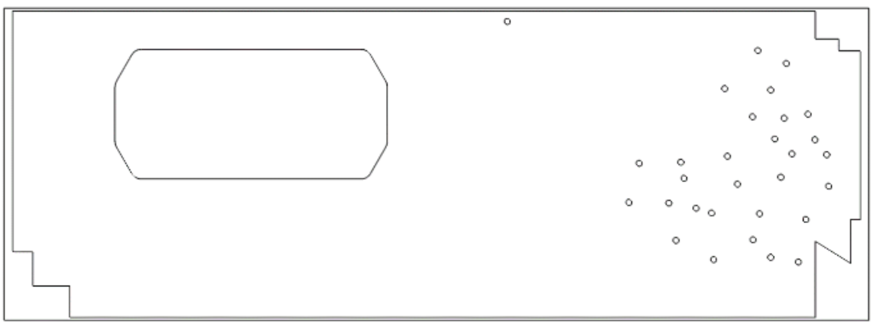


Fig. 5.45: Repeating Geometry H. Own visualization

As visualized in Figure 5.46, most participants labeled the laser cutting complexity 1 or 2. We have only one outlier, participant P25, who labeled the laser cutting complexity 4 once. This results in an average laser cutting complexity of 1.4.

For unloading complexity with the SortMaster Speed, visualized in Figure 5.47, we again have most mentions of either 1 or 2. Only participant P23 consistently labeled complexity 4. This results in an average complexity for part handling with the SortMaster Speed of 1.6.

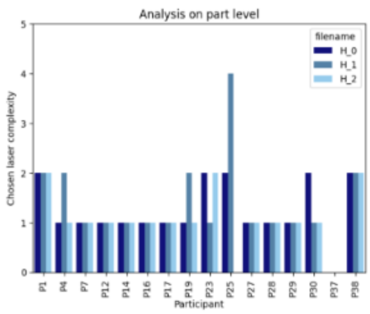


Fig. 5.46: Analysis of complexity labeling for laser cutting for repeating geometry H. Own visualization.

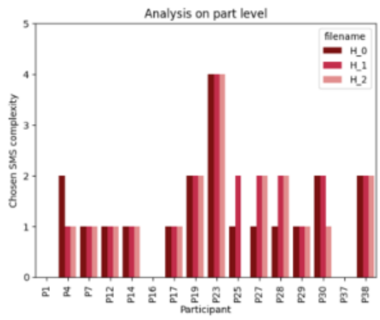


Fig. 5.47: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry H. Own visualization.

Figure 5.48 shows the categorized explanations for the laser cutting complexity for geometry H. No issues were mentioned 31 times and 4 times, no explanation was given. The undercut in the lower right corner of the outer contour being problematic was mentioned four times, while the notches, the inner contours, and the shape being problematic were each mentioned three times. The contour in general, the outer contour, and the size being problematic were each mentioned once.

The categorized explanations for geometry H and the complexity of part handling with the SortMaster Speed are visualized in Figure 5.49. No issues were mentioned 21 times and no detailed explanations were given four times. The most mentioned characteristic influencing the part complexity was the size being problematic with five mentions, followed by the placement of the suction cups with four mentions. The weight being problematic, the placement of the pins, and bending were each mentioned twice, while the notches, possible scrap cutting, the placement of the ejection cylinder, the falling detection, and the undercut were each mentioned once. We assume that the one big inner contour on the left side and the accumulation of small circular inner contours on the right side of the geometries make the placement of the suction cups and the pins of the SortMaster Speed more difficult. The weight and the size depend on the rather large area of the geometry, as well as the bending being problematic. The possible scrap cutting can refer to both the large inner contour and the undercut in the lower right corner of the outer contour.

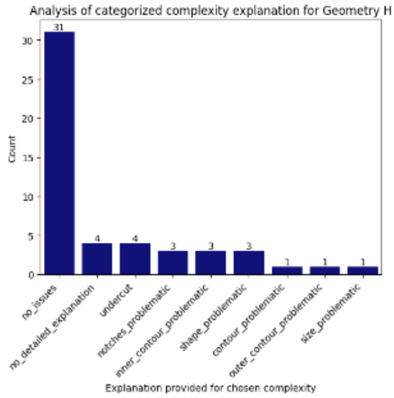


Fig. 5.48: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry H. Own visualization.

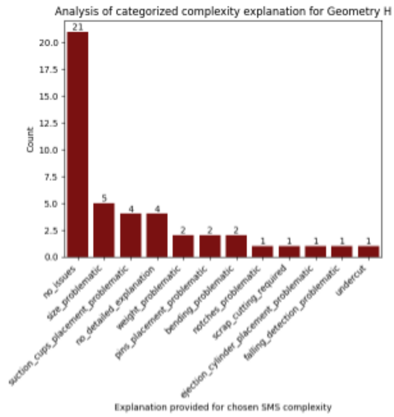


Fig. 5.49: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry H. Own visualization.

5.4.1.9 Geometry I

Geometry I, visualized in Figure 5.50, is a small circle with two small, circular inner contours. Due to its size, it applies to part handling with both the SortMaster Speed and the Smart Gate. Geometry I has two inner contours and an area of 113.79 cm^2. It expands 121.63 mm in both the x- and y-direction. The cutting degree is 0.02, and the cutting length is 459.75 mm. The centroid lies on the part.

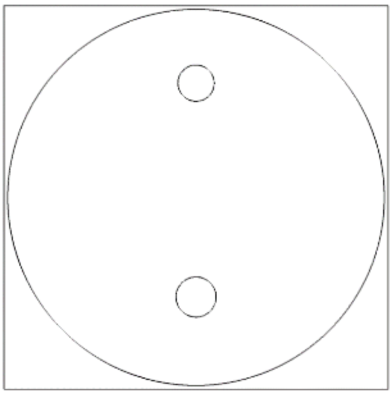


Fig. 5.50: Repeating Geometry I. Own visualization

The assigned complexity values for laser cutting and geometry I are shown in Figure 5.51. The participants seem to agree on low complexity with mostly complexity 1 and four times complexity 2. This results in an average laser cutting complexity of 1.1.

Figure 5.52 shows the assigned complexities for part handling with the SortMaster Speed. The whole complexity range has been used: While many participants consistently labeled the complexity for the SortMaster Speed with 1 and sometimes 2, we have two times complexity 4 and three times complexity 5. This results in an average complexity for part handling with the SortMaster Speed of 1.6.

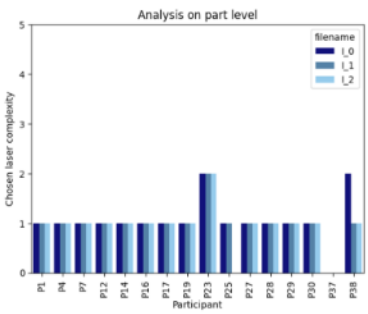


Fig. 5.51: Analysis of complexity labeling for laser cutting for repeating geometry I. Own visualization.

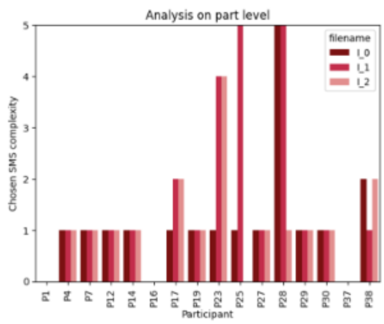


Fig. 5.52: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry I. Own visualization.

The complexity of part handling with the SmartGate is visualized in Figure 5.53. Except for participant P23, who labeled geometry I two times with complexity 2 for part handling with the Smart Gate, the participants labeled complexity 1. This gives us an average SmartGate complexity of 1.1.

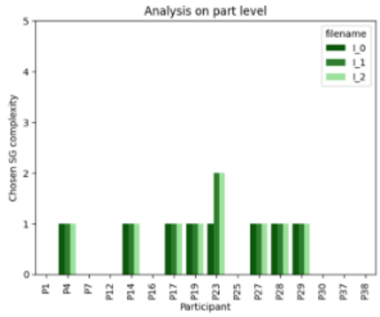


Fig. 5.53: Analysis of complexity labeling for part handling with the SmartGate for repeating geometry I. Own visualization.

Figure 5.54 shows the categorized explanations for the chosen laser complexity of geometry I. While no issues were mentioned 40 times and no detailed explanation was given one time, the contour being problematic was mentioned twice, and the inner contour being problematic was mentioned once. We assume that this targets the circularity of geometry I as well as its inner contours, as circular contours may tilt during the laser cutting process, leading to production issues.

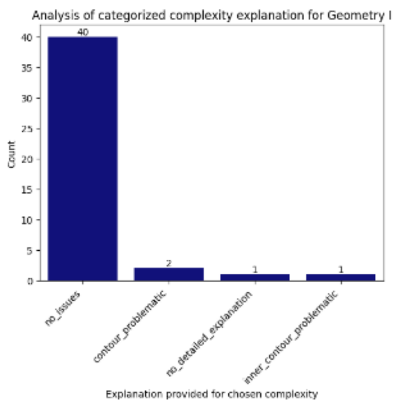


Fig. 5.54: Analysis of the categorized answers for the chosen complexity for laser cutting for repeating geometry I. Own visualization.

The categorized explanations of geometry I and part handling with the SortMaster Speed are depicted in Figure 5.55. No issues were given 29 times and no detailed explanation was given three times. While five people mentioned the size being problematic, the prefix being problematic was mentioned once. This is reflected in the size of geometry I, as it ranges on the lower end of the technical capacity of the SortMaster Speed.

The categorized explanations for part handling with the SmartGate are depicted in Figure 5.56. The only two labeling of 2 both stated that a tilting of the geometry may occur, the remaining labelings see no issues. Circular geometries may tilt, so again we can see the link between complexity labeling, explanation, and geometry.

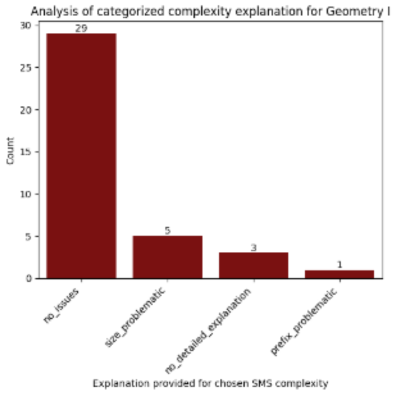


Fig. 5.55: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry I. Own visualization.

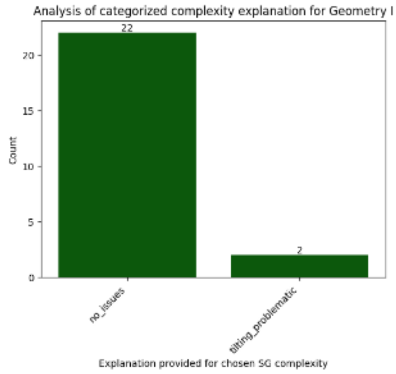


Fig. 5.56: Analysis of the categorized answers for the chosen complexity for part handling with the SmartGate for repeating geometry I. Own visualization.

5.4.1.10 Geometry J

Geometry J is depicted in Figure 5.57. It is an almost rectangular geometry with two rounded corners and a large undercut in the center of the part. With an area of 3.14 cm^2, it is the smallest repeating geometry. It expands 31.5 mm in the x-direction and 12.1 mm in the y-direction. The cutting length is 100.96 mm, and the cutting degree is 0.

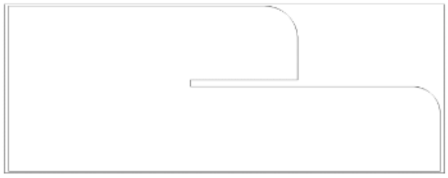


Fig. 5.57: Repeating Geometry J. Own visualization

In Figure 5.58, we see a high variance in the complexity labeling for the process step laser cutting. While many participants consistently labeled with complexity 1 or alternated between complexity 1 and 2, high complexity is labeled five times by four different participants, with one participant labeling with 5, the highest complexity. The average laser cutting complexity is 1.8.

In contrast to the complexity of laser cutting, we can only see low complexities chosen for part handling with the SmartGate and geometry J, as depicted in Figure 5.59. Three participants consistently labeled complexity 1, four participants alternated between complexity 1 and 2, and one participant consistently labeled with complexity 2. This results in an average SmartGate complexity of 1.3 for geometry J.

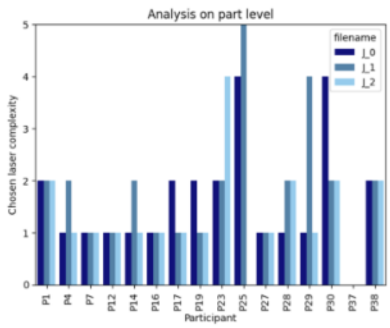


Fig. 5.58: Analysis of complexity labeling for laser cutting for repeating geometry J. Own visualization.

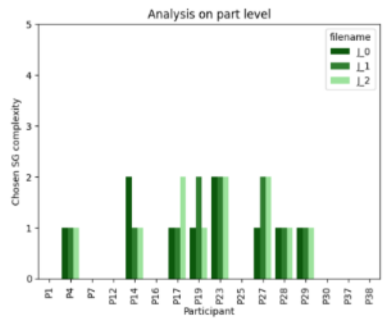


Fig. 5.59: Analysis of complexity labeling for part handling with SortMaster Speed for repeating geometry J. Own visualization.

The categorized explanations for the chosen laser cutting complexity for geometry J are visualized in Figure 5.60. With 23 times, no issues were mentioned the most, while three times, no detailed explanation was given. The undercut was mentioned five times, followed by scrap cutting and the size being problematic with four mentions each. The contour in general being problematic was mentioned three times, as well as the notches. The tilting, inner contour, and pierced hole were mentioned two times each, while the heat, the placement of the ejection cylinder, the falling detection, and the kerf size being problematic were each mentioned once. We assume the undercut in the middle of the geometry is responsible for the mentioning of the undercut, the heat, the kerf size, the scrap cutting, the contour, and the pierced hole. The mention of the size may be due to both the undercut and the size of the part.

Figure 5.61 shows the categorized explanations for geometry J and part handling with the SmartGate. No issues were mentioned 16 times. The undercut being problematic was mentioned five times, the placement of the ejection cylinder two times, and the notches and tilting being problematic were each mentioned once. Again, we see the categorized explanations reflected in the geometry, as geometry J has the filigree undercut in the middle.

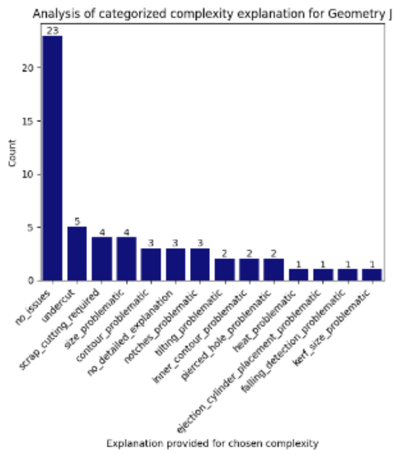


Fig. 5.60: Analysis of the categorized answers for the chosen complexity for part handling with SortMaster Speed for repeating geometry J. Own visualization.

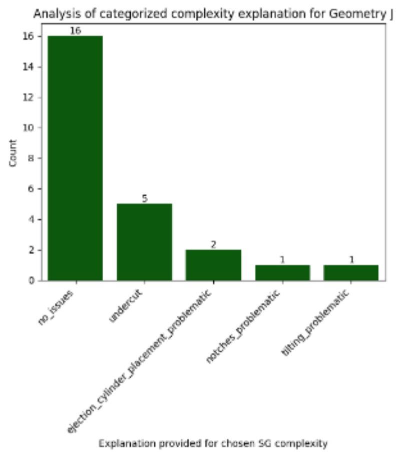


Fig. 5.61: Analysis of the categorized answers for the chosen complexity for part handling with the SmartGate for repeating geometry J. Own visualization.

5.4.2 Conclusion

The analysis of the repeating geometries has shown that the experts label the complexity consistently: Each expert passed the repetition test for at least one process step. Only one expert did not pass the repetition test for the process step laser cutting, and two experts did not pass the repetition test for the process step part handling with the SortMaster Speed. For the process step part handling with the SmartGate, only half of the experts passed the repetition test. We assume that the reason for this is that only two of the ten repeating geometries covered this process step. This leads to a big deviation of 50 % in the labeling if only one geometry has been labeled inconsistently. For comparison, one geometry being labeled with a big deviation for the process step laser cutting would lead to a deviation rate of 10 %, and for the process step part handling with the SortMaster Speed, it would lead to a deviation rate of approximately 11%. For these two process steps, the deviation from labeling one geometry highly inconsistent would lie under the defined limit. The reason that only two of our repeating geometries cover the process step part handling with the SmartGate is in the little representation of this process step in the whole labeling dataset of 80 geometries since this process step only applies to small geometries. However, the majority of the geometries in our labeling dataset are bigger than 160 mm length and width. All in all, we conclude that the experts are capable of estimating the complexity of parts in sheet metal processing.

The analysis of the repeating geometries further has shown a consensus on the complexity of many geometries and process steps. Examples of this are geometry A, D, and G for both laser cutting and part handling with the SortMaster Speed. We have other geometries where the experts highly varied in the labeling, like geometry J for laser cutting, and geometries C and I for part handling with the SortMaster Speed. In addition, many experts delivered similar explanations for the complexity they assigned, like undercuts and inner contours. Moreover, we can see the link between the explanations given by the experts and the part characteristics.

Now, we want to investigate if we can transfer the labeling results to other geometries using an algorithm.

5.5 Transferring the Labeling Results to New Geometries

We want to transfer the results of the complexity to other geometries. By doing so, we also check the generalizability of our results. We decided to implement the algorithms Random Forest Regressor and Random Forest Classifier for the transfer of results and testing for generalizability, as these algorithms fit our research problem and offer interpretability. Before, we analyzed the influencing factors of the geometry features.

5.5.1 Analysis of Influencing Factors

To analyze the influence of the geometrical features on the algorithm, we first calculated the mean complexity values per process step based on the complexity labeling participants who passed the repetition test. If applicable, we removed empty values, e.g. for part handling process step that did not apply. Then, we initialized a random forest classifier with 100 trees and a fixed random seed. We applied Leave-One-Out Cross Validation (LOOCV) to evaluate the model's performance and calculated the mean accuracy and standard deviation over all LOOCV iterations. We present the five most important features per process step in the following.

5.5.1.1 Laser cutting

For laser cutting, the random forest classifier achieved an accuracy of 73.75 % and a standard deviation of accuracy of 0.44. While the accuracy seems promising, the rather high standard deviation indicates that our model is unstable.

Table 5.7 presents the five most important features and their importance. Overall, no feature domains, and the most important features have relatively similar importance scores between 0.06 and 0.12. The ratio of the area of the convex hull and the part's area including inner contours is the most important geometrical feature with an importance of 0.121. The cutting degree achieved an importance of 0.087, followed by the amount of inner contours with an importance of 0.064. The circumference of an adapted circle reached an importance of 0.063. In contrast, the ratio of the contour length of the outer contour and the circumference of an adapted circle reached an importance of 0.061.

Geometrical Feature	Importance
The ratio of the area of the convex hull and the part's area, including inner contours	0.1210001
Cutting degree	0.087270
Amount of inner contours	0.064230
Circumference of an adapted circle	0.063605
The ratio of contour length of the outer contour and the circumference of an adapted circle	0.061319

Table 5.7: Factor analysis of the five most important features for the process step laser cutting

In comparison to the occurrences of categorized explanations for the process step laser cutting shown in Figure 5.7, the inner contours are mentioned the most second only to no issues, which is reflected by the amount of inner contours being one of the five most important features of the random forest classifier. The undercuts and scrap cutting being required were mentioned on places four and five, respectively. These explanations are reflected in the five most important geometrical features in the cutting degree, the ratio of the area of the convex hull and the part's area, including inner contours, and the amount of inner contours.

5.5.1.2 Part Handling with the SortMaster Speed

For part handling with the SortMaster Speed, the random forest classifier reached an accuracy of 70 % and a standard deviation of accuracy of 0.46. Similar to the process step laser cutting, the accuracy seems to be promising, while the standard deviation of the accuracy indicates an unstable model.

Table 5.8 presents the most important geometrical features and their importance. Similar to the process step laser cutting, no single feature dominates. The most important feature is the ratio of the contour length of the outer contour and the circumference of an adapted circle with an importance of 0.108, followed by the ratio of the part's circumference and the circumference of the convex hull with an importance of 0.089. The ratio of the area ignoring inner contours of the part and the area of the bounding box achieved an importance of 0.065, while the length of the x-axis for the rotated part polygon´s minimum rectangle achieved an importance factor of 0.06. The last feature in the table is the ratio of the area of the convex hull and the part's area, including inner contours, which achieved an importance of 0.059.

Geometrical Feature	Importance
The ratio of contour length of the outer contour and the circumference of an adapted circle	0.108376
The ratio of the part's circumference and the circumference of the convex hull	0.088823
The ratio of the area ignoring inner contours of the part and the area of the bounding box	0.065191
Length of the x-axis for the rotated part polygon´s minimum rectangle	0.060792
The ratio of the area of the convex hull and the part's area, including inner contours	0.058896

Table 5.8: Factor analysis of the five most important features for the process step part handling with the SortMaster Speed

The occurrences of categorized explanations for the process step part handling with the SortMaster Speed in Figure 5.8 indicate that the placement of the suction cups and the pins being problematic were most often mentioned by the labeling participants, followed by undercuts and bending being problematic. Both the placements of the pins and the suction cups hint at inner contours making the placement more challenging, which are reflected in the ratio of the area of the convex hull and the part's area, including inner contours. However, one would expect these placements to be more directly reflected in the most important features by the amount of inner contours, which they are not. The undercuts are reflected in both the ratio of the contour length of the outer contour and the circumference of an adapted circle and the ratio of the part's circumference and the circumference of the convex hull, as these two features may indicate non-linear outer contours. The bending being problematic is reflected in the length of the x-axis for the rotated part polygon´s minimum rectangle, as the risk of bending increases in longer parts.

5.5.1.3 Part Handling with the SmartGate

The random forest classifier achieved an accuracy of 90 % and a standard deviation of accuracy of 0.3 for the process step part handling with the Smart Gate. In contrast to the process steps of laser cutting and part handling with the SortMaster Speed, the random forest classifier achieved a higher accuracy and a lower standard deviation of accuracy, indicating a more stable model and a better classification. However, one should keep in mind that the sample size for the part handling with the SmartGate was significantly lower than for the other two process steps.

Table 5.9 presents the five most important factors for the process step part handling with the SmartGate. The most important feature is the length of the part's bounding box in x-dimension with an importance of 0.24, followed by the antipodal distance with an importance of 0.15. The three remaining factors are of similar importance, with 0.08 for the contour length of the part's convex hull, 0.08 for the length of the outer contour of the part, and 0.07 for the length of the x-axis for the rotated part polygon´s minimum rectangle. As the requirements for part handling with the SmartGate are that the part's size has to be within 160 mm x 160 mm, it is reasonable that the random forest classifier concentrates on features indicating the size of the part like the length in x-dimension or the antipodal distance.

Geometrical Feature	Importance
Length of the part's bounding box in x-dimension	0.234903
Antipodal distance	0.144600
Contour length of the part's convex hull	0.077110
Length of the outer contour of the part	0.074491
Length of the x-axis for the rotated part polygon´s minimum rectangle	0.072869

Table 5.9: Factor analysis of the five most important features for the process step part handling with the SmartGate

Figure 5.9 from Subsection 5.3.3.3 shows the occurrences of categorized explanations for the process step part handling with the SmartGate. The tilting being problematic is mentioned most often, followed by the size being problematic and the placement of the ejection cylinder being problematic as well as undercuts. Tilting occurs usually with circular parts, which are not represented in the five most important factors. The size being problematic is represented in the three factors length of the part's bounding box in x-dimension, antipodal distance, and length of the x-axis for the rotated part polygon´s minimum rectangle. The placement of the ejection cylinder depends on inner contours, which are not represented in the five most important factors. The undercuts may be hinted at by the contour length of the part's convex hull and the length of the outer contour of the part.

5.5.2 Implementing the Algorithms

First, we implemented a Random Forest Regressor with both k-fold cross validation with k=5 and leave one out cross validation. The performance metrics achieved by this algorithm suggest varying levels of predictive accuracy and consistency across different process steps and cross-validation techniques.

Next, we tried a random forest classifier, hoping that the lower granularity with complexity classes rather than continuous complexity values would achieve better results. First, We tried three classes small, medium, and high complexity, with the medium complexity ranging from 1.2 to 1.8. We tested the three cross-validation methods repeated k-fold cross-validation, stratified k-fold cross-validation, and leave one out cross-validation. This algorithm also was not capable of reliable classification of the complexity classes. We observed significantly better results for the complexity classes with many instances, like the 53 medium complex parts for laser cutting and the 31 highly complex parts for part handling with the SortMaster Speed. We have seen the poorest results for the classes with only a handful of instances, like parts that are highly complex for laser cutting or parts that are highly or medium complex for part handling with the SmartGate. This indicates that the algorithm would benefit from more geometries that are evenly distributed across the complexity classes. All in all, the algorithm fails to at least reliably identify highly complex parts of the process steps. However, the algorithm seems to be well-suited for the identification of the applicable part-handling process. This distinction requires less sophisticated part characteristics since this solely is dictated by the parts' width and length.

Lastly, we decided to investigate the classification results for the two classes small and high complexity, following the labeling scale. We defined small complexity as parts with a complexity lower than 1.4, and high complexity parts with a higher complexity. Again, we used "not_applicable" for parts not applicable to part handling with the SortMaster Speed or the SmartGate. Since the implementation of the classification algorithm with two classes worked best for the process step laser cutting, we will explain only these results in detail.

Table 5.10 shows the performance metrics for the process step laser cutting and two complexity classes.

Complexity Class	Accuracy	Recall	f1-Score	Support
high	0.38	0.24	0.29	25
small	0.7	0.82	0.76	55

Table 5.10: Performance Metrics per complexity class for Random Forest Classifier and the Process Step laser cutting.

For the high complexity class, the algorithm achieved an accuracy of 38%. This indicates that 38% of instances belonging to the high complexity class were correctly classified, in comparison to 50% accuracy for three complexity classes. The recall, which measures the ability of the model to correctly identify instances of the high complexity class, is at 24% slightly higher than the 20% for three complexity classes. The F1-Score, which balances precision and recall, is 0.29. There are 25 instances of the "high" complexity class.

Although we have far more instances of high complexity with only two complexity classes, the algorithm's ability to classify highly complex geometries worsened.

The algorithm performed significantly better for the small complexity class, achieving an accuracy of 70%. This suggests that 70% of instances belonging to the "small" complexity class were correctly classified. The recall for the small complexity class is 82%, indicating that the model effectively identified 82% of actual instances of this class. The F1-Score, a harmonic mean of precision and recall, is 0.76. There are 55 instances of the "small" complexity class.

In summary, the algorithm's performance varies across different complexity classes. It performs relatively better for the "small" complexity class compared to the "high" complexity class. The "small" complexity class demonstrates higher accuracy, recall, and F1-Score, indicating that the model is more effective in correctly classifying instances of this class. However, for the high complexity class, the model's performance is notably poorer, with lower accuracy, recall, and F1-Score.

Figure 5.62 shows the confusion matrix for the process step laser cutting and two complexity classes. Of the 25 highly complex parts, only six were correctly classified, while 19 parts were incorrectly classified as small. Of the 55 parts with small complexity, 45 were classified correctly, while 10 parts were incorrectly classified as high.

In summary, the algorithm is not capable of reliable classification for the process step laser cutting of highly complex parts, even with only two complexity classes and more evenly distributed instances in each complexity class.

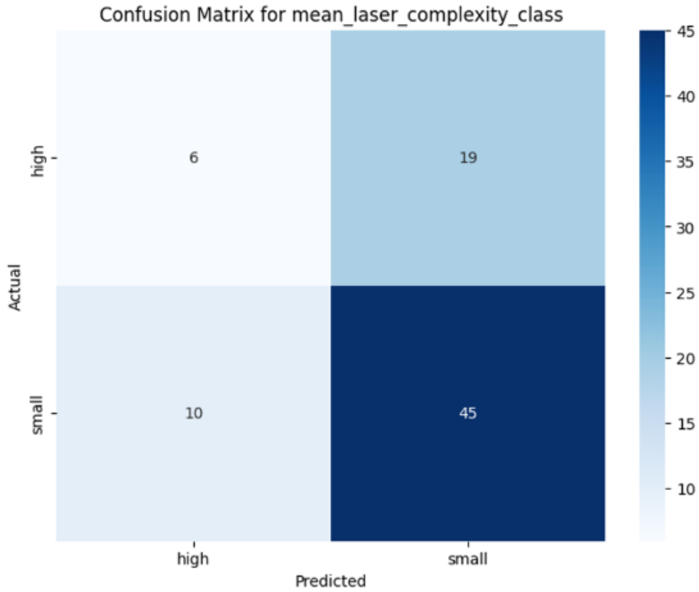


Fig. 5.62: Confusion Matrix for the process step laser cutting and the two complexity classes small - high

The performance metrics for two complexity classes and the process step part handling with the SortMaster Speed are depicted in Table 5.11.

The algorithm achieved an accuracy of 81%, indicating that 81% of instances belonging to the high complexity class were correctly classified. The recall, which measures the proportion of actual high complexity instances that were correctly classified, is 90%. The F1-Score, a balance between precision and recall, is 0.85. There are 48 instances of the "high" complexity class. In comparison to the classification of highly complex parts and three complexity classes, the algorithm now achieves a higher accuracy and a higher recall for 48 parts instead of 31 parts. However, the performance is still not good enough for implementation in daily tasks.

For the small complexity class, the algorithm achieved an accuracy of 69%. This means that 69% of instances belonging to the small complexity class were correctly classified. The recall for the small complexity class is 52%, indicating that the model identified 52% of actual instances of this class. The F1-Score, a harmonic mean of precision and recall, is 0.59. There are 21 instances of the "small" complexity class. In comparison to the classification of parts with a small complexity out of three complexity classes, the algorithm achieves significantly better results. This compares the results of a complexity class with 11 instances instead of 21.

The algorithm achieved perfect accuracy, recall, and F1-Score for the not applicable class, indicating that all instances of this class were correctly classified. There are 11 instances of the "not applicable" class.

In summary, the algorithm performed well for the high complexity class with high accuracy, recall, and F1-Score. It showed relatively lower performance for the small complexity class, especially in terms of recall, but still achieved reasonable accuracy and F1-Score. Additionally, the model performed perfectly for the "not applicable" class, indicating excellent classification for the part-handling process.

Complexity Class	Accuracy	Recall	f1-Score	Support
high	0.81	0.9	0.85	48
small	0.69	0.52	0.59	21
not applicable	1	1	1	11

Table 5.11: Performance Metrics per complexity class for Random Forest Classifier and the Process Step Part Handling with the SortMaster Speed.

For the part handling process steps and two complexity classes, the algorithm's performance is very poor for the high complexity class, with no instances correctly classified. It performs moderately well for the small complexity class, achieving decent accuracy, recall, and F1-Score. However, the results are not good enough for new geometries. The algorithm only demonstrates excellent performance for the "not applicable" class, with high accuracy, recall, and F1-Score, indicating that it is capable of distinguishing between parts exclusively applying for part handling with the SmartGate and those exclusively applying for part handling with the SortMaster Speed.

In summary, the Random Forest Classifier with leave one out cross-validation performed best. However, the achieved performance metrics for three complexity classes as well as for two complexity classes are insufficient for implementation in daily tasks, with 81% being the highest accuracy, achieved for parts that are highly complex for part handling with the SortMaster Speed and two complexity classes. Nonetheless, the algorithm can excellent distinguish between parts that are exclusively applicable for part handling with the SortMaster Speed and those exclusively applicable for part handling with the SmartGate.

5.5.3 Evaluation

We planned to evaluate the results of our algorithm with ten new geometries. We would follow the same procedure as for the labeling geometry dataset by randomly selecting ten new geometries from the original dataset and altering these geometries to comply with non-disclosure agreements and protect intellectual property. After letting the algorithm—which was trained on the labeling results—classify the ten new geometries, we would have let the experts who passed the repetition test evaluate the algorithm's classification result. However, the poor performance of the algorithm made such an evaluation pointless since we would not incorporate an algorithm with so low-performance metrics in daily activities.

We assume the combinations of the algorithm, the geometrical features, and the labeling variance to be responsible for the unsatisfying results: First, we have a very little database with only 80 individual geometries. By implementing test-train-split to evaluate the algorithms' performance, we limit the database even more. In addition, we have highly imbalanced complexity labeling, where the majority of the parts have been labeled as low complexity. By incorporating more geometries in the labeling process in general and especially more highly complex geometries, we could improve the database for the algorithm. However, increasing the geometries to be labeled may increase the dropout rate, leading to poorer labeling results. Another assumption is that the calculated geometrical features did not cover the relevant complexity-influencing characteristics: While the relation between part complexity and geometrical characteristics was clear during the analysis of the repeating geometries, this relation was not as easy to capture for the chosen algorithms. By incorporating more metrics that better reflect the categorized explanations of the experts, such as the area per inner contour, or a more sophisticated calculation of undercuts, maybe we could improve the algorithms' performance.

5.6 Discussion and Critical Reflection

Due to the endless possibilities of geometries, a statistical representativity of our labeling geometries was impossible to achieve. Instead, we randomly selected 80 geometries out of a database of over 16,000 customer geometries. To comply with non-disclosure agreements and to protect intellectual property, we manually altered these randomly selected geometries, following the results of the individual depth interview: As described in Subsection 4.3, we asked one potential participant for characteristics of highly complex geometries to prepare the labeling database of 80 geometries. By installing the repetition test as an evaluation mechanism, we ensured the quality of our data collection by evaluating the participants' labeling consistency over time. We subjectively chose 30 % of high deviations for eliminating inconsistent labeling since we did not find suitable limits in the literature. However, one needs to keep in mind that we did not provide the middle option "3" in the rating scale, which might have provoked bigger deviations in the labelings. Furthermore, the participants may have been influenced during the labeling process by the prior geometries. The participants gained more experience in complexity labeling each week, although the repeating geometries' order did not change which may have influenced their labeling.

To keep our expert pool as large as possible, we also considered the interviewee from the individual depth analysis for the complexity labeling as participant P1. To allow for an evaluation of the consistency of the participants' labeling, we randomly selected ten geometries out of the 80 geometries that we manually altered to be repeated in each week of the three weeks of the labeling, our repetition test. We subjectively chose 80 geometries as a database and ten geometries to be repeated, since these numbers seemed to be a good trade-off between having a high enough number to get trustworthy results and not having time-consuming labeling. As we have seen in the analysis of the repetition test in Figure 5.3, participant P1 only passed the repetition test for laser cutting with a critical deviation of 0.1 and failed the repetition test for the process steps part handling with the SortMaster Speed and part handling with the SmartGate with a deviation of 0.44 and 0.5, respectively. One could argue that our complexity labeling results would have been better with conducting the individual depth interview with participants who do not have any deviations, like the participants P4 or P14, or who have only small deviations, like the participants P19, P23, P27, P28, or P29. However, before the complexity labeling, we had no quantitative information on the participant's knowledge of complexity-influencing part characteristics. It is possible that we could achieve a more sophisticated perspective by re-conducting the individual depth interview with participants who passed the repetition test and then the complexity labeling, or by conducting a subsequent complexity labeling with the participants who passed the repetition test that focuses especially on complex geometries.

To further analyze the validity of our research, we evaluated the internal and external validity. According to Campbell [2017], the internal validity examines if the research measured what it was supposed to measure. In our case, we aimed our research approach to investigate geometrical part characteristics that influence its manufacturability, also called complexity. Our research approach has indeed identified characteristics that influence the parts' complexity, demonstrating the internal validity of our research approach: For the process step of laser cutting, geometrical characteristics such as inner contours, undercuts, and notches were mentioned the most. For part handling with the SortMaster Speed, inner contours make the placement of pins and suction cups more challenging. Further geometrical characteristics mentioned often for this process step were undercuts and long parts that may bend. For the process step part handling with the Smart Gate, possible tilting was mentioned most often. However, one needs to keep in mind that the complexity-influencing part characteristics are not limited to those that we identified.

The generalizability of the research results is called external validity [Döring and Bortz, 2016; Campbell, 2017]. We evaluated both the generalizability of our research approach for the part complexity assessment as well as the results. By adapting our research approach for the assessment of part complexity to our exemplary production unit, we demonstrated its generalizability. This is why we strongly assume that our part complexity assessment methodology can also be adapted to further technologies and production units. However, one needs to keep in mind that the online tool we developed to support our complexity labeling needs to be adapted to the production processes and process steps of the chosen production units or technologies. The transferability of our resulting part complexity influencing part characteristics is limited. First, the results only apply to our chosen production unit for the labeling. Before transferring these results to other production units—even with identical process steps like laser cutting—we strongly recommend further evaluation, if not adapting our research methodology to the other production units or technologies. Second, the transferability of our resulting part complexity influencing part characteristics for the same production unit, but new geometries is inflicted by the small database as well as its imbalancedness: Due to the small dataset of 80 unique geometries and its imbalancedness with a majority of parts being labeled as low complex, we could not achieve sufficient performance metrics of the chosen algorithms to transfer the results to new geometries. However, we are confident that the performance of the Random Forest algorithm would benefit from creating a larger database by having more geometries labeled, and by incorporating more highly complex within this geometry to reduce the imbalancedness.

There are several suggestions to improve the research results in further studies. First, one could increase the number of participants through measures such as introducing a reward for the participants who complete the labeling and by asking customers. For the latter, one should only include customers with a complete ramp-up-phase of the production unit of usually six months in which the production unit is made ready for daily use. Second, one could adapt the part complexity assessment methodology to further production units and technologies, increasing the confidence in our methodology and gaining more knowledge about complexity influencing part characteristics in general. Third, the results could be improved by covering more geometries and especially more highly complex geometries, using the first results of our studies for the generation of the labeling database. Fourth, the part complexity could be assessed before and after the optimization of production processes to keep the complexity influencing part characteristics up to date and generate knowledge about the way the optimization affects the production process.

5.7 Interim Result: Part Complexity Influencing Part Characteristics

The second research question of this thesis is "How do the part characteristics influence the part complexity in sheet metal processing?". We validated our part complexity assessment methodology presented in Section 4 by putting it into practice. 37.5 % of the participants completed at least two of the three weeks of the labeling and hence, are further considered in the evaluation. The analysis of the repeating geometries has proven that the labeling participants label the part complexity consistently for the process steps. The high rate of participants failing the repetition test for part handling with the SmartGate may lie in the small number of parts applying to this process step in the dataset and hence, in the subset of repeating geometries. The elimination of participants failing the repetition test on the process step level enhances the quality of our labeling results. The resulting part complexities show an imbalance since labeling with the low complexity classes 1 and 2 is predominant, while only a minority of the complexity labelings are for the high complexity classes 4 and 5.

To analyze the explanations given by the participants for the chosen part complexity and process step, we created codebooks, one for each process step. These codebooks contain the categories as well as a description of what this category means to summarize the explanations given by the participants. This categorization enables a better analysis since it uniforms the language and summarizes explanations that have been phrased differently by the participants. Since the aim was to identify geometrical characteristics of complex parts, the category "no issues" was assigned when the chosen complexity was 1. If a higher complexity was chosen without an explanation, like "...", the category "no detailed explanation" was assigned. In addition to the codebooks, we present the occurrence of each category for the respective codebook.

Subsequently, we analyzed the ten repeating geometries. We illustrate each geometry and describe its geometrical features. We present and interpret the complexity labelings as well as the categorized explanations. For many geometries, one can observe a consensus for both the part complexity and the underlying reasons. For some geometries, the complexities vary, indicating the need for deeper analysis. Part characteristics that seem to influence the part complexity are undercuts and inner contours.

To transfer the labeling results to new geometries, we analyzed the influencing factors and implemented both classification and regression algorithms. The analysis of the influencing factors showed a correlation between the five most important features for the algorithm and the occurrence of explanations for the part complexity given by the participants. Despite lowering the granularity by transforming the average complexities into complexity classes, the algorithms did not achieve satisfactory performance metrics. We assume the small dataset of only 80 geometries and the imbalance within the labelings to be the reason, as well as a need for more sophisticated part characteristics to further support the algorithm.

Furthermore, we reflect on our research approach. We especially shed light on the elimination of the average value in the labeling rating scale, that one labeling participant also participated in the individual depth interview for the preparation of the labeling dataset, and the definition of the thresholds for failing or passing the repetition test.

In summary, we validated the part complexity assessment methodology developed in Section 4 by putting it into practice. The experts have proven their capability of assessing part complexity on the process step level. We answered research question 2, "How do the part characteristics influence the part complexity in sheet metal processing?", by identifying part complexity influencing part characteristics and identified future work to enable the transfer of our labeling results to other geometries using a classification algorithm.

Chapter 6
Application Possibilities of Part Complexity

This section aims to answer this dissertation's third research question, "How can part complexity contribute to the demand for data-driven information about the customers along the product life cycle?" First, we present focus groups as the chosen research approach in Subsection 6.1. Subsequently, we explain the preparation of our focus group in Subsection 6.2, covering the introductory information (see Subsection 6.2.1), the participants (see Subsection 6.2.2), the setup (see Subsection 6.2.3), and the time plan (see Subsection 6.2.4). While Subsection 6.3 gives insights into the conduction of our focus group, Subsection 6.4 presents the resulting part complexity use cases from the focus group in detail. After we compare the focus group results to the literature review in Subsection 6.5, we discuss and reflect our research approach in Subsection 6.6. Subsection 6.7 concludes this section with a broad summery of the results and answers the research question.

6.1 Method: Focus Group

We chose focus groups as our methodology for identifying new application possibilities for part complexity measures: First, we rely on expert knowledge and need a research methodology that incorporates experts. Second, we want the experts to interact with each other to promote discussions and broaden the results. Third, we want this interaction not only between experts from one area but between experts from as many relevant areas as possible.

Focus groups are structured interviews with 6-10 people [Cooper and Schindler, 2003; Powell and Single, 1996] or 4-12 people [Tong et al., 2007] that are a heterogeneous group of experts providing different perspectives [Cooper and Schindler, 2003]. Focus groups are used to explore different views on a wide variety of topics, such as health issues [Tong et al., 2007; Powell and Single, 1996], technical topics [Cooper and Schindler, 2003], and many more. Focus groups usually meet for between one and ten sessions until no new information is retrieved [Powell and Single, 1996].

In focus groups, the participants are encouraged to interact with each other and discuss the results [Cooper and Schindler, 2003; Tong et al., 2007; Powell and Single, 1996]. The disadvantages of group interviews are that there is only little time to extract information from each participant and difficulty in organizing and moderating group discussions [Cooper and Schindler, 2003]. The moderator's job is to manage overly dominant participants and ensure that everybody can contribute [Cooper and Schindler, 2003] and ensure a good dialogue in general [Powell and Single, 1996]. Focus groups typically meet for 1 to 3 hours [Cooper and Schindler, 2003] or 90 to 120 minutes [Powell and Single, 1996]. The authors of Powell and Single [1996] recommend that a note-taker documents participants' behavior like dominant body language in case there is no video documentation. Focus groups should start with an introductory session at the beginning of the focus group so that the researcher, moderator, and participants get to know each other [Powell and Single, 1996].

The authors of Powell and Single [1996] researched focus groups for health care settings, e.g. when sensitive personal information like birth stories are shared, and recommend that only people who do not know each other participate in the focus group to avoid difficulties within the group, e.g. due to different seniority levels, and to get more honest answers. Furthermore, it is not recommended to follow the recommendations of other people who should participate in the focus group [Powell and Single, 1996].

The authors of Tong et al. [2007] introduced a checklist intending to improve the scientific reporting on focus groups. Their checklist covers the areas of the research team, the study design, and the subsequent analysis of the findings. Examples of items in their checklist are the relationship between the researcher and the participants, information about the study design like participant selection and the interview guide, and information about the subsequent data analysis. We document our focus group using the checklist of Tong et al. [2007] in Subsection 6.3. We follow the literature, where possible. When needed, we adapt the method to our research endeavor.

6.2 Planning the Focus Group

This subsection presents the planning of the focus group with the aim to identify further use cases of part complexity. First, we prepared the introductory information for the focus group in Subsection 6.2.1. Then, we selected the participants in Subsection 6.2.2. Subsection 6.2.3 presents the preparation and setup of the focus group, while Subsection 6.2.4 contains the time plan for the focus group.

6.2.1 Introductory Information

In the beginning of the focus group, we shared introductory information about the definition of part complexity from Subsection 4.1, as shown in Figure 6.1.

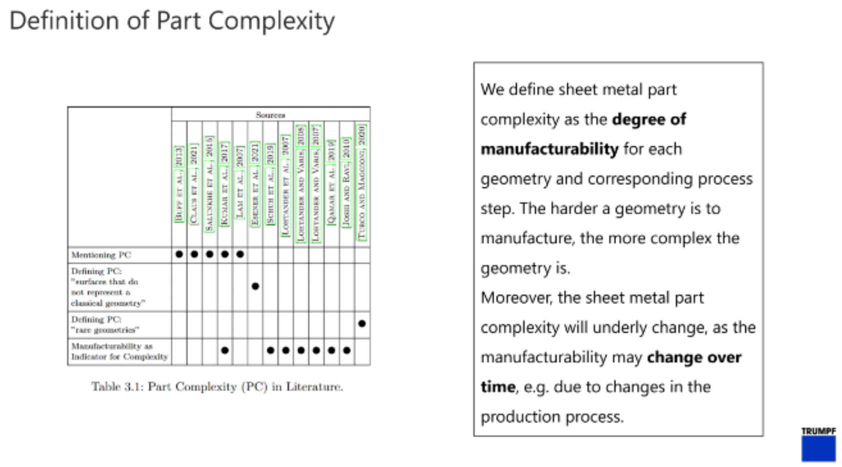


Fig. 6.1: Introductory Information for the Focus Group: Definition of Part Complexity. Own visualization.

Subsequent, we presented the approach for the assessment of part complexity (see Figure 4.1 in Subsection 4.2) as shown in Figure 6.2 and the supporting labeling tool (see Figure 4.7 in Subsection 4.3.3) as shown in Figure 6.3. Then, we introduced the ten repeating geometries.

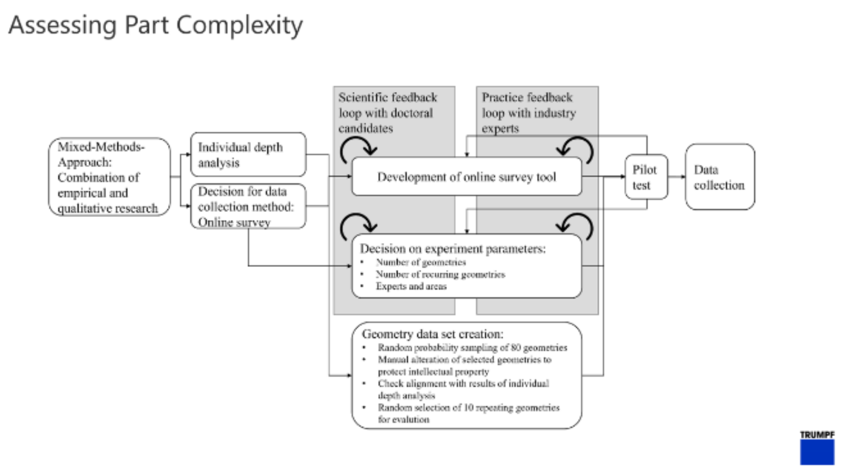


Fig. 6.2: Introductory Information for the Focus Group: Assessing Part Complexity. Own visualization.

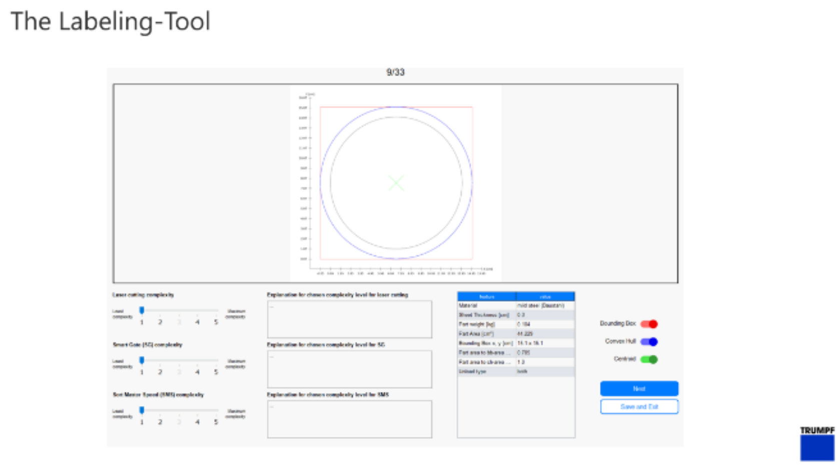


Fig. 6.3: Introductory Information for the Focus Group: The Labeling Tool for Part Complexity. Own visualization.

We decided to only show a selection of the repeating geometries to save time and not overload the introductory information, so we explained the repeating geometries A, B, C, E, and I in detail. We exemplary show the slide for geometry I in Figure 6.4

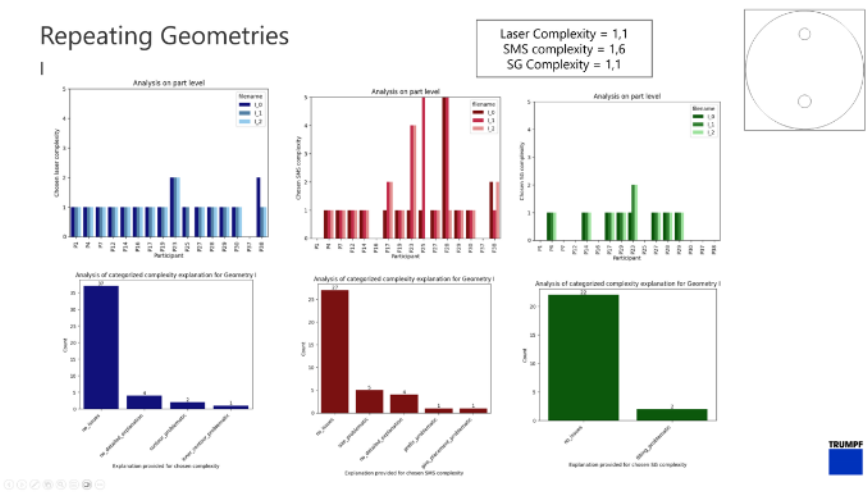


Fig. 6.4: Introductory Information for the Focus Group: Repeating Geometry I. Own visualization.

We summarize the conclusion from Subsections 4.5 and 5.7 that part characteristics influence the part manufacturability, that we were able to identify characteristics that influence the part complexity, and that we are confident that by enlarging the database, the results can be generalized. Afterwards, we share the part complexity use cases found in the literature of production optimization and production technology selection presented in Subsection 3.2.1.

To identify further part complexity use cases in the focus group, we developed the template shown in Figure 6.5. We brought these templates printed on paper for the focus group, serving a double purpose: First, the template would document the results in a standardized way. Second, the focus group participants were not required to use their laptops, hopefully leading to fewer distractions. To enhance the understanding of the template, we prepared an example template.

The template provides check boxes to indicate to which stakeholder group the use case belongs as well as three text boxes. The first text box, description, should describe the new part complexity use case. As an example, we brought the use case of customer comparison with a KPI set to support consulting activities and customer specific offers. The next text box, status quo, should contain a description of the current situation. In our example, the current situation is a customer comparison on the basis of their vertical range of manufacture and their sales with our industry partner. The last text box should contain the future advantage with part complexity. In our example, the future advantage with part complexity is the enrichment of the customer comparison with part complexity based on field data. This information may support consulting activities such as benchmarking the customers' production and offering them more fitting solutions. Figure 6.6 shows the exemplary part complexity use case presented as part of the introductory information for the focus group.

Template for the Description of the Part Complexity Use Cases

Use Case: ☐ Product and Portfolio Management ☐ Research and Development
☐ Sales and Consulting

Description:

Status Quo:

Future advantage with part complexity:

Fig. 6.5: Template for the focus group. Own visualization.

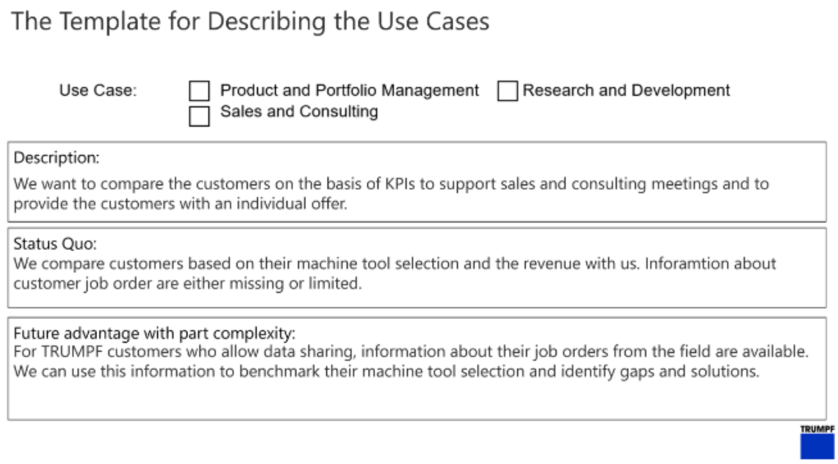


Fig. 6.6: Introductory Information for the Focus Group: Exemplary Use Case. Own visualization.

6.2.2 Participants

The goal was to have three or four participants from each stakeholder group, identified in Subsection 1.1, of product and portfolio management, research and development, and sales and consulting. This leads to a total of nine to twelve participants. We did not follow the recommendation of Powell and Single [1996] that the participants should not know each other and not to follow recommendations of participants who else should participate for several reasons: First, we only had access to one company, meaning that the participants would know each other, especially since we asked members of the same department to ensure a broad perspective from this stakeholder group. Second, we wanted to have experienced people participating in the focus group to ensure meaningful results, so we followed the recommendations of people who could not attend themselves but recommended replacements.

6.2.3 Focus Group Preparation and Setup

We asked a co-moderator to plan and hold the focus group together. The aim was to benefit from the co-moderator's experience and to divide the responsibilities: With the more experienced co-moderator focusing on time-keeping or moderating in case of differences with the focus group participants, the researcher can concentrate solely on achieving the results. To avoid afternoon sleepiness and ensure a good mood during the focus group, we decided to have pots with sweets available during the productive phases of the focus group and to bring donuts for the breaks. In addition, we brought Kinder Eggs, sweets with a figurine, for the feedback round to make it more interesting. After each participant has received a Kinder Egg, they have to give feedback incorporating their figurines.

6.2.4 Time Plan

From our own experience, focus groups are best when their schedule is flexible enough to provide the possibility of breaks and changes that are decided together with the focus group participants. As an orientation, we developed the time plan presented in Table 6.1 to estimate the time required for each step in the focus group and ensure we were not running out of time. We planned from the beginning to use the schedule as orientation and decide spontaneously during the focus group for changes and breaks to capture the most information possible.

We decided on a half-day focus group, starting at 1.30 pm and ending at 5 pm. We aimed for a 3-hour focus group, including 30 minutes reserved for breaks to avoid decision fatigue and having a buffer of an additional 30 minutes. Due to time and capacity constraints, we wanted to conduct the focus group in one session to capture the most relevant use cases of part complexity. As visualized in Table 6.1, we introduced ourselves first and presented the agenda of the focus group. Subsequently, the participants introduced themselves in 60 to 90 seconds. We reserved 45 minutes for the technical introduction and the template described in Subsection 6.2.1. We planned two parts for the working group with a duration of 30 minutes each. First, the stakeholder groups collect use cases and then prioritize them using points. The more points a use case has, the more important it is. Second, the stakeholder groups should describe the three most important use cases using the template, present their results, and clarify questions. Afterward, we planned to thank the participants for their time and collect their feedback using the Kinder Eggs. We reserved 20 minutes for the feedback. In the last ten minutes, we planned to summarize the results of the focus group.

Focus Group Time Plan		
Greeting	Introduction of the moderators, agenda of the focus group	3-5 min
Get to know	Each participant introduces him- or herself	1-1.5 min per person, 15-20 min total
Technical introduction	Presentation of part complexity and clarifying questions of the participants	30 min
Example of a Use Case	Presentation of an exemplary use case using the template to communicate the expectations of the focus group towards the participants, including questions	10-15 min
Break		20-30 min
Working Group - Part 1	Collecting use cases for part complexity within the stakeholder groups and prioritization of the collected use cases within the stakeholder groups by ranking with points	30 min
Working Group - Part 2	Describing the three most important use cases within the stakeholder groups and presenting the use cases to the other groups and clarifying questions	30 min
Closing	Thanking for participation	
Feedback	Collecting the participants' feedback	20 min
focus group Summary	Summary of the focus group results	10 min

Table 6.1: Time Plan of the focus group.

6.3 Conducting the focus group

To document the focus group, we adapt the checklist introduced by Tong et al. [2007]. The researcher, the moderator, and the participants work at the same company, and some, but not all participants work in the same department as the researcher. Two participants first met the researcher and moderator during the focus group. The researcher shared the goal of the focus group at its beginning to ensure that everybody was on the same page. For methodological orientation and theory, information about part complexity was shared at the beginning of the focus group in the form of a presentation supported by slides. The participants were selected purposefully to ensure that each of the three stakeholder groups was represented in the focus group. The participants were approached via e-mail. Since two participants dropped out on short notice due to illness, eight people participated in the focus group. The focus group took place in the workplace of the researcher, participants, and moderator. The moderator was the only person present who did not conduct the research or participate in the focus group. Due to data confidentiality, we do not provide information about the participants' demographic data. We did not conduct a pilot test to test the focus group design. We used the template shown in Figure 6.5 as an interview guide that also serves as field notes. We did not conduct repeat interviews, which may lead to insaturated data: It is likely that by repeating the focus group with other stakeholders and representatives, more use cases of part complexity can be identified. We decided against audio and visual recording to create an atmosphere where everyone could speak freely, and documentation was ensured by the templates. No transcripts were returned to participants. The focus group took place on March 5th, 2024, from 1 p.m. to 5.30 p.m.

Due to some participants having trouble finding the location, we started approximately 15 minutes later. In addition, some participants declined the focus group on short notice a couple of hours in advance, which led to an under-representation of the stakeholder group sales and consulting with only one participant. Hence, we allocated one participant from the stakeholder group product and portfolio management to the stakeholder group sales and consulting since he had experience in this field and we had four participants already from this group. This led to three participants representing product and portfolio management, three for research and development, and two for sales and consulting.

In addition, some participants had to attend meetings throughout or at the end of the focus group, so they had to leave for a while during the focus group or leave the focus group earlier. This led to a high fluctuation of the participants during the focus group. However, we were only a small group of eight participants, we had a moderator and a technical expert, and every participant was present during the introductory session. This enabled a small catch-up when the participants arrived so that they could re-enter the focus group and participate.

Moreover, we expected the stakeholder groups to identify use cases for part complexity specific to their area of origin. However, during the presentation of the results of the first working group, we discovered high similarities in the identified use cases. This is why we decided together with the focus group participants to collect the individual use cases and to describe them in small groups without assigning them to specific stakeholder groups. Due to the number of use cases being smaller than expected, we decided against the previously planned prioritization and let the participants specify each use case.

6.4 Resulting Use Cases of Part Complexity in Sheet Metal Processing

This subsection presents the use cases for part complexity resulting from the focus group. The subsection consists of three different sections, one for each of the stakeholder groups product and portfolio management (see Subsection 6.4.1), research and development (see Subsection 6.4.2), and sales and consulting (see Subsection 6.4.3). Each use case is presented in the template from Figure 6.5 and subsequently described in detail. The participants did not name every use case. Hence, we number the use cases to distinguish them in this thesis. The use case names defined by the participants are documented where applicable. Since the language of the focus group was German, we translated the resulting use cases into English. The original templates can be seen in Appendix A.1.

6.4.1 Product & Portfolio Management

The focus group identified one use case of part complexity for the product and portfolio management stakeholder group, presented in Table 6.2. The participants did not name this use case.

Use Case 1
Description: The product and portfolio management continuously optimize the portfolio. They want to identify portfolio gaps and make improvements. By clustering the customers based on the application and part complexity, the portfolio can be designed purposefully.
Status Quo: Utilization of the benchmark sheets (calculating the average, only optimized for 2D laser cutting) for internal performance grading of the series and competitor analysis. Comparison of part complexity based on technical data like part weight and part size leads to very simple analyses.
Future advantage with part complexity: Further step to represent the situation on the customer shop floor. Better clustering of the customers according to the use case is possible. More purposeful requirements engineering is possible, as well as for more complex systems.

Table 6.2: Use Case 1 - Product & Portfolio Management.

With one major task being the optimization of the portfolio, the product and portfolio management identifies portfolio gaps and define optimization measures. To do so, the product and portfolio management needs to get an overview of the customers, using methods such as clustering. Currently, the product and portfolio management employs the benchmark sheets, visualized in Table 2.1 from Subsection 2.3.2, to research the internal performance of the different machine tool series and for competitor analyses. Considering that the benchmark sheets rely on average values and have been optimized for 2D laser cutting, not for each of the machine tool series, this does not provide optimum results. To provide more up-to-date analyses, product and portfolio management uses technical data like part weight and part size to compare the part complexity. Due to the limited available data, these analyses are rather simple. For future applications, the product and portfolio management views the concept of part complexity as a further step to represent the current situation on the customers' shop floors. The customers' shop floor can be depicted in more depth, providing greater insight into the use of the portfolio and the customers' needs if information about the part complexity and hence, the part manufacturability is available. In addition, customer clustering can be enhanced by part complexity information, leading to customer clustering better fitting to the use cases, such as "customers with higher part complexity". Lastly, the product and portfolio management mentions requirement engineering benefitting from information about part complexity, especially requirements engineering targeting more complex systems like highly advanced machine tools or interlinking machine tools, automation components, and storage options.

In summary, although the participants filled out one template for part complexity use cases, they identified the three part complexity use cases customer clustering, product usage, and understanding the requirements towards the portfolio for product and portfolio management.

6.4.2 Research & Development

For the stakeholder group research and development, the focus group identified three part complexity use cases.

Use Case 2: Risk assessment for part cost calculation
Description: We want to offer a realistic risk markup for the part cost calculation based on the part complexity.
Status Quo: Markup based on gut feeling or experience for alleged complex parts.
Future advantage with part complexity: Enabling fair and realistic offers. Job shoppers like EaaS bear fewer risks. We offer a new business case "Calculate-as-a-Service" (CaaS) as a webshop for customers.

Table 6.3: Use Case 2 - Research & Development.

The first research and development use case is the risk assessment for part cost calculation, depicted in Table 6.3, where the manufacturing cost of parts is calculated. To consider cost drivers such as re-manufacturing and repetition of process steps due to difficult parts, a markup for complex parts shall be included. Currently, this markup is added to the part cost calculation based on gut feeling or the experience of the calculators with alleged complex parts, leading to both over- and under-calculation of the part costs. In the future, part complexity may enable fair and realistic manufacturing cost offers due to the increased data-driven objectivity. The focus group especially sees future advantages for job shoppers, who are characterized by producing different parts with only small batch sizes, which does not allow for the manufacturing experience of the parts comparable to product shoppers who manufacture larger batch sizes of a smaller variety of different parts. A use case that may highly benefit from part complexity is Equipment-as-a-Service, also known as Pay-per-Part, which does not sell the machine tools but the usage of the machine tools, based on the cost of the manufacturing of each part on the machine tools. Another use case for part complexity-based part cost calculation identified by the focus group is Calculate-as-a-Service, a webshop for customers to calculate the parts' manufacturing costs.

One needs to keep in mind that cost is mentioned in the literature in the context of part complexity for both production technology selection [Greco et al., 2022] and production optimization [Lohtander and Varis, 2008; Qamar et al., 2019; Joshi and Ravi, 2010; Ben Amor et al., 2022] (see Subsection 3.2). However, while many authors agree on a link between part complexity and cost [Qamar et al., 2019; Joshi and Ravi, 2010; Ben Amor et al., 2022], we did not find a use case combining part complexity and the calculation of part costs including a markup for risks due to the part complexity.

Use Case 3: Developing new technologies or machines
Description: We want to develop (new) technologies and/or machines based on complexity thresholds.
Status Quo: We try to optimize technologies individually, independent of their performance regarding known complex customer parts.
Future advantage with part complexity: Planning of new development projects: Purposeful, customer-oriented development of machines, so that we can quantify the added value to the customer. Offers transparency for the customers in the development process.

Table 6.4: Use Case 3 - Research & Development.

The second part complexity use case for research and development is shown in Table 6.4. The focus group states that they want to develop new technologies and machines based on complexity thresholds, so how suitable a technology or machine is for a certain range of complexity. Currently, the technologies and machine tools are optimized individually, without taking into consideration how the technologies and machine tools perform for customer parts that are known to be highly complex. This approach leaves room for optimization since the customers' job orders and hence the future use of the machines and technologies is not considered in depth. In the future, information about part complexity can assist new development projects by enabling the customer-oriented development of machines and quantification and transparency of the added value to the customers, such as a decrease of the complexity for a certain percentage of the customers' job orders, potentially leading to a more robust production.

Use Case 4: Optimization of shift planning
Desription: We want to optimally utilize the machines selected based on the customer product portfolio to minimize production downtimes. In addition, we want to optimize the production order.
Status Quo: Until now, there is no organization in day and night shifts based on the part complexity. Oftentimes, the decision is based on the technology level, e.g. such that punching machines in combination with automation components are put in the night shift.
Future advantage with part complexity: Downtimes in the night shift can be avoided, especially for machines with automation components.

Table 6.5: Use Case 4 - Research & Development.

The third and last use case of part complexity for research and development, depicted in Table 6.5, is the optimization of shift planning. The focus group says that they want to optimally utilize the selected machines based on the customer product portfolio, so what machines to use for the parts, and to optimize the production order to minimize downtimes. Currently, the parts are not selected based on their complexity if they are going to be produced in the day or night shift, but on the technology level: Parts that can be produced on machine tools that are connected to automation components on the customer site, e.g. that enable automated loading and unloading of parts, are put in the night shift. In contrast to this, machine tools that are not connected to automation components on the customer site are usually scheduled for the day shift with more people present. The focus group sees the future advantage with part complexity that by selecting the orders for the night shift not only on the technology level but also on part complexity, the downtimes in the night shift can be reduced, improving the production's productivity.

6.4.3 Sales & Consulting

The focus group identified four use cases of part complexity for the sales and consulting stakeholder group, which is half of the use cases identified.

Use Case 5
Description: Development of new business cases like performance benchmarking, e.g. with a peer-to-peer comparison
Status Quo: Currently, such a comparison is only viable on metrics like "laser on". There is no reliable database regarding the part complexity or the production range. The machine forgets all information regarding a part as soon as the part has left the machine.
Future advantage with part complexity: New business case: The customer gets his performance in comparison to his peers, customers with a similar part range, visualized. Idea: Part data are anonymized and then processed according to the EU Data Act. Subsequently, this information can be made available to comparable customers.

Table 6.6: Use Case 5 - Sales & Consulting.

The first sales and consulting use case is depicted in Table 6.6. The focus group sees the development of new business cases as one use sales and consulting use case that could benefit from part complexity. As an example, they name performance benchmarking and especially peer-to-peer comparison. Currently, customers can only be compared on metrics such as "laser on", which do not give insight into the productivity or usage of the machines and instead only if the laser of the laser cutting machine is active. Moreover, the development of new business cases and customer comparisons suffer from the lack of a reliable database providing information about the part complexity or the production range, as the machine does not save information about the parts. In the future, part complexity can enable new business cases such as customer comparison that considers the part range, providing a more useful comparison with other customers that are likely to face similar challenges. Another idea named by the focus group is to anonymize the part data and process it according to the EU Data Act to share this information with comparable customers.

Use Case 6
Description: We want to provide a tool for both sales and customers for the identification of the best machine configuration for the use case.
Status Quo: Application engineers conduct feasibility studies. Based on these feasibility studies, the machine series and the options are selected. The basis is expert knowledge, in addition, the system is not scalable. The whole application is extrapolated based on a few parts. This leads to a high risk that the offered system does not fulfill the customer's requirements.
Future Advantage with Part Complexity: Scalable approach for automated feasibility studies. The whole production system can be analyzed, not a single machine. In addition, the customer can be shown a path of growth. Goal: automated, usage-specific system configuration. Requirement: Field data or benchmark. Alternatively: representative, big enough sample.

Table 6.7: Use Case 6 - Sales & Consulting.

The second sales and consulting use case is shown in Table 6.7. The participants did not assign a name to Use Case 6. During the sales process, a tool shall be provided for both sales and customers to identify the best machine configuration for the customer's use case, as not only do the machine tools themselves have different options to choose from but can be combined with automation components and storage options. These possibilities increase the challenge of identifying the best-fitting machine set-up for the customer's needs. As of now, application engineers conduct feasibility studies to examine whether and if positive, how good a machine can produce a set of customer parts. These analyses are the foundation for choosing the machine series and the machine options for the customer, in combination with the expert knowledge of the salespeople. This subjective information makes the selling process prone to outcome quality deviations, while the feasibility studies are time-consuming and not scalable. These two caveats limit the number of customers the salespeople can address. In addition, the feasibility studies are based on only a few parts that are extrapolated, leading to a high risk that the offered system of machine tools does not fulfill the customer's requirements. The focus group sees several benefits from adding information about part complexity to this use case: First, they assume that information about the part complexity instead of using actual customer parts for the feasibility study will enable automated feasibility studies, making them scalable. If customer parts are studied, the technologies to be observed are limited by the production processes required by these customer parts. In contrast to this, part complexity information allows for examining whole productions instead of a limited number of production technologies. In addition, part complexity would allow to show the customer a path of growth by altering the part complexity parameters to visualize different scenarios of changes in the customers' job orders. The focus group sees automated and usage-specific configuration of production systems as a goal for this sales and consulting use case. Requirements for this automated and usage-specific configuration of production systems are field data or sample data big enough to be representative.

Use Case 7
Description: I want to compare the customers that produce similar parts and tell the customers how they perform compared to their peer group.
Status Quo: I can segment the customers solely depending on the industry fields. Job shops are hardly comparable.
Future advantage with part complexity: Customers, especially job shops, can be segmented based on the part complexity and systems.

Table 6.8: Use Case 7 - Sales & Consulting.

Table 6.8 shows the third sales and consulting use case of part complexity. The participants did not define a name for Use Case 7. The use case aims to compare customers who produce similar parts and to show customers how they perform compared to their peer group. This use case is similar to Use Case 5, depicted in Table 6.6. The difference between these two use cases is that Use Case 5 focuses on developing new business models enabled by part complexity, while Use Case 7 concentrates on customer segmentation. Currently, these customer segmentations depend on the customers' industry fields, which limits them to product shoppers who produce many times the same products and know in which industry they deliver. In contrast to this, job shoppers produce many different products with small batch sizes and often do not know in which industry they deliver. The focus group sees the future advantage of customer segmentation with part complexity information in the fact that then all customers, but especially job shops can be segmented based on their part complexity and their production systems.

Use Case 8: Production planning
Description: I as production manager want to schedule possible rework from the beginning and create required quality checks for difficult parts automatically in the production plan. As a production manager, I want to produce the parts (system selection) where they can be produced process-reliable.
Status Quo: I need to estimate rework manually for each part or not consider the rework at all. I have to manually create the quality check in the work plan. The customer nests based on experience and gut feeling, which parts are produced on which system.
Future advantage with part complexity: The time for rework will be determined automatically based on the part complexity. Quality checks are created automatically in the production, based on the part complexity. Suggestions for nestings and systems are generated automatically and can be modified, aiming to reduce the production planning effort.

Table 6.9: Use Case 8 - Sales & Consulting.

Table 6.9 presents the fourth part complexity use case for the sales and consulting stakeholder group and the last use case identified by the focus group. For production planning, the production managers want to schedule highly possible rework from the beginning to avoid rushing the production or failing to meet delivery deadlines. Moreover, the production time plan can be created more robust by incorporating quality checks for complex parts from the beginning instead of solely identifying faulty parts by accident. In addition, the production managers want to schedule the parts for the machines and production systems with the least complexity, where the parts have the highest chance of reliable production. Currently, the production managers estimate the rework manually for each part or not consider possible rework, in addition to manually deciding where to put quality checkpoints. This inhibits the risk of timely inaccurate production plans that do not meet the production targets. Furthermore, the production technologies are selected based on gut feeling and experience for each part instead of based on data. In the future, part complexity can support production managers, as the time for rework could automatically be calculated based on the part's complexity, as well as part-specific quality checks. In addition, the production technologies can be selected based on the part complexity, and similarly complex parts can be nested together on the metal sheets.

6.5 Comparison with Literature

This subsection maps the findings from the focus group to those from the literature review. First, we describe the table summarizing this mapping, followed by a general description of the focus group results. Subsequently, we describe the use cases and how they map to the literature in detail and conclude with the key takeaways.

Table 6.10 presents the findings of our focus group in the context of the use cases revealed in the literature review from Section 3. We added the two part complexity use cases from Section 3.2 to Table 3.1 from Subsection 3.1. Then, we added the use cases identified in the focus group that were not covered by literature to Table 6.10. Table 6.10 distinguishes between those use cases from the literature review and those from our focus group in the second and third columns.

6.5.1 General Description of Focus Group Results

The focus group identified new use cases for part complexity that were neither covered in the literature review regarding the need for data-driven methods along the product life cycle (see Subsection 3.1) nor regarding the part complexity use cases (see Subsection 3.2). The focus group identified three additional use cases for the sales and distribution category and one for the product usage category. These added use cases demonstrate that the need for data-driven methods along the product life cycle is even greater than known in the literature and that there are more part complexity use cases than production optimization and production technology selection. The focus group confirmed use cases for the BOL and MOL phases but did not identify the advantages of part complexity for the End of Life stage. The focus group did not confirm use cases for the repair phase of MOL.

6.5.2 Mapping the Use Cases in Detail

Use Case 1 is the only use case from the product and portfolio management stakeholder group. In the market analysis phase of BOL, Use Case 1 confirms the three use cases customer segmentation, opportunity identification, and specification of customer requirements. In the product usage phase of MOL, it confirms the product usage monitoring. The three use cases from the market analysis phase may benefit from the information collected during the product usage monitoring in MOL, representing a connection between these use cases.

Use Case 2 is the first use case identified by the research and development stakeholder group and adds the use case production cost assessment to the product usage phase of MOL, but does not confirm use cases from the literature. Use Case 3 confirms customer-centric product development and improving future product generations from the product development phase in BOL: Use Case 4 is the last one from research and development and confirms the smart production planning with the analysis of customer orders from the product manufacturing phase in BOL.

The first use case of the sales and consulting stakeholder group, Use Case 5, confirms the client groups from sales and distribution and the product usage monitoring from product usage, both belonging to MOL. Use Case 5 is the only use case covering more than one phase from the same product life cycle stage. Use Case 6 adds the data-driven sales assistance, the data-driven customer consulting, and the product configuration during sales to sales and

Use Case	Identified in the Literature	Identified by the Focus Group	PM	Research & Development			Sales & Consulting			
			Use Case 1	Use Case 2	Use Case 3	Use Case 4	Use Case 5	Use Case 6	Use Case 7	Use Case 8
Beginning of Life (BOL)										
Market Analysis										
Customer identification	●									
Customer segmentation	●		●						●	
Opportunity identification	●		●							
Specification of customer requirements	●		●							
Definition of product features	●									
Definition of quality requirements	●									
Analysis of historical data	●									
Demand and trend mining algorithm for predictive life cycle design	●									
Product Development										
Product design	●									
Customer-centric product development	●				●					
Research and understand customer behavior	●									
Research and understand customer preferences	●									
Improving future product generations	●				●					
Definition of waste management practice	●									
Definition of circular product requirements	●									
Cost assessment	●									
Product Manufacturing										
Selection of (sustainable) suppliers	●									
Optimization of supply chain network	●									
Simulate and test product	●									
Training of a real-time scheduler	●									
Smart production planning with the analysis of customer orders	●					●				●
Feature extraction from step files for improving operation control	●									
Quality Assurance	●									●
Production Technology Selection	●									●
Production Optimization	●									●
Middle of Life (MOL)										
Sales & Distribution										
Client groups	●						●		●	
Sales prediction	●									
Sustainable procurement of product	●									
Data-driven sales assistance		●						●		
Data-driven customer consulting		●						●		
Product configuration during sales		●						●		
Product Usage										
Ensure product performance	●									
Product Usage Monitoring	●		●				●			
Production Cost Assessment		●		●						
Repair										
Predictive maintenance	●									
Automated anomaly detection, leading to new revenue streams, digitized servitization, and decrease prices for product services	●									
After-sales service	●									
End of Life (EOL)										
Recycle activities	●									
Dismissal activities	●									
Data-driven phasing out decisions	●									

Table 6.10: Mapping the Focus Group Results to the Literature Findings. PM= Product and Portfolio Management.

distribution. Similar to Use Case 2, Use Case 6 does not confirm a use case from the literature. Use Case 7 confirms the customer segmentation of the market analysis phase of BOL, like Use Case 1 from the stakeholder group product and portfolio management, and client groups from the sales and distribution phase of MOL, like Use Case 5 from sales and consulting. Both use cases likely use techniques that group customers. Use Cases 1 and 7 are the only use cases covering BOL and MOL. In BOL, both use cases focus on market analysis. Use Case 8 is the last use case and confirms the smart production planning with the analysis of customer orders, also confirmed by Use Case 4 from research and development, as well as the quality assurance, production technology selection, and production optimization, all from the product manufacturing phase of BOL. With four confirmed use cases from the literature, Use Cases 1 and 8 confirm the most.

6.5.3 Summary: What are the Key Takeaways?

The focus group aimed to identify where part complexity may fill the need for data-driven methods along the product life cycle. Use cases were confirmed for BOL and MOL, and further use cases were added to MOL. The focus group covered BOL more than MOL with eleven confirmed use cases, while MOL has eight use cases that were either confirmed or added. This represents the coverage of the respective in the literature. The focus group did not confirm or add use cases for EOL, which is the phase that is least represented in the literature. Hence, it is not excluded that part complexity may support the need for data-driven methods in this phase. It may be possible that the benefits of part complexity decrease along the product life cycle or that the use cases are identified following the product life cycle. Two observations back the latter assumption: First, no additional use cases were identified for BOL, while eleven use cases have been confirmed. This hints at many benefits for BOL stemming from part complexity, and that the number of BOL use cases is already rather sophisticated, especially since this is the phase with the most already identified use cases. Second, all four additional use cases have been added to MOL by the focus group, indicating that the search for use cases in need of data-driven methods along the product life cycle is far from over and that the number of use cases will increase soon. All product and portfolio management use cases are represented in the literature, while research and development added one use case, and sales and consulting added three use cases. product and portfolio management confirmed four use cases, research and development 3 use cases, having 4 in total, and sales and consulting confirmed 7 use cases, one double, and added three use cases, having in total 10 use cases. This hints at the most need for part complexity from the sales and consulting stakeholder group, which also is the least covered one in the literature from the three stakeholder groups participating in the focus group. Both product and portfolio management and sales and consulting confirmed the use case customer segmentation, while both research and development and sales and consulting confirmed the use case smart production planning with the analysis of customer orders product and portfolio management and sales and consulting both confirmed the use case product usage monitoring. product and portfolio management and research and development do not have an overlap in the confirmed use cases. In the future, part complexity may benefit from synergies since each stakeholder group confirmed at least one use case confirmed by another stakeholder group. The use cases that have been confirmed by more than one focus group use case are customer segmentation, smart production planning with analysis of customer orders, client groups, and product usage monitoring. It appears that these use cases have the highest need in practice, making it attractive to develop these use cases first.

6.6 Discussion and Critical Reflection

We identified five limiting factors of our focus group approach: (1), our results may be limited by the focus group being conducted only once and only at one company. Future work may broaden the results by conducting the focus group over a period of time and considering other companies, as well as broadening the pool of participants by considering further stakeholder groups. (2), the introductory information on customer comparison we provided to illustrate the template from Figure 6.5 was picked up twice by the focus group in Use Cases 5 and 7. We may have influenced the focus group with this information, also influencing the results. Deciding between not influencing the resulting use cases at all and making sure that the focus group understands the template, providing more detailed information, and ensuring higher quality results seems to be the better choice. However, if we design an illustrative example for the template again, we would choose an example that is less related to the topic. (4), only one person from the stakeholder group sales and consulting was present in the workshop. Although this person has been supported by a member of the product and portfolio management stakeholder group with sales and consulting experience, this group has been underrepresented, maybe leading to weaker results than with a balanced focus group. (5), no one dealing with End of Life tasks has been present in the focus group, further explaining the lack of confirmed use cases for this product life cycle stage.

We collected feedback from our focus group participants at the end of the session to reflect on our research approach (see Subsection A.2). The participants view part complexity as an important topic. They found the focus group to be well-prepared, especially the food we provided to avoid moments of fatigue in the later afternoon. They see the prioritization of the use cases as the next step, with cost calculation as the most important use case of part complexity. Part complexity may be an enabler for many other topics and increase their "coolness". However, the fundamentals for part complexity, especially the required data and the data quality, are missing. While covering the whole production process chain is a prerequisite to covering the smart factory, the process step of bending may be easier to accomplish than laser cutting.

6.7 Interim Result: The Applicability of Part Complexity

This section aims to answer the third research question: **"How can part complexity contribute to the demand for data-driven information about the customers along the product life cycle?"**

First, we conducted a focus group to identify further use cases of part complexity, apart from the two part complexity use cases known in the literature of production technology selection and production optimization. We created the template shown in Figure 6.5 to standardize the resulting use cases. Representatives from the three stakeholder groups product and portfolio management, research and development, and sales and consulting participated in this focus group. Our focus group identified eight use cases of part complexity: One from product and portfolio management, three from research and development, and four from sales and consulting. Subsection 6.4 presents these use cases in further detail. Subsequently, we extended the results of the literature review regarding the need for data-driven methods along the product life cycle with the two part complexity use cases, summarized in Table 6.10.

To refer back to our research question, it has been confirmed that part complexity can contribute to the demand for data-driven methods along the product life cycle in a variety of use cases from BOL and MOL applications. Moreover, more use cases for both data-driven methods and part complexity will likely be identified in the future. The resulting part complexity use cases are limited—among other factors—by conducting the focus group only once and the participants stemming from only one company. Subsection 6.6 presents the limitations in detail. To overcome these limitations, the focus group could be repeated, more participants from other stakeholder groups could be considered, and the focus group could be conducted in other companies. In addition, one needs to improve the fundamentals for part complexity, such as the required data and data quality, following our participants' feedback.

Chapter 7
Conclusion

This concludes this dissertation. While Subsection 7.1 summarizes the contributions, Subsection 7.2 presents the limitations of these contributions. Subsection 7.3 concludes this dissertation with presenting the future work.

7.1 Summary of Contributions

This dissertation's first contribution is the methodology for sheet metal part complexity assessment and responds to our first research question, "How can we determine part complexity in sheet metal processing?". To answer this question, we developed a mixed-methods approach for assessing part complexity, containing several evaluation mechanisms.

First, we evolved our definition of part complexity based on the literature review. Subsequently, we developed a methodology for the assessment of sheet metal part complexity. We decided to conduct computer-assisted self-interviews with experts for the chosen production unit, stemming from the areas of production management, development, and remote and machine operation. These machine experts shall label a chosen set of geometries regarding their complexity for the applicable production process steps. We decided to use 80 geometries to be labeled over three weeks to balance a large database and time consumed by the labeling process to ensure good results while avoiding participants dropping out. To evaluate the labeling answers, we created a subset of 10 of these geometries to be repeated each week so that we can analyze the participants' labeling behavior over time. We pre-defined the material to be mild steel with a sheet thickness of 3 mm, since this configuration was the most produced one for the chosen production unit and the last 12 months before the labeling. To implement our methodology in practice, we developed a supporting labeling tool. This labeling tool presents the participants with the geometry to be labeled. It provides labeling scales from 1 (least complexity) to 5 (maximum complexity) without offering the neutral middle option "3". Participants are also required to provide explanations for their chosen complexity ratings in mandatory comment boxes. The labeling tool also covers additional information like the part weight or area and can visualize the bounding box, the convex hull, and the centroid of the geometry. Although this methodology was developed specifically for sheet metal part complexity, it may be adapted to other domains.

The second contribution responds to the second research question, "How do the part characteristics influence the part complexity in sheet metal processing?". We demonstrated the applicability of our methodology from the first contribution by putting it into practice for an exemplary production unit. Of the 40 participants, 16 completed at least two weeks of labeling, which was the minimum requirement for being considered in the analysis, resulting in a response rate of 37.5 %. Additionally, 15 participants passed the repetition test for laser cutting, 14 for part handling with the SortMaster Speed, and 8 for part handling with the SmartGate. This leads to the conclusion that the participants label consistently enough to identify characteristics that influence the part complexity. We created so-called codebooks to categorize the participants' answers regarding these part complexity influencing characteristics. These codebooks contain the categories for the reasonings given by the participants for why they chose the respective complexity as well as a definition for this category. While the codebooks of the three production process steps share a lot of similarities like the inner contour of the parts problematic, they also contain process step-specific categories like the placement of the suction cups of the SortMaster Speed. Since most of the geometries were labeled with only a little complexity, our resulting data sets are highly imbalanced. The detailed analysis of the ten repeating geometries has shown that the participants have labeled similar for many geometries, although not for all. In addition, a correlation between the labeled complexity, the given explanation, and the geometry characteristics can be observed. To transfer our results to new geometries, we employed a random forest regressor and a random forest classifier and analyzed the five most important geometrical features. The comparison of the five most important features for each process step and the occurrences of the labeling participants given for their chosen process step complexity revealed a link between these two: The most occurred explanations were partially being represented by the most important features. Despite using different cross-validation methods and reducing the granularity by transforming the numerical complexity values into complexity classes, we did not achieve satisfactory accuracy results. Although we could not transfer our labeling results to new geometries, we identified part complexity influencing geometry characteristics, such as undercuts and inner contours.

The third and last contribution answers the research question "How can part complexity contribute to the demand for data-driven information about the customers along the product life cycle?". To identify use cases of part complexity along the product life cycle, we conducted a focus group with participants from the previously identified stakeholder groups of product and portfolio management, research and development, and sales and consulting. We prepared a template with three sections description, status quo, and future advantage with part complexity to standardize the resulting use cases. The focus group identified eight use cases in total, one from product and portfolio management, three from research and development, and four from sales and consulting, such as portfolio optimization, risk assessment for part calculation, development of new technologies, optimization of shift planning, benchmarking based on performance or with the peer group, machine configuration, and production planning. These use cases confirmed eleven use cases from the literature. In addition, the focus group discovered four more use cases: Data-driven sales assistance, data-driven customer consulting, product configuration during sales, and production cost assessment. The use case from product and portfolio management confirmed the customer segmentation, opportunity identification, and specification of customer requirements from the market analysis stage of Beginning of Life, and the product usage monitoring from the product usage stage of Middle of Life. The three use cases from research and development confirmed the customer-centric product development and improving future product generations from the product development stage and the smart production planning with the analysis of customer orders from the product manufacturing stage. Both stages belong to Beginning of Life. In addition, this stakeholder group added the production cost assessment from the product usage stage of Middle of Life. For Beginning of Life, the four use cases from sales and consulting confirmed the customer segmentation from the market analysis stage as well as the smart production planning with the analysis of customer orders from the product manufacturing stage, quality assurance, production technology selection, and production optimization. For Middle of Life, this stakeholder group confirmed the client groups from the sales and distribution stage and the product usage monitoring from the product usage stage. Moreover, this stakeholder group added the use cases of data-driven sales assistance, data-driven customer consulting, and product configuration during sales to the sales and distribution stage. No use cases were confirmed or added to End of Life, the last phase of the product life cycle. This expands both the use cases along the product life cycle which may benefit from data-driven methods as well as the two use cases of part complexity known in the literature, production optimization and production technology selection. In conclusion, part complexity may contribute to a variety of use cases in the stages of market analysis, product development, product manufacturing, sales and distribution, and product usage.

7.2 Limitations

Our mixed-methods methodology for the assessment of part complexity inhibits several limitations: (1), the representativity of our geometry data set is impacted by its size. We did not calculate the required number of geometries for a representative data set of the indefinite number of sheet metal geometries but by what makes our methodology conductable for the participants. The final geometry data set consists of 80 geometries, of which 10 are to be repeated in each of the three weeks of the complexity labeling to observe the labeling consistency over time. The repetition of geometries further limits the number of individual geometries and hence, the representativity of the geometry data set. (2), we manually altered these geometries to protect intellectual property, which may have influenced the data set and hence, the labeling results. In addition, we conducted the individual depth interview with only one person and included this person as a participant in the labeling, which may have further influenced the results. This person only passed the repetition test for laser cutting but not the two part-handling process steps. (3), the applicability of our results is limited by the pre-defined material and sheet thickness. Without further analysis, our results are only applicable to mild steel with a sheet thickness of 3 mm. (4), we eliminated the middle option "3" in the rating scale, which may have provoked higher deviation in the labeling. (5), we only covered two geometries suitable for the process step part handling with the SmartGate in our repeating data set. In combination with our arbitrarily chosen deviation of 30 % as the threshold for passing the repetition test, this led to a high drop-out rate of 50 % for this process step. (6), the participants may have been influenced by the previously labeled geometries and gained labeling experience with each week, which may have influenced the results further. The participant's learning effect could have impacted the results, potentially masking the true complexity of certain geometries. (7), we were unable to generalize our labeling results to new geometries.

Our research approach for the identification of further part complexity use cases is also impacted by flaws. (1), we covered only one company. In addition, we focused on the previously defined stakeholder groups of product and portfolio management, research and development, and sales and consulting. This may have limited the resulting use cases, especially for the later stages in the product life cycle. (2), we did not repeat our focus group, which makes data saturation and hence, the identification of all possible use case highly unlikely. (3), the introductory information regarding the customer comparison was picked up twice from the focus group, which may indicate an influence on the resulting use cases.

7.3 Future Work

In future work, one may re-evaluate the scale design from 1 (least complexity) to 5 (maximum complexity) without providing the middle option "3". We chose this design to provoke the participants to decide on the part complexity instead of choosing the neutral answer due to decision fatigue. In contrast to our scale, one may test a continuous scale design ranging from 1 (least complexity) to 4 (maximum complexity) or a complete scale from 1 (least complexity) to 5 (maximum complexity). A continuous scale may help reduce indecision while maintaining clarity, while a full 1-5 scale with a midpoint allows participants to indicate when the complexity is neither low nor high, leading to a more nuanced understanding of part complexity. Both approaches could lead to more reliable and valid data, depending on how the participants interpret and use the scale.

The labeling database may be increased by letting more experts label more geometries to enable the transfer of the results using algorithms. By increasing the volume of labeled geometries, machine learning algorithms can be better trained to predict complexity for unseen geometries, thereby facilitating the transferability of results. In addition, customers could participate in the complexity labeling. To avoid distortion of our results, we make the age of the machine tool a minimum of 6 months prerequisite to participate in the labeling. After 6 months, we can assume that the machine's start-up has been completed. The dropout rate may be decreased with rewards. More geometrical features may also be incorporated into the geometry data set. Expanding the range of features in the dataset will enhance the methodology's capacity to capture complexity, thus improving the analysis and prediction accuracy. Generally, the part complexity assessment methodology should be adapted to further production technologies until the whole sheet metal process chain is covered. The adaptability of the methodology may also be underlined by adapting it to other domains.

To broaden the understanding of the part complexity use cases, the focus group should be repeated, covering more stakeholder groups and also more companies. In addition, the use cases that are already identified should be implemented in practice.

References

Acerbi, F. and Taisch, M. (2020). Towards a data classification model for circular product life cycle management. In *Product Lifecycle Management Enabling Smart X: 17th IFIP WG 5.1 International Conference, PLM 2020, Rapperswil, Switzerland, July 5–8, 2020, Revised Selected Papers 17*, pages 473–486. Springer.

Ahmadov, Y. and Helo, P. (2018). A cloud based job sequencing with sequence-dependent setup for sheet metal manufacturing. *Annals of Operations Research*, 270(1):5–24.

Aiyer, M., Panigrahi, J. K., and Das, B. (2018). Successful customer relationship management in business process integration and development of applications for project management. *International Journal of Mechanical Engineering and Technology*, 9(2):637–643.

Ben Amor, S., Tahan, A., and Louhichi, B. (2022). The impact of geometric complexity on printing time and cost for additive manufacturing (am) process. In *Advances in Mechanical Engineering and Mechanics II: Selected Papers from the 5th Tunisian Congress on Mechanics, CoTuMe 2021, March 22–24, 2021*, pages 203–210. Springer.

Blümke, J. and Hof, H.-J. (2023). Binding the battery to the pass: An approach to trustworthy product life cycle data by using certificates based on pufs. *International Journal on Advances in Security*, 16(1&2):44–53.

Bodein, Y., Rose, B., and Caillaud, E. (2014). Explicit reference modeling methodology in parametric cad system. *Computers in Industry*, 65(1):136–147.

Brinkhoff, T., Kriegel, H.-P., Schneider, R., and Braun, A. (1995). Measuring the complexity of polygonal objects. In *ACM-GIS*, volume 109. Citeseer.

Buff, B., Magnus, C., Zhu, J. H., and Meier, H. (2013). Robot-based incremental sheet metal forming–increasing the geometrical complexity and accuracy. In *Key Engineering Materials*, volume 549, pages 149–155. Trans Tech Publ.

Camba, J. D., Contero, M., Pérez-López, D., and Company, P. (2019). A database framework for the characterization and classification of parametric models based on complexity metrics to support data analytics. In *International Manufacturing Science and Engineering Conference*, volume 58745, page V001T02A007. American Society of Mechanical Engineers.

Campbell, D. T. (2017). Factors relevant to the validity of experiments in social settings. *Sociological methods*, pages 243–263.

Chakroun, A., Hani, Y., Turki, S., Rezg, N., and Elmhamedi, A. (2023). Development of predictive maintenance models for a packaging robot based on machine learning. In *IFIP International Conference on Advances in Production Management Systems*, pages 674–688. Springer.

Cheung, W. M., Mileham, A. R., Newnes, L. B., Marsh, R., and Lanham, J. D. (2011). Data-driven through-life costing to support product lifecycle management solutions in innovative product development. *International Journal of Product Lifecycle Management*, 5(2-4):122–142.

Chougule, R. and Ravi*, B. (2005). Variant process planning of castings using ahp-based nearest neighbour algorithm for case retrieval. *International journal of production research*, 43(6):1255–1273.

Clark, J. D. (1972). *Ignition!: An informal history of liquid rocket propellants.* Rutgers University Press.

Claus, F., Hagen, H., and Hamann, B. (2021). Calculating the gravity-free shape of sheet metal parts. *The International Journal of Advanced Manufacturing Technology*, 113(11):3401–3417.

Contero, M., Pérez-López, D., Company, P., and Camba, J. D. (2023). A quantitative analysis of parametric cad model complexity and its relationship to perceived modeling complexity. *Advanced Engineering Informatics*, 56:101970.

Cooper, D. R. and Schindler, P. (2003). *Business research methods.* Mcgraw-hill.

Cooper, R., Edgett, S., and Kleinschmidt, E. (2001). Portfolio management for new product development: results of an industry practices study. *r&D Management*, 31(4):361–380.

Deokar, A. Y., Bavdhankar, A. M., Degaonkar, R. R., Sardar, V. B., and Rajhans, N. (2016). Simulation and optimization of layout of sheet metal manufacturing plant.

Dober, P., West, S., Wiesner, S. A., and Ebel, M. (2023). Service lifecycle management in complex product-service systems. In *IFIP International Conference on Advances in Production Management Systems*, pages 32–46. Springer.

Döring, N. and Bortz, J. (2016). Forschungsmethoden und evaluation. *Wiesbaden: Springerverlag.*

ElMaraghy, W., ElMaraghy, H., Tomiyama, T., and Monostori, L. (2012). Complexity in engineering design and manufacturing. *CIRP annals*, 61(2):793–814.

Esener, E. et al. (2021). Accurate localization technique for stamping sheet metal parts with complex surfaces. *Indian Journal of Engineering and Materials Sciences (IJEMS)*, 28(4):409–419.

Feng, Y., Zhao, Y., Zheng, H., Li, Z., and Tan, J. (2020). Data-driven product design toward intelligent manufacturing: A review. *International Journal of Advanced Robotic Systems*, 17(2):1729881420911257.

Fosnacht, K., Sarraf, S., Howe, E., and Peck, L. K. (2017). How important are high response rates for college surveys? *The Review of Higher Education*, 40(2):245–265.

Greco, A., Manco, P., and Gerbino, S. (2022). On the geometrical complexity index as a driver for selecting the production technology. In *Design Tools and Methods in Industrial Engineering II: Proceedings of the Second International Conference on Design Tools and Methods in Industrial Engineering, ADM 2021, September 9–10, 2021, Rome, Italy*, pages 3–12. Springer.

Horvat, A., Granato, G., Fogliano, V., and Luning, P. A. (2019). Understanding consumer data use in new product development and the product life cycle in european food firms–an empirical study. *Food quality and preference*, 76:20–32.

Hosseini, M. and Shabani, M. (2015). New approach to customer segmentation based on changes in customer value. *Journal of Marketing Analytics*, 3:110–121.

Jensen, S. F., Kristensen, J. H., Adamsen, S., Christensen, A., and Waehrens, B. V. (2023). Digital product passports for a circular economy: Data needs for product life cycle decision-making. *Sustainable Production and Consumption*, 37:242–255.

Joshi, D. and Ravi, B. (2010). Quantifying the shape complexity of cast parts. *Computer-Aided Design and Applications*, 7(5):685–700.

Kandeil, D. A., Saad, A. A., and Youssef, S. M. (2014). A two-phase clustering analysis for b2b customer segmentation. In *2014 International Conference on Intelligent Networking and Collaborative Systems*, pages 221–228. IEEE.

Kassner, L., Gröger, C., Mitschang, B., and Westkämper, E. (2015). Product life cycle analytics–next generation data analytics on structured and unstructured data. *Procedia CIRP*, 33:35–40.

Krause, A., Dannerbauer, T., Wagenmann, S., Tjaden, G., Ströbel, R., Fleischer, J., Albers, A., and Bursac, N. (2024). Enhancing efficiency and environmental performance of laser-cutting machine tools: An explainable machine learning approach. *Procedia CIRP*, 130:1674–1679.

Kumar, S., Singh, R., Panghal, D., Salunkhe, S., and Hussein, H. (2017). Feature extraction and manufacturability assessment of sheet metal parts. In *AI Applications in Sheet Metal Forming*, pages 41–66. Springer.

Lachmayer, R., Mozgova, I., Sauthoff, B., and Gottwald, P. (2014). Evolutionary approach for an optimized analysis of product life cycle data. *Procedia Technology*, 15:359–368.

Lam, T., Sze, W., and Tan, S. (2007). Nesting of complex sheet metal parts. *Computer-Aided Design and Applications*, 4(1-4):169–179.

Leberruyer, N., Bruch, J., Ahlskog, M., and Afshar, S. (2023). Enabling an ai-based defect detection approach to facilitate zero defect manufacturing. In *IFIP International Conference on Advances in Production Management Systems*, pages 634–649. Springer.

Lee, B.-E. and Suh, S.-H. (2009). An architecture for ubiquitous product life cycle support system and its extension to machine tools with product data model. *The International Journal of Advanced Manufacturing Technology*, 42:606–620.

Lee, J., Kao, H.-A., and Yang, S. (2014). Service innovation and smart analytics for industry 4.0 and big data environment. *Procedia CIRP*, 16:3–8.

Li, J., Tao, F., Cheng, Y., and Zhao, L. (2015). Big data in product lifecycle management. *The International Journal of Advanced Manufacturing Technology*, 81(1):667–684.

Lian, Z., Godil, A., Rosin, P. L., and Sun, X. (2012). A new convexity measurement for 3d meshes. In *2012 IEEE Conference on Computer Vision and Pattern Recognition*, pages 119–126. IEEE.

Liu, Y., Tong, W., Li, Q., Yao, F., Li, Y., Li, H. X., and Huang, J. (2022). Study on complexity of precast concrete components and its influence on production efficiency. *Advances in Civil Engineering*, 2022.

Lohtander, M., Lanz, M., Varis, J., and Ollikainen, M. (2007). Breaking down the manufacturing process of sheet metal products into features. *Mechanics*, 64(2):40–48.

Lohtander, M. and Varis, J. (2007). Manufacturing features in cutting shapes and punching holes in sheet metal. In *19th International Conference on Production Research ICPR-19*. Valpariso, Chile. CD-proceedings.

Lohtander, M. and Varis, J. (2008). Manufacturability of large sheet metal part. In *Proceedings of 13th International Conference. Mechanika*. 13th International Conference.

MacCarthy, B. L. and Pasley, R. C. (2021). Group decision support for product lifecycle management. *International Journal of Production Research*, 59(16):5050–5067.

Mackenzie, N. and Knipe, S. (2006). Research dilemmas: Paradigms, methods and methodology. *Issues in educational research*, 16(2):193–205.

Marchetta, M. G., Mayer, F., and Forradellas, R. Q. (2011). A reference framework following a proactive approach for product lifecycle management. *Computers in Industry*, 62(7):672–683.

Maulina, N. R., Surjandari, I., and Rus, A. M. M. (2019). Data mining approach for customer segmentation in b2b settings using centroid-based clustering. In *2019 16th International Conference on Service Systems and Service Management (ICSSSM)*, pages 1–6. IEEE.

McKinsey (2016). How to succeed: strategic options for european machinery. shifting growth patterns, increasing pace of digitization, and organizational change. VDMA.

Pham, D. T., Dimov, S. S., Setchi, R. M., Peat, B., Soroka, A. J., Brousseau, E. B., Huneiti, A. M., Lagos, N., Noyvirt, A. E., Pasantonopoulos, C., et al. (2004). Product lifecycle management for performance support. *J. Comput. Inf. Sci. Eng.*, 4(4):305–315.

Powell, R. A. and Single, H. M. (1996). Focus groups. *International journal for quality in health care*, 8(5):499–504.

Qamar, S. Z., Chekotu, J. C., Al-Maharbi, M., and Alam, K. (2019). Shape complexity in metal extrusion: definitions, classification, and applications. *Arabian Journal for Science and Engineering*, 44:7371–7384.

Radvar-Esfahlan, H. and Tahan, S.-A. (2014). Robust generalized numerical inspection fixture for the metrology of compliant mechanical parts. *The International Journal of Advanced Manufacturing Technology*, 70(5):1101–1112.

Rieger, E. and Oleszek, S. (2023). The digital thread concept for integrating the development disciplines for mechatronic products. In *IFIP International Conference on Advances in Production Management Systems*, pages 261–272. Springer.

Rinciog, A., Mieth, C., Scheikl, P. M., and Meyer, A. (2020). Sheet-metal production scheduling using alphago zero. In *Proceedings of the Conference on Production Systems and Logistics: CPSL 2020*. Hannover: publish-Ing.

Rivera-Castro, R., Pilyugina, P., Pletnev, A., Maksimov, I., Wyz, W., and Burnaev, E. (2019). Topological data analysis of time series data for b2b customer relationship management. *arXiv preprint arXiv:1906.03956*.

Salunkhe, S., Kumar, S., and Teraiya, S. (2015). Automatic feature recognition of sheet metal parts.

Schuh, G., Bergweiler, G., Fiedler, F., Bickendorf, P., and Colag, C. (2019). A review on flexible forming of sheet metal parts. In *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pages 1221–1225. IEEE.

Simkin, L. (2008). Achieving market segmentation from b2b sectorisation. *Journal of Business & Industrial Marketing*.

Song, Z. and Kusiak, A. (2009). Optimising product configurations with a data-mining approach. *International Journal of Production Research*, 47(7):1733–1751.

Sreenu, P. and Gupta, R. K. (2014). Extraction of process parameters from a sheet metal part model. In *Applied Mechanics and Materials*, volume 592, pages 888–893. Trans Tech Publ.

Srinivasan, V. (2021). Open standards for product lifecycle management.

Stoll, O., West, S., Pirola, F., and Sala, R. (2023). Lifecycle management of digitally-enabled product-service systems offerings: The next challenge for manufacturers. In *IFIP International Conference on Advances in Production Management Systems*, pages 3–16. Springer.

Stormi, K., Laine, T., and Elomaa, T. (2018). Feasibility of B2C customer relationship analytics in the b2b industrial context.

Suh, N. P. (2005). Complexity in engineering. *CIRP annals*, 54(2):46–63.

Tao, F., Qi, Q., Liu, A., and Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems*, 48:157–169.

Terzi, S., Bouras, A., Dutta, D., Garetti, M., and Kiritsis, D. (2010). Product lifecycle management–from its history to its new role. *International Journal of Product Lifecycle Management*, 4(4):360–389.

Tjaden, G. (2024). 80 2d laser cutting geometries.

Tjaden, G., Baier, A., Strache, M., Regelmann, C., and Meyer, A. (2023a). Maximizing customer satisfaction in sheet metal processing: A strategic application of the customer health score. In *IFIP International Conference on Advances in Production Management Systems*, pages 136–150. Springer.

Tjaden, G., Feyhl, L., and Meyer, A. (2023b). Prototyping a data-driven customer segmentation utilizing machine usage data for product portfolio management. *Procedia CIRP*, 120:572–577.

Tjaden, G., Große, N., and Meyer, A. (2024). Understanding part complexity: A novel approach for the identification of complexity-influencing part characteristics. In *IFIP International Conference on Advances in Production Management Systems*, pages 394–409. Springer.

Tjaden, G., Meyer, A., and Rinciog, A. (2022). Towards adaptable customer segments and reference geometries. In *IFIP International Conference on Advances in Production Management Systems*, pages 321–328. Springer.

Tong, A., Sainsbury, P., and Craig, J. (2007). Consolidated criteria for reporting qualitative research (coreq): a 32-item checklist for interviews and focus groups. *International journal for quality in health care*, 19(6):349–357.

TRUMPF (2023). Trumpf machines & systems. `https://www.trumpf.com/en_GB/products/machines-systems/`. Accessed: 10.11.2023.

Turco, A. L. and Maggioni, D. (2020). The knowledge and skill content of production complexity. *Research Policy*, page 104059.

Udroiu, R. and Bere, P. (2018). *Product Lifecycle Management: Terminology and Applications*. BoD–Books on Demand.

Valentan, B., Brajlih, T., Drstvenšek, I., and Balič, J. (2011). Development of a part-complexity evaluation model for application in additive fabrication technologies. *Stroj. Vestnik J. Mech. Eng*, 10:709–718.

VDMA (2022). Mechanical engineering – figures and charts 2022. `https://www.vdma.org/documents/34570/4890926/MaBiZ_2022.pdf/b4bc8559-1c4b-bd0c-b6bd-da0d9c90cca4?t=1649843992368`. Accessed: 09.11.2023.

Wang, L., Liu, Z., Liu, A., and Tao, F. (2021). Artificial intelligence in product lifecycle management. *The International Journal of Advanced Manufacturing Technology*, pages 1–26.

Watanabe, K., Okuma, T., and Takenaka, T. (2020). Evolutionary design framework for smart pss: Service engineering approach. *Advanced Engineering Informatics*, 45:101119.

Wu, M.-J., Zhao, K., and Fils-Aime, F. (2022). Response rates of online surveys in published research: A meta-analysis. *Computers in Human Behavior Reports*, 7:100206.

Zhang, Y., Ren, S., Liu, Y., Sakao, T., and Huisingh, D. (2017). A framework for big data driven product lifecycle management. *Journal of Cleaner Production*, 159:229–240.

Appendix

A.1 Description of Part Complexity Use Cases

This section of the appendix documents the use cases identified with the focus group.

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ Produkt- und Portfolio-Management | ☐ Forschung und Entwicklung | ☒ Vertrieb und Beratung

Beschreibung:
Entwicklung neuer Geschäftsmodelle wie Performance-Benchmarking (Peer2Peer Vergleich)

Status Quo:
Bisher nur auf z.B. „Laser Ein" Zeit möglich.
Keine verlässliche Datenbasis zu der Teilegeometrie bzw. Produktionsspektrum.
Maschine vergisst alle Infos zum Bauteil sobald das Teil die Maschine verlassen hat.

Zukünftiger Vorteil mit Teilekomplexität:
Neues Geschäftsmodell: Kunde bekommt seine Performance im Vergleich zu „Peers" angezeigt, also Kunden welche ähnliche Teilespektrum haben.
Idee: Geodaten werden anonymisiert, dann entsprechend dem EU Data Act verarbeitet.
Dann können diese Informationen allen vergleichbaren Kunden zur Verfügung gestellt werden

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☒ Produkt- und Portfolio-Management | ☐ Forschung und Entwicklung | ☐ Vertrieb und Beratung

Beschreibung:

Das Produktmanagement und Portfoliomanagement optimieren stetig das MT Portfolio. Das PM & PPM möchte Portfolio-lücken identifizieren und Verbesserungen vornehmen. Durch Clusterung der Kunden aufgrund der Applikation und Teilekomplexität kann das Portfolio zielgerichteter gestaltet werden.

Status Quo:

Nutzung von Benchmarktafeln (Durchschnittsbildung, nur für 2D Schneiden optimiert) für interne Performanceabstufungen der Serie sowie Wettbewerbsanalysen.

Vergleich von Teilekomplexität aufgrund technischer Daten (Teilegewicht, Teilegröße, etc.) → sehr einfache Analyse ...

Zukünftiger Vorteil mit Teilekomplexität:

Weiterer Schritt um die Situation auf dem Shopfloor des Kunden real abzubilden.

Bessere Clusterung der Kunden nach Anwendungsfall möglich.

Gezieltere Anforderungserhebung möglich, auch für komplexere Systeme.

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ Produkt- und Portfolio-Management | ☐ Forschung und Entwicklung | ☒ Vertrieb und Beratung

Beschreibung:

Wir wollen dem Vertrieb und dem Kunden ein Tool an die Hand geben, mit dem er die optimale Maschinenkonfiguration für seinen Anwendungsfall finden kann.

Status Quo:

Anwendungstechniker machen Machbarkeitsstudien, darauf aufbauend wird die Maschinenserie und die Optione ausgewählt.
Basis dafür ist Expertenwissen, zudem ist das System nicht skalierbar.
Die gesamte Anwendung wird auf Basis weniger Teile hochgerechnet.
⇒ hohes Risiko, dass angebotene System nicht den Kundenbedürfnissen entspricht

Zukünftiger Vorteil mit Teilekomplexität:

Skalierbarer Ansatz da automatisierte Machbarkeitsstudie.
Gesamtes Produktionssystem kann analysiert werden, nicht nur Einzelmaschine.
Zudem kann dem Kunden ein Wachstumspfad aufgezeigt werden. (Go/Grow/Flow)
Ziel: automatisierte, nutzungsspezifische ~~[illegible]~~ System-konfiguration
Voraussetzung: Daten aus dem Feld bzw. Benchmark / alternativ: repräsentativ ausreichend große Stichprobe

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ **Produkt- und Portfolio-Management** | ☐ **Forschung und Entwicklung** | ☒ **Vertrieb und Beratung**

Produktions Planung

Beschreibung:

- Ich als Produktionsleiter möchte mögliche mehr Arbeit durch Nacharbeit von vorne rein einplanen und nötige Qualitätskontrollen bei schwierige Bauteile automatisch im Produktionsplan anlegen.
- Als Produktionsleiter möchte ich Teile dort produzieren (Systemauswahl), wo sie auch prozesssicher produziert werden können

Status Quo:

- Ich muss Nacharbeit manuell für jedes Bauteil abschätzen oder berücksichtige sie gar nicht.
- Qualitätskontrolle muss ich manuell in Arbeitsplan [illegible] anlegen.
- Kunde verschachtelt basierend auf Erfahrung & Bauchgefühl welche Teile auf welcher Anlage produziert werden

Zukünftiger Vorteil mit Teilekomplexität:

~~Bauteile mit höher [illegible] für Nacharbeit werden automatisch~~

- Zeiten für Nacharbeit werden automatisch über Bauteilkomplexität festgelegt.
- Qualitätskontrollen werden automatisch in Produktionsplan angelegt, je nach Teilekomplexität
- Vorschläge für Verschachtelungen & Anlagenauswahl werden automatisch generiert, können aber auch angepasst werden
  → Aufwandsreduzierung für Produktionsplanung

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ Produkt- und Portfolio-Management | ☒ Forschung und Entwicklung | ☐ Vertrieb und Beratung

Technologie-/ Maschinenentwicklung

Beschreibung:

Wir wollen (neue) Technologien und/oder Maschinen auf Basis von Komplexitätsschwellwerten entwickeln.

Status Quo:

Wir versuchen Technologien individuell zu optimieren, unabhängig von deren Performance bezogen auf bekannter komplexer Kunden Teilegeometrien.

Zukünftiger Vorteil mit Teilekomplexität: (Planung von Entwicklungsprojekten)

Zielgerichtete, kundenorientierte Entwicklung von Maschinen, sodass wir deren Mehrwert dem Kunden gegenüber quantifizieren können (z.B. Komplexitätsschwellwert <2).

Bietet Transparenz für Kunden im Entwicklungsprozess!!

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ Produkt- und Portfolio-Management | ☒ Forschung und Entwicklung | ☐ Vertrieb und Beratung

Optimierung ~~Produktionslayout~~ ~~Prd~~ Schichtplanung

Beschreibung:

Wir wollen, die von uns basierend auf dem Kundenproduktportfolio ausgewählten Maschinen, optimal nutzen ~~anordnen~~, um Stillstand ~~Wege~~ innerhalb der Produktion zu minimieren. Darüber hinaus wollen wir die Bearbeitungsreihenfolge optimieren.

Status Quo:

~~Factory layout nicht auf Basis der Teilekomplexität~~

Bisher keine Einteilung in Tag- bzw. Nachtschicht-tauglichkeit basierend auf Teilekomplexität.
Entscheidung auf Technologieebene (Stanz-Komb. + Sheet Master für Nachtschicht)

Zukünftiger Vorteil mit Teilekomplexität:

Stillstände in Nachtschicht können vermieden werden (vor allem bei Maschinen mit Automatisierungseinheiten) ☺

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ **Produkt- und Portfolio-Management** | ☒ **Forschung und Entwicklung** | ☐ **Vertrieb und Beratung**

Risikobewertung für Teilekostenkalkulation

Beschreibung:

Wir wollen durch die Integration des Komplexitätskennwerts einen realitätsgetreuen Risikozuschlag für die Kostenkalkulation anbieten.

Status Quo:

Bauchgefühl-/Erfahrungs-geprägter Zuschlag für vermeintlich komplexe Teile.

Zukünftiger Vorteil mit Teilekomplexität:

Faires und realistische Angebote möglich.

Job shopper (z.B. CaaS) tragen weniger Risiko.

Wir bieten neues Geschäftsmodell „CaaS" – Calculate as a Service

Webshop für Kunden möglich durch CaaS möglich

Template für die Beschreibung der Anwendungsfälle der Teilekomplexität

Anwendungsfall: ☐ Produkt- und Portfolio-Management | ☐ Forschung und Entwicklung | ☒ Vertrieb und Beratung

Beschreibung:

Ich möchte die Kunden, die ähnliches produzieren, miteinander vergleichen und den Kunden sagen wie sie im Vergleich mit der Peer-Group performen.

Status Quo:

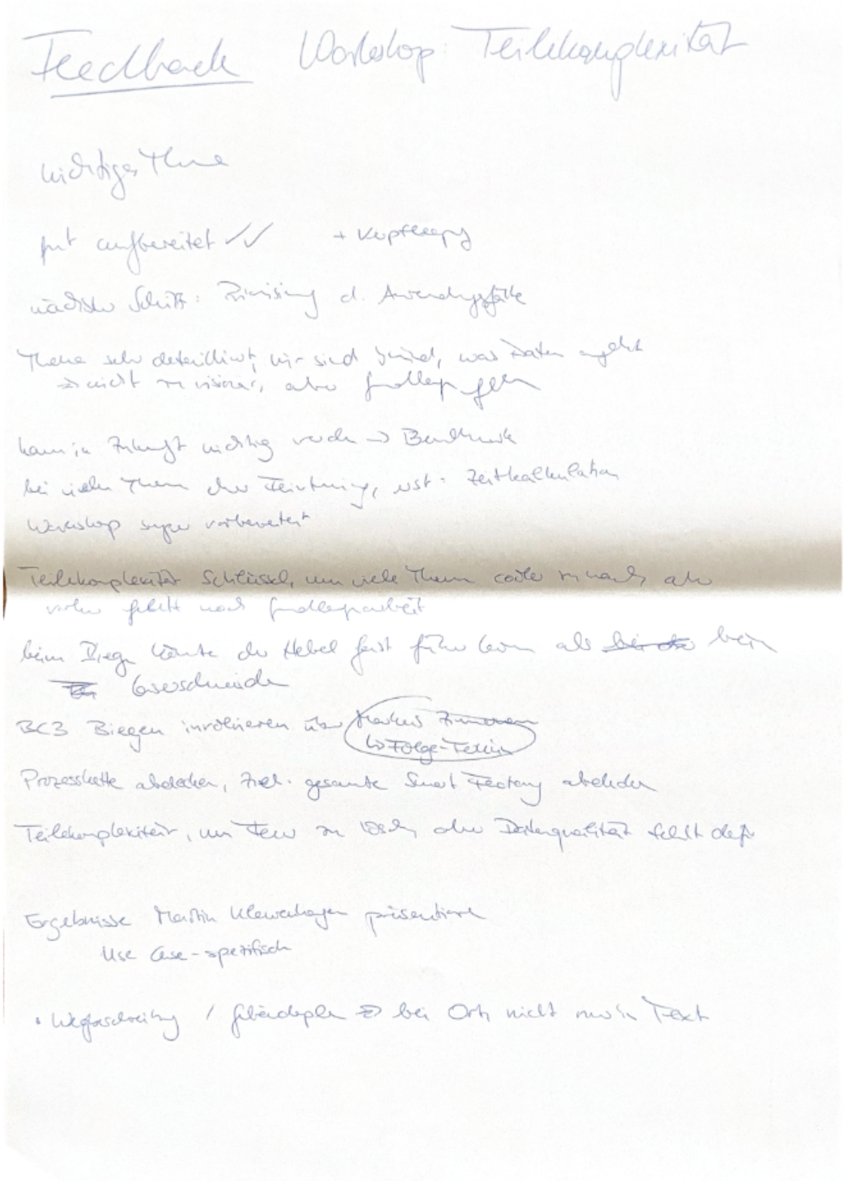
Ich kann Kunden nur anhand von Branchen segmentieren. Jobshops können kaum verglichen werden.

Zukünftiger Vorteil mit Teilekomplexität:

Kunden, insbesondere Jobshops, können anhand der Teilekomplexität und Anlagen segmentiert werden.

A.2 Focus Group Feedback

This section documents the feedback collected from the focus group participants.


Feedback Workshop Teilekomplexität

wichtiges Thema

gut aufbereitet ✓✓ + [illegible]

nächster Schritt: Priorisierung d. Anwendungsfälle

Thema sehr detailliert, wir sind gespannt, was [illegible]
⇒ nicht zu visionär, aber [illegible]

kann in Zukunft wichtig werden → Benchmark

bei vielen Themen der Zeichnung, inkl. Zeitkalkulation

Workshop super vorbereitet

Teilekomplexität Schlüssel, um viele Themen [illegible], aber
vorher fehlt noch Grundlagenarbeit

beim Biegen könnte der Hebel fast größer sein als [illegible] beim
[illegible] Gesenkschmieden

BC3 Biegen involvieren über Markus [illegible]
↳ Folge-Termin

Prozesskette abdecken, incl. gesamte Smart Factory abdecken

Teilekomplexität, um Teile zu [illegible] oder Datenqualität fehlt derz.

Ergebnisse Martin [illegible] präsentieren
Use Case-spezifisch

• Wegbeschreibung / [illegible] ⇒ bei Ort nicht nur in Text