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Value Stream Mapping for Internal Logistics using Process Mining

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Editors' Preface

Production engineering is crucial for the advancement of our industrial society because the performance of manufacturing companies depends heavily on the equipment and resources employed, the production processes applied, and the established manufacturing organization. A company's full potential for corporate success can only be taken advantage of by optimizing the interaction between humans, operational structures, and technologies. Being able to remain competitive while balancing the varying and often conflicting priorities of complexity, cost, time, and quality requires constant thought, adaptation, and the development of new manufacturing structures. Thus, there is an essential need to reduce the complexity of products, manufacturing processes, and systems. Yet, at the same time, it is also vital to gain a better understanding and command of these aspects.

The objective of the research activities at the Institute for Machine Tools and Industrial Management (*iwb*) is to continuously improve product development and manufacturing planning systems, manufacturing processes and production facilities. A company's organizational, manufacturing, and work structures, as well as the underlying systems for order processing, are developed under strict consideration of employee-related requirements and sustainability issues. Although an increasing degree of automation is unavoidable, labor will remain an important component in production processes. Thus, questions concerning the optimization of human involvement in all planning and development processes are of utmost importance.

The volumes published in this book series reflect and report the results from the research conducted at *iwb*. Research areas covered span from the design and development of manufacturing systems to the application of technologies in manufacturing and assembly. The management and operation of manufacturing systems, quality assurance, availability, and autonomy are overarching topics, which affect all areas of our research. In this series, the latest results and insights from our application-oriented research are published. This will foster an improvement in the transfer of knowledge between universities and towards a wide industrial sector.

Gunther Reinhart Michael Zäh

Acknowledgments

This project would not have been possible alone. I wish to thank all the people who supported me and enabled me to complete this doctoral thesis.

I am deeply grateful to Professor Dr.-Ing. Gunther Reinhart for supervising my doctoral thesis, supporting my research project and providing the research environment at the *iwb*. I am very thankful to Professor Stephen C. Graves for hosting me at the Massachusetts Institute of Technology (MIT). Our weekly discussions always allowed me to reflect upon previous work and to further develop my research. I also thank Professor Dr.-Ing. Michael F. Zäh for taking over as chair of the examination committee and Professor Dr.-Ing. Johannes Fottner for being part of the examination committee.

The research project included the Bayerische Motorenwerke (BMW) AG, which allowed me to provide valuable insights into the automotive industry. I would like to thank Marco Prüglmeier for his personal support and for enabling all the necessary activities at BMW, as well as all other contributing project members.

I would like to pay my special thanks to Jonas, Christian, Josef, Severin, Benedikt, Felix, Harald, Andi, Michi, Julia, Achim, and all my other colleagues at the *iwb*. The knowledge and personality that you showed during projects and discussions was always valuable and fun, and made working here special. I would also like to thank Norman and Rafael for sharing your interdisciplinary expertise, and Max, Christian, Charlotte, Julian, Robert, Philipp, Lorena, Quirin, Raffaela, and all other students for your contributions to this research project.

On a personal note, I want to thank my mother Ulrike and the rest of my family, and my close friends for being part of my personal development. Most of all, I want to thank you, Sonja. You always supported me when necessary and distracted me whenever possible. Without you, it would not have been possible.

Abstract

Pen-and-paper-based value stream mapping is the established tool for recording processes, identifying waste, and deriving recommendations for action. Today, however, its application in the manufacturing and logistics industry requires a high level of effort and is challenging due to product and process complexity and issues involving dynamics.

Process mining is a relatively young research discipline that helps to utilize event data to discover, analyze, and improve processes. Process mining connects business process modeling and analysis with data mining. Nowadays, the day-to-day business of internal logistics is based on information systems, which create a vast amount of event data.

Therefore, the overarching objective of the thesis is to enable an effective and efficient application of value stream mapping in internal logistics using process mining. The main contribution of this thesis is the integration of the research streams of value stream mapping and process mining.

The main results include an internal logistics ontology and algorithms for data preprocessing and mining the value streams. Six process mining techniques create a holistic view of each value stream and a comprehensive picture of all value streams. A methodology for an industrial application and guidelines for event data validation and the analysis according to lean production theory in internal logistics are proposed to ensure a practical benefit to the work.

The industrial application includes three case studies that demonstrate the feasibility, effectiveness, and efficiency of the approach in practice. The findings are used to evaluate and reflect the strengths and limitations of the approach.

Glossary

Concept drift The change of a process between the beginning and the end of an event log (BOSE et al. 2011, p. 391).

Data mining Data mining is a process that aims to generate knowledge from data and present the findings in ways that are useful to the user. Data mining includes discovering non-trivial patterns, relations, and trends. (SCHUH et al. 2019, p. 876)

Event log An event log is a collection of events of operational data (cf. VAN DER AALST 2016).

Internal logistics Internal logistics refers to the receipt of parts, warehousing (e.g., storing, sequencing), and line feeding through to line-side presentation (cf. BOYSEN et al. 2015; NEGRI et al. 2017; SALI & SAHIN 2016).

Lean production Lean production is an integrated socio-technical system whose main objectives are eliminating waste and increasing efficiency by concurrently adding value to the customer and reducing lead times (based on JONES & WOMACK 1997; OHNO 1988; REINHART 2017; SHAH & WARD 2007).

Mixed-model assembly line In a mixed-model assembly line production, "varying models are manufactured on the same production system, the production processes of which are similar enough so that setup times are not present or negligible." (BOYSEN et al. 2007, p. 678)

Ontology An ontology is an explicit specification of a conceptualization (GRUBER 1995, p. 1).

Practical guideline A piece of information that suggests how something should be done and that is related to experience, real situations, or actions rather than ideas (based on *Cambridge Dictionary* 2014).

Process A process is a set of specific and ordered activities across time and place, with a beginning and an end, intended to reach a specific goal (cf. DAVENPORT 1992; HAMMER & CHAMPY 1993).

Process mining "The idea of process mining is to discover, monitor and improve real processes by extracting knowledge from event logs." (VAN DER AALST et al. 2012, p. 172)

Reference process A main process that consists of a unique set of standardized activities (based on DÖRNHÖFER et al. 2016; ROZINAT et al. 2007).

Value stream A value stream is all the activities, both value-added and non-value-added, currently required to bring a product through the main flows (ROTHER & SHOOK 1999, p. 1).

Value stream mapping Value stream mapping is a pencil and paper tool that helps you to see and understand the flow of material and information as a product makes its way through the value stream (ROTHER & SHOOK 1999, p. 2).

Contents

1 Introduction

1.1 Initial situation

Over the last decades, lean production has become the de facto standard for production and manufacturing systems (PSOMAS & ANTONY 2019; REINHART 2017). Lean production is well accepted both in academia and in industry because it results in superior performance and can provide a competitive advantage (SHAH & WARD 2007, p. 785). Invented in Japan, the *Toyota Production System (TPS)* is based on the two main components of just-in-time (JIT) and autonomation (OHNO 1988). The primary goal of the TPS is to eliminate waste, increase efficiency, and subsequently reduce costs (OHNO 1988). In 1990, WOMACK et al. (1990) evolved TPS with a benchmark study of *lean production* compared to mass production. The comprehensive study covers both the technical and the work system perspective and highlights the advantages of using less of everything: e.g., space, human effort, and inventory (WOMACK et al. 1990, p. 13). Further development has introduced *lean thinking* with five key principles: specify value, identify the value stream, flow, pull, and pursue perfection (JONES & WOMACK 1997). In addition to this major work, many studies on lean production address many aspects, such as the technical and human perspective or the philosophical and practical orientation (e.g., HOLWEG 2007; PETTERSEN 2009; PSOMAS & ANTONY 2019; SHAH & WARD 2003, 2007). Hence, the definition presented in the following is a reflection upon discussions between the author, researchers, and industry experts.

Definition. Lean production is an integrated socio-technical system whose main objectives are eliminating waste and increasing efficiency by concurrently adding value to the customer and reducing lead times (based on JONES & WOMACK 1997; OHNO 1988; REINHART 2017; SHAH & WARD 2007).

These days, the understanding of production also includes related processes, including logistics (SPATH 2010), and recent developments (e.g., *lean logistics*) have adapted lean thinking (e.g., GÜNTHNER & BOPPERT 2013; JONES et al. 1997).

Value stream mapping is a pen-and-paper tool to map the current value stream and see waste within the process (ROTHER & SHOOK 1999). ROTHER & SHOOK (1999, p. 1) define a value stream as "all the actions (both value-added and non-value-added) currently required to bring a product through the main flows essential to every product: (1) the production flow from raw material into the arms of the customer [...]".

In practice, value stream mapping is frequently used for creating transparency, analyzing, and improving a variety of processes in the manufacturing industry; the automotive industry is the main application (SHOU et al. 2017, p. 3909). If existing methods of process analysis for internal logistics[1] are compared, value stream mapping has been proven to be the most suitable (W. BAUER et al. 2014, p. 483) and most frequently used tool (GÜNTHNER & SCHNEIDER 2011, p. 44). The literature review of SHOU et al. (2017), including 91 articles in the manufacturing industry, highlights the strengths of value stream mapping: improvements on inventory and lead times are the top benefits with average achievements of 70% and 56%, respectively. FORNO et al. (2014) reviewed the main difficulties of value stream mapping in 57 articles, and both reviews reveal that the application presents difficulties in practice. Based on the findings of FORNO et al. (2014) and SHOU et al. (2017) and the study of SPATH (2010) about value stream mapping with 304 manufacturing companies, the following limitations have been identified:

- *Missing support for product and process complexity.* Today, products contain hundreds of parts and sub-assemblies that follow different paths and processes. Then, value stream mapping can be seriously challenging or can even break down (BRAGLIA et al. 2006; FORNO et al. 2014). In the comprehensive study, manufacturing companies most frequently reported that value stream mapping is limited if the production requires many product variants and if product groups require different processes (SPATH 2010, p. 68).

- *Missing support to capture dynamics.* As value stream mapping is a static pen-and-paper tool, the accuracy level and the ability to capture dynamics are limited (FORNO et al. 2014; Y.-H. LIAN & VAN LANDEGHEM 2007). If processes are not stable or change frequently, the current state map of the value stream only provides a limited snapshot or is obsolete (FORNO et al. 2014; SPATH 2010). In

[1] Internal logistics refers to the receipt of parts, warehousing (e.g. storing, sequencing) and line feeding through to line side presentation (cf. BOYSEN et al. 2015; NEGRI et al. 2017; SALI & SAHIN 2016).

particular, time and quantity data measurements are impractical (FORNO et al. 2014, p. 781). Additionally, many companies fail to apply value stream mapping continuously and in the same frequency as often as products and processes change (FORNO et al. 2014). However, continuous monitoring for several months is required to see the effects of changes and improvements (HINES et al. 1998, p. 243).

- *High manual effort.* The high level of effort involved in collecting the data and the time spent on constructing the current state map are frequently reported as the costliest stages (FORNO et al. 2014; SHOU et al. 2017). This cost prevents the continuous application of value stream mapping (FORNO et al. 2014, p. 787). The cost, in combination with an increasing product and process complexity, and process invisibility, can prevent practitioners from collecting sufficient data by direct observation (FORNO et al. 2014; SHOU et al. 2017).

KNOLL et al. (2019b, p. 130) demonstrate that these existing limitations are even more challenging for internal logistics in the context of high product and process complexity, as well as dynamics. In contrast to manufacturing, the value streams can be highly individual for each product variant and sub-assembly: supplier, material flow and inventories, and customer demand. Further on, a wide variety of process types (e.g., warehousing, JIT), activities (e.g., transport, pick), and resources (e.g., storage, supermarkets) exist. Consequently, value stream mapping for every part and its individual value stream is not technically and economically applicable.

1.2 Motivation

In the age of *Industrie 4.0*, massive amounts of data are created during manufacturing and logistics operations. This operational data can be used to understand, analyze, and improve processes in the context of complex production and manufacturing systems (i.e., BAUERNHANSEL et al. 2016; REINHART 2017). For that purpose, *data mining* has been successfully established in the manufacturing industry within the last decade (e.g., KÖKSAL et al. 2011; SCHUH et al. 2019).

The relatively young research discipline of *process mining* has evolved as a subset of data mining. Process mining connects data mining with business process modeling and analysis (VAN DER AALST et al. 2012, p. 172). Process mining uses algorithms to create process models based on operational event data (VAN DER AALST et al. 2012). Consequently, creating process models is highly automated and scales to cover both process complexity and time-dependent dynamics. Today, process mining has gained significant importance when analyzing business processes in domains such as healthcare or IT (DAKIC et al. 2018; ROJAS et al. 2016).

Definition. "The idea of process mining is to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's (information) systems." (VAN DER AALST et al. 2012, p. 172)

In theory, process mining can support lean production (VAN DER AALST 2016). "What these approaches have in common is that processes are 'put under a microscope' to see whether further improvements are possible. Clearly, process mining can help to analyze deviations and inefficiencies." (VAN DER AALST 2016, p. 48) For instance, VAN DER AALST (2016, p. 48) illustrates that the "process discovery can be used to eliminate all non-value-added activities and reduce waste." In contrast, the application of process mining in the domain of manufacturing and logistics is rarely reported (DAKIC et al. 2018; KNOLL et al. 2019c; VAN CRUCHTEN & WEIGAND 2018). The literature review of DAKIC et al. (2018) shows that only 8% of the publications focus on manufacturing, and 3% focus on logistics (DAKIC et al. 2018, p. 871).

In general, a process mining project can be separated into four stages (adapted from ECK et al. 2015; VAN DER AALST et al. 2012). Different challenges have been identified for the application in internal logistics in each stage:

- *Planning and data extraction.* Any process mining project starts with planning: defining objectives and questions and extracting event data from information systems. This requires an understanding of the domain and the data. (VAN DER AALST et al. 2012, p. 177) Data extraction can be challenging in the context of complex and heterogeneous information systems, such as manufacturing and logistics (BECKER et al. 2017; WESTKÄMPER et al. 2013). Particularly, this step requires combining domain knowledge (e.g., lean production) with technical knowledge about information systems, underlying data tables, and attributes. Further on, the vocabulary used differs radically. (CALVANESE et al. 2016) In the context of process mining, domain ontologies have been proven to provide support for this step (CALVANESE et al. 2016; INGVALDSEN & GULLA 2008).

- *Data preprocessing.* Standardized event logs are required to apply process mining. However, “the step to collect the event log used as input for process mining is far from trivial” (VAN DER AALST & WEIJTERS 2004, p. 238) and “sometimes significant efforts are needed to correlate events belonging to the same process instance.” (VAN DER AALST et al. 2012, p. 177) Numerous data tables must be merged to correlate event logs, and attributes must be located in each data table (INGVALDSEN & GULLA 2008). Algorithms that correlate operational data of the material flow and can scale to the high volume of data are required to perform this step in the context of logistics (KNOLL et al. 2019b, p. 427). For example, five million transfer orders are processed monthly, on average, in internal logistics in the automotive industry (KNOLL et al. 2017).

- *Mining.* A variety of process mining techniques, concepts, and methodologies can be applied in a process mining project (VAN DER AALST 2016). Innumerable algorithms for process discovery and conformance checking are frequently combined with other techniques (e.g., clustering). However, “[...] there are no process discovery techniques that produce overarching models able to relate and analyze different groups and process variants.” (VAN DER AALST 2013, p. 3) Furthermore, most work “[...] has been concerned with the general concept of process mining, with little focus on domains.” (YAHYA et al. 2016, p. 383) Further tailoring to the process characteristics is required to apply process mining to logistics: selecting algorithms and advanced techniques to cover product and process complexity and integrating domain-specific characteristics such as inventory or handling costs (KNOLL et al. 2019c).

- *Analysis and evaluation.* The challenge is to exploit event data meaningfully using event logs and process mining techniques (VAN DER AALST et al. 2012, p. 174). Therefore, “the diagnostic [analysis step] should be simple, accurate, and suggestive for the next, more detailed step in the analysis.” (GRAVES 1981, p. 664) However, a plethora of technical concepts requires support for practitioners, which is currently lacking (Y. WANG et al. 2014a, pp. 196–197). In particular, this requires linking process mining with practical outcomes for the logistics domain, such as established types of waste according to lean production. Further on, product and process complexity and dynamics require effectively handling the complexity of the analysis. For example, to identify wasteful value streams or activities (KNOLL et al. 2019c).

1.3 Objectives of the thesis

The evidence for lean production and value stream mapping has been successfully demonstrated across the manufacturing and logistics industry (SHAH & WARD 2007; SHOU et al. 2017). However, value stream mapping is not complete because of the gap between theory and practice (SHOU et al. 2017, p. 3921). There is still a need for improvements in handling both product and process complexity, capturing the process dynamics and deviations from reality, and reducing the high level of manual effort when creating the current state map (cf. FORNO et al. 2014; SHOU et al. 2017).

Recent developments in data mining introduce process mining techniques "[...] to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's (information) systems" (VAN DER AALST et al. 2012, p. 172). Theory states that process mining can support lean production objectives and reduce waste (VAN DER AALST 2016, p. 48).

Motivated by existing shortcomings and recent developments in the field of process mining, the thesis contributes to the state of the art and the application in industrial practice. The overarching goal is to *enable an effective and efficient application of value stream mapping in internal logistics using process mining.* Therefore, three supporting objectives are defined:

O1. *Supporting the planning and data preparation.*
The tasks of identifying, extracting, and preprocessing data must be adapted to internal logistics to support planning and data preparation.

O2. *Mapping the value stream using process mining.*
Adapting and tailoring existing process mining techniques and concepts for value stream mapping are required to holistically map the value stream using process mining. Later, missing aspects must be developed, if required.

O3. *Supporting the analysis according to lean production theory.*
Practical guidelines for analyzing value streams using process mining in the context of product and process complexity must be developed to support process improvement.

1.4 Research methods and environment

Established research methods have been used in the research project to achieve the main objective and the three subgoals. The following section briefly describes the methods in the context of the research project: (1) formulating the *Research Questions (RQs)*, (2) adapting the *Design Research Methodology (DRM)*, and (3) specifying the research scope and environment.

1.4.1 Research Questions (RQs)

Three RQs provide guidance (cf. *RQ1, RQ2, and RQ3*) to further specify the objectives independently of the research domain:

RQ1. Which data is required, and how must that data be prepared for value stream mapping for internal logistics using process mining?

RQ2. Which process mining methods, concepts, and algorithms are capable of extracting and characterizing process models while capturing product and process complexity?

RQ3. Which steps are required to enable a systematic analysis according to lean production theory?

1.4.2 Adapting the Design Research Methodology (DRM)

The research project has been conducted according to the DRM. “A DRM is defined here as an approach and a set of supporting methods and guidelines to be used as a framework for doing design research.” (BLESSING & CHAKRABARTI 2009, p. 9) According to KOCH (2017), the DRM is one of the most comprehensive and detailed research methods in the field of manufacturing engineering available today[2]. Thereby, the DRM includes building theory and supports the improvement of existing models and support. Figure 1.1 outlines the theoretical foundation of the four-step methodology that has been adapted to the research project.

[2] Please refer to KOCH (2017, pp. 7–9) for a detailed discussion of the suitability and applicability of the DRM.

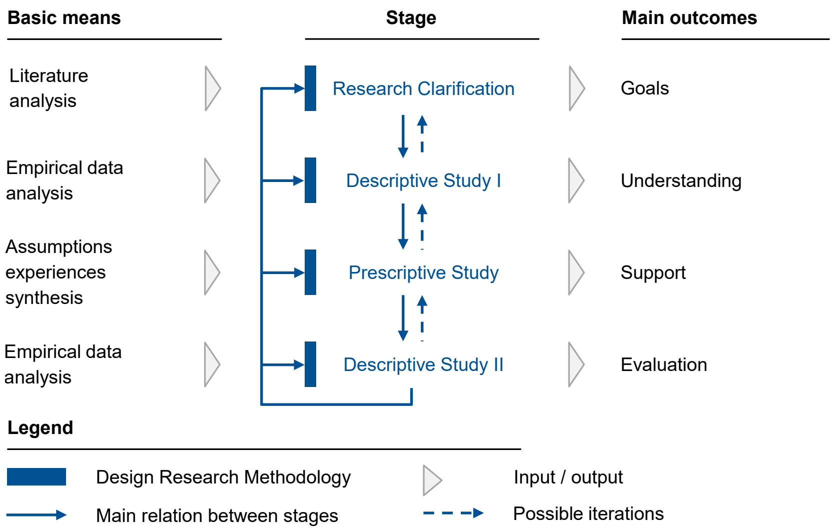


Figure 1.1: Design Research Methodology (BLESSING & CHAKRABARTI *2009, p. 15)*

The *Research Clarification* aims to find evidence that supports the research objectives (BLESSING & CHAKRABARTI 2009). An initial understanding of the current situation and limitations of value stream mapping is required to formulate objectives. Value stream mapping is an established approach, and numerous studies in academia and industry exist. Thus, a review-based approach has been selected to derive discrepancies from the desired situation. The industrial practice provides further evidence.

Descriptive Study I enhances the initial understanding and influencing factors (BLESSING & CHAKRABARTI 2009). A systematic review approach has been developed, focusing on process mining applications in the manufacturing and logistics industry to cover the variety of articles spread across research fields. Existing literature has been characterized and classified based on the methodology, i.e., process mining algorithms, and application context, i.e., internal logistics, of process mining.

The *Prescriptive Study* focuses on the development of support (BLESSING & CHAKRABARTI 2009) by integrating value stream mapping and process mining. The findings of the reviews in process mining and value stream mapping have been used to specify the requirements of the approach. The conceptual design outlines the approach with its relationships and an applicable methodology for practitioners. The detailed design focuses on developing and specifying the concept based on process mining and lean production theory.

Descriptive Study II focuses on the impact and if the desired support can be achieved (BLESSING & CHAKRABARTI 2009). The concept has been implemented in industry, and three case studies have been conducted to evaluate the support. The evaluation includes the fulfillment of requirements, a cost-benefit calculation, and a discussion of limitations.

If required, further specifications of the research methods (e.g., the review approach) are provided in each chapter of the thesis.

1.4.3 Research scope and environment

Research scope

The scope of the thesis is value stream mapping for internal logistics supplying a mixed-model assembly line production. Internal logistics refers to the receipt of parts, warehousing (e.g., storing, sequencing), and line feeding through to line-side presentation (BOYSEN et al. 2015; NEGRI et al. 2017; SALI & SAHIN 2016). In a mixed-model assembly line production, varying models are manufactured on the same production system with similar production processes (BOYSEN et al. 2007, p. 678). Hence, the following limitations exist:

- *Technical tool perspective of lean production.* Lean production provides an umbrella for a variety of practices, techniques, and tools. The thesis focuses on the technical perspective of the value stream mapping tool. Lean practices and techniques must be established before or when applying the tool.
- *Value stream design.* Because of the identified shortcomings of pen-and-paper-based value stream mapping, the scope of the work is set on the current state and the analysis of the value stream (e.g., types of waste). The step of value stream design to create an improved state of the value stream can be supported by previous work (e.g., DURCHHOLZ 2014) and is not part of this thesis.
- *Performance measurement system.* Various performance metrics, also referred to as key performance indicators, are recorded when mapping and analyzing value streams. These metrics can be used to characterize waste, e.g., waste

of inventory. However, many articles have been published on performance measurement, and literature indicates the company-specific nature of these metrics (e.g., GUNASEKARAN & KOBU 2007). Thus, only an initial set of performance metrics can be provided in the thesis.

Research environment

The research project was conducted at the Institute for Machine Tools and Industrial Management (*iwb*), Technical University of Munich (TUM). The research project included the Bayerische Motorenwerke (BMW) AG and, therefore, provides valuable insights into the automotive industry. Findings have been discussed and evaluated with more than 20 logistics experts. Later, this research project benefited from the research cooperation with the MIT Sloan School of Management, MIT. Professor Stephen C. Graves contributed to the development of the inventory profiling algorithm and the analysis of inventory.

1.5 Structure of the thesis

The remainder of the thesis is organized as follows (cf. Figure 1.2). Chapter 1 describes the initial situation and motivation and derives the objectives of the thesis. Chapter 2 provides the theoretical understanding of related research fields and the application context of internal logistics, value stream mapping, and process mining theory. Chapter 3 proposes a review approach to derive a representative overview of existing literature. Applications of process mining in the fields of manufacturing and logistics are critically reviewed and related to value stream mapping. Chapter 4 addresses existing shortcomings of value stream mapping and process mining and integrates both research fields. The concept includes a methodology for an industrial application and relates four main research modules. The methodology for the industrial application consists of four consecutive steps and enables value stream mapping for internal logistics using process mining. Chapter 5 describes the theoretical development and the research results of the four main research modules. Chapter 6 describes how the proposed concept is applied in an industrial application. In addition, the fulfillment of the requirements, the cost-benefit calculation, and existing limitations are critically discussed to evaluate the concept. Chapter 7 concludes the thesis and provides an outlook for future research activities.

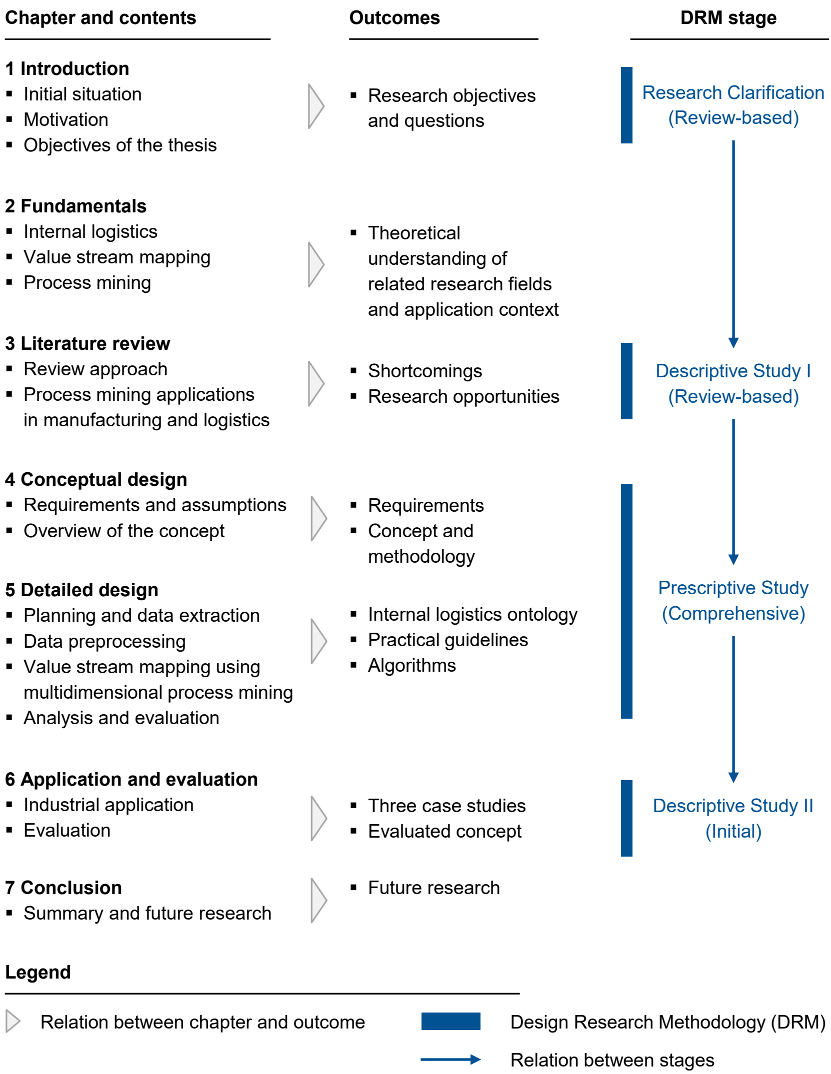


Figure 1.2: Structure of the thesis and research design

2 Fundamentals

This chapter outlines fundamental aspects of internal logistics (cf. Section 2.1) and value stream mapping (cf. Section 2.2). After an introduction about the objectives, types and perspectives of process mining, and fundamental and advanced concepts and methodologies of process mining are proposed (cf. Section 2.3).

2.1 Internal logistics

2.1.1 Objectives, scope, and processes

Consumers and companies need products and materials at times and places other than when and where those products and materials are produced. Therefore, "logistics has to manage physical goods in space and time in order to execute orders." (GUDEHUS & KOTZAB 2012, p. 4) The term logistics has been widely discussed, and many definitions address various aspects (cf. RUTNER & LANGLEY 2000; SCHUH & V. STICH 2013).

Objectives

Logistics ensures the availability of the right product, in the right quantity and the right condition, at the right place, at the right time, for the right customer, at the right cost (RUTNER & LANGLEY 2000, p. 73). A refinement of the *Seven R's of Logistics* introduces a variety of *logistics performance* dimensions like on-time delivery and customer satisfaction, flexibility, low loss and damage, and cost efficiency (CHOW et al. 1994). In a nutshell, these dimensions can be simplified to *effectiveness* and *efficiency*. Efficiency is doing things right, and effectiveness is doing the right thing (CHOW et al. 1994, p. 23). Non-value-added activities can be evaluated in terms of effectiveness and efficiency. Consequently, logistics is a process that creates value (RUTNER & LANGLEY 2000, p. 73).

"A *logistics value-added* service either provides additional service(s) or exceeds customer service requirements that further reduce the supply chain costs or increase the partners' profits and gains competitive advantage in the marketplace." (RUTNER & LANGLEY 2000, p. 79)

Scope

Logistics can be classified into *procurement logistics*, *internal logistics*, and *distribution logistics*. Here, internal logistics, also referred to as intra-logistics, or in-house logistics, connects the receiving areas, internal sources and destinations, and the shipping docks of the same site or plant. (GUDEHUS & KOTZAB 2012, p. 7)

> **Definition**. *Internal logistics* refers to the receipt of parts, warehousing (e.g., storing, sequencing), and line feeding through to line-side presentation (cf. BOYSEN et al. 2015; NEGRI et al. 2017; SALI & SAHIN 2016).

Processes

Numerous definitions exist for the term "process" (cf. LINDSAY et al. 2003). A popular definition says a process is a "set of partially ordered activities intended to reach a goal" (HAMMER & CHAMPY 1993, p. 39). More precisely, DAVENPORT (1992) defines a process as a "specific ordering of work activities across time and place, with a beginning, an end, and clearly identified inputs and outputs: a structure for action" (DAVENPORT 1992, p. 5).

> **Definition**. A *process* is a set of specific and ordered activities across time and place, with a beginning and an end, intended to reach a specific goal (cf. DAVENPORT 1992; HAMMER & CHAMPY 1993).

Many types of logistics processes exist. Inbound logistics, outbound logistics, reverse logistics, or disposal logistics can be differentiated according to the direction of material flows (GUDEHUS & KOTZAB 2012). Inbound logistics refers to the call order, transport logistics, receipt of parts, storing parts, sequencing of parts, delivery to line, and line-side presentation (BOYSEN et al. 2015, p. 109).

> **Definition**. A *logistics process* is a process that consists of material and information flow activities (cf. ARNOLD et al. 2010; GÜNTHNER & BOPPERT 2013).

A *logistics reference process* is a logistics process that consists of a unique set of standardized material and information flow activities that are related to resources (based on DÖRNHÖFER et al. 2016; ROZINAT et al. 2007). An example of a logistics reference processes is to inspect packages at the goods receiving, to transport packages to the high rack using a forklift, to store packages, and to distribute packages to the assembly line. A logistics reference process is implemented and executed in the production plant.

Ten standardized material flow activities (cf. Figure 2.1) and four information flow activities (e.g., label, scan, document, and generate order) can be used to design logistics reference processes (GÜNTHNER & BOPPERT 2013, p. 138). A comprehensive description of internal logistics is presented in Section 5.1.1.

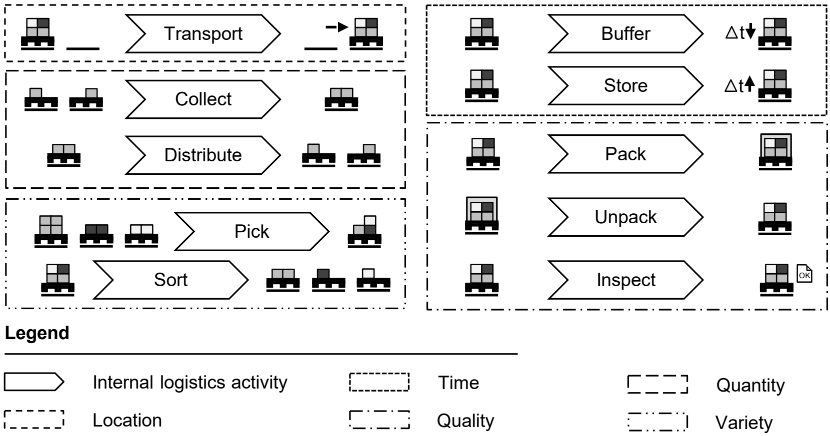


Figure 2.1: Standardized material flow activities in internal logistics (extract, based on GÜNTHNER & BOPPERT *2013, p. 138)*

2.1.2 From lean production to lean logistics

Over the last decades, lean production has been adapted to logistics. *Lean logistics* takes its fundamental philosophy from lean production (JONES et al. 1997, p. 170). The objective of lean logistics is to meet the requirements of manufacturing while maintaining high flexibility, short lead times, and cost efficiency (KLUG 2010, p. 254). The key concepts of value, value streams, flow, pull, and perfection have been adapted for process improvement within lean logistics (JONES et al. 1997, p. 171). Many extensions have been developed, for example, to standardize processes or to improve process stability (cf. GÜNTHNER & BOPPERT 2013; KLUG 2010).

In lean logistics, the main principle is the understanding of adding value and reducing waste (cf. DÖRNHÖFER 2016; JONES et al. 1997). Generally speaking, waste is any activity that consumes resources but creates no value (JONES & WOMACK 1997, p. 1148). Consequently, "eliminating waste must be a business' first objective" (OHNO 1988, p. 129). JONES et al. (1997, p. 154) claim that it is easy to see the steps that add value, but it is much more difficult to see waste in logistics. Some activities in logistics can be seen as adding value while others, e.g., storage, additional transport, or quality issues, are seen as waste (DÖRNHÖFER et al. 2016, p. 14). Similarly, GOLDSBY & MARTICHENKO (2005, p. 14) state that waste in production has received attention, but relatively little is mentioned about the wastes in logistics. Consequently, various definitions exist. Table 2.1 describes the fundamental understanding for this work.

Table 2.1: Seven types of waste in lean production and lean logistics (cf. GOLDSBY & MARTICHENKO *2005;* GÜNTHNER & BOPPERT *2013;* OHNO *1988)*

Lean production	Lean logistics	Description
Transportation	Transportation	Unnecessary transport of parts under production.
Inventory	Inventory	Stacks of parts waiting to be completed or to be shipped.
Motion	Handling	Unnecessary movement of people working on products.
Waiting	Waiting	Unnecessary waiting by people to begin the next step.
Overproduction	Over-supplying	Supplying and producing material, goods, energy and products not needed.
Over-processing	Undefined processes	Processing the product with extra steps.
Defects	Defects	Defects in the product.

This theoretical understanding of lean logistics and the resulting potentials for improvement have been evaluated in many real-world applications (cf. FORNO et al. 2014; SHOU et al. 2017; SPATH 2010). Process improvements range from simple *continuous improvement projects* to *reengineering* logistics reference processes. An exemplary study with 20 practitioners in the German automotive industry identified the largest saving potentials for just-in-sequence (JIS) processes in the reduction of inventory and space requirements (THUN et al. 2007, p. 1796).

2.1.3 Information systems

Nowadays, internal logistics cannot operate without information systems due to performance requirements and involving complexity (TEN HOMPEL & SCHMIDT 2010, p. 2). J. BAUER (2014, p. 8) concludes that manually operating internal logistics could not keep up with the needs of the plant. Organizations use Warehouse Management Systems (WMS) to cope with performance requirements (RAMAA et al. 2012, p. 975).

> **Definition**. A WMS primarily controls the movement and storage of materials within a warehouse (cf. RAMAA et al. 2012; TEN HOMPEL & SCHMIDT 2010).

WMS have extended their scope to support many aspects of internal logistics, including procurement, receiving incoming goods, and picking and sequencing of goods (SCHUH & V. STICH 2013, p. 276). A WMS creates transfer orders based on the production orders to supply production with the right amount of material. Subsequently, a transfer order integrates the (digital) information flow with the physical material flow (SCHUH & V. STICH 2013, pp. 276–277).

> **Definition**. A *transfer order* triggers the process and activities that transform the state of the unit load and stores related activity occurrences (cf. LIBERT et al. 2010; SCHUH & V. STICH 2013; TEN HOMPEL & SCHMIDT 2010).

In practice, a WMS can be a standalone system or integrated into an Enterprise Resource Planning (ERP) system (RAMAA et al. 2012, p. 976). Numerous WMS solutions are available on the market (TEN HOMPEL & SCHMIDT 2010, p. 255). Due to the importance of transfer orders for this work, the data models of eight WMS are analyzed to ensure the availability of transfer orders.

The analysis covers four commercial WMS (e.g., *SAP R3 ERP WM*) and four open source WMS (e.g., *openWMS*) and confirms that every WMS uses transfer orders. Each transfer order is stored in the database and holds information about the logistics process. In particular, (1) the part (e.g., variant of a part or sub-assembly and quantity), (2) the location (source and destination), and (3) time of occurrence are recorded. Notably, the analysis shows that the number of data tables (and columns) varies among these WMS (cf. Appendix A.1.1).

2.2 Learning to see: Value stream mapping

"A value stream is all the actions (both value-added and non-value-added) currently required to bring a product through the main flows essential to every product: (1) the production flow from raw material into the arms of the customer [...]." (ROTHER & SHOOK 1999, p. 1) ROTHER & SHOOK (1999, p. 1) conclude that the value stream focuses on "the big picture, not just individual processes, and improving the whole, not just optimizing the parts." Thus, mapping a value stream includes (sub-)processes, data boxes (metrics), inventory, and associated information (cf. ROTHER & SHOOK 1999).

> **Definition**. "Value stream mapping is a pencil and paper tool that helps you to see and understand the flow of material and information as a product makes its way through the value stream." (ROTHER & SHOOK 1999, p. 2)

Nowadays, value stream mapping has become a popular method for lean production (SHOU et al. 2017, p. 3906) and is used "to identify value-adding activities and those considered wasteful of materials and the flow of information" (FORNO et al. 2014, p. 779). Benefits relate to the broad view of the entire flow and waste, the simple and standardized presentation, and making decisions more visible to monitor previous changes and improvements (FORNO et al. 2014, pp. 779–780).

Firstly, value stream mapping starts with the selection of a product family. Secondly, the current state map of the production situation is recorded. Here, value stream mapping focuses on the actual pathways and does not rely on standard times or information. ERLACH (2010, p. 31) emphasizes that transparency on the actual state is elementary. Thirdly, waste and potential for improvement are identified to develop the future state. Fourthly, the future state is achieved[1]. (cf. ROTHER & SHOOK 1999)

Value stream mapping has been proven to be the most suitable (W. BAUER et al. 2014, p. 483) and most frequently used tool (GÜNTHNER & SCHNEIDER 2011, p. 44) for recording, analyzing, and improving processes in internal logistics. DÖRNHÖFER (2016, p. 22) concludes that "transparency about processes and inventory is the key to identify waste and potential for improvement".

[1] Please refer to ROTHER & SHOOK (1999) and ERLACH (2010) for further concepts and practical guidelines.

2.3 Process mining

This section introduces process mining. Objectives, types, perspectives (cf. Section 2.3.1), fundamental concepts (cf. Section 2.3.2), and advanced concepts and methodologies (cf. Section 2.3.3) are briefly discussed.

2.3.1 Objectives, types, and perspectives

Process mining is a relatively young research discipline that bridges the gap between data mining, on the one hand, and business process modeling and analysis, on the other hand. In the field of data mining, established techniques, including classification, clustering, and regression, are widely adapted to solve specific learning tasks. However, most data mining techniques are not process-centric. (VAN DER AALST et al. 2012, p. 172) In contrast, modeling, analyzing, and improving business processes are common tasks in the field of business process management and operations management. According to VAN DER AALST (2016, p. 56), "making a good model is an art rather than a science". Typical errors are related to models that (1) describe an idealized version of reality, (2) use the wrong level of abstraction, and (3) are unable to capture human behavior (VAN DER AALST 2016, p. 56).

Objectives of process mining

Over the last decade, event data have become available, and process mining techniques have been developed. According to the *IEEE Task Force on Process Mining*, the "challenge is to exploit event data in a meaningful way [...]. Process mining aims to do exactly that." (VAN DER AALST et al. 2012, p. 174)

> **Definition**. "The idea of process mining is to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's (information) systems." (VAN DER AALST et al. 2012, p. 172)

According to VAN DER AALST (2016, p. 32), "the digital universe and the physical universe become more and more aligned." Today's information systems log enormous amounts of event data, including the manufacturing and logistics domain (cf. REINHART 2017; VAN DER AALST 2016). Therefore, the overarching objective of process mining is to "use event data to extract process-related information" (VAN DER AALST 2016, p. 25). Consequently, process mining provides an unbiased, objective, and historical view using event data and reduces the effort due to automated algorithms. The key concepts of event logs and process models that reflect the real world and how they apply to process mining are shown in Figure 2.2.

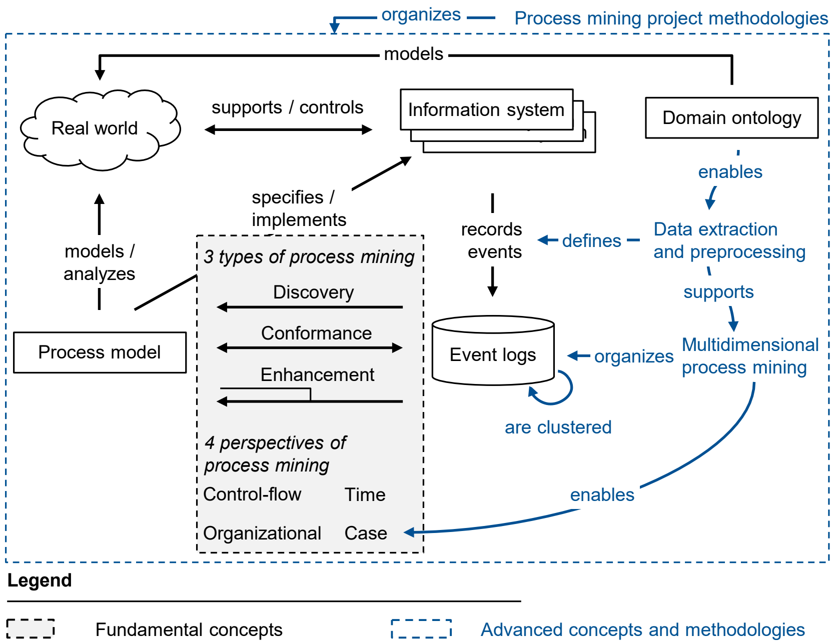


Figure 2.2: Process mining context model: types, perspectives, and related concepts (based on BOLT & VAN DER AALST *2015;* CALVANESE *et al. 2016;* ECK *et al. 2015;* VAN DER AALST *2016)*

Types of process mining

Three types of process mining are proposed to address the relationship between the key concepts of event logs and process models (cf. VAN DER AALST et al. 2012).

- *Process discovery*. Process discovery takes an event log to create a process model without using any a priori information. Typically, the resulting process model is further processed or visualized. Hence, process discovery is the most prominent process mining technique. (VAN DER AALST et al. 2012, p. 175)

- *Conformance checking*. Conformance checking compares and measures the alignment between a model and an event log and verifies if the model conforms to reality (VAN DER AALST et al. 2012, p. 175).

- *Enhancement*. The idea of enhancement is to extend or improve an existing process model using information about real-world behavior recorded in the event log (VAN DER AALST et al. 2012, p. 175).

Perspectives of process mining

The three types of process mining cover four fundamental perspectives of a process, which have been discussed extensively in the literature (VAN DER AALST 2016, p. 34).

- *Control-flow perspective*. The control-flow perspective focuses on the occurrence and ordering of activities. The goal of mining the control-flow is to find a good characterization of all possible paths. The result is typically expressed as a *Petri net*. Consequently, the control-flow perspective constitutes the foundation of process mining and is usually the starting point for a process analysis. (cf. MANNHARDT 2018; VAN DER AALST 2016)

- *Time perspective*. The time perspective is concerned with the timing and frequency of events. The time perspective can be used, for instance, to discover bottlenecks and extend a process model. (VAN DER AALST et al. 2012, p. 176)

- *Organizational perspective*. The organizational perspective, also referred to as resource perspective, focuses on the information about resources hidden in the event log, e.g., actors (VAN DER AALST et al. 2012, p. 176).

- *Case perspective*. The case perspective, also referred to as the data or information perspective, focuses on attributes of events or cases. Attributes such as cost are proposed to enhance the analysis. (VAN DER AALST et al. 2012, p. 176)

> The three types of process mining connect the key concepts of event logs and process models. In contrast, the four process mining perspectives focus on the different aspects of a process, most dominantly the control-flow perspective.

2.3.2 From event logs to process models

This section focuses on the fundamental concepts of process mining. Event logs, process discovery algorithms, and process models are presented.

Event logs

The starting point for process mining is an event log, which assumes that “it is possible to sequentially record events such that each event refers to an activity (i.e., a well-defined step in some process) and is related to a particular case (i.e., a process instance).” (VAN DER AALST et al. 2012, p. 174) Consequently, a *process* consists of *cases*. A *case* consists of *events* such that each event relates to precisely one case. Events within a case are *ordered* and can have *attributes*. Providing such event logs may be very challenging, such as correlating the cases of raw event data or snapshots of incomplete cases. (VAN DER AALST 2016, pp. 129–143)

Definition (Event, attribute). Let E be the *event universe*, the set of all possible event identifiers, and let AN be a set of *attribute names*. For any event $e \in E$ and name $n \in AN$, $\#_n(e)$ is the value of the attribute n for event e.

Definition (Case, trace). Let C be the *case universe*, the set of all possible case identifiers. Each case refers to a trace σ with a finite sequence of events. For any case $c \in C$ and name $n \in AN$, $\#_n(c)$ is the value of the attribute n for case c.

Definition (Event log). An *event log* is a set of cases $L \subseteq C$ such that each event appears only once. (VAN DER AALST 2016, pp. 130–134)

An example event log is shown in Table 2.2. If possible, process mining techniques use extra attributes, e.g., the cost and resource recorded with the event (VAN DER AALST et al. 2012, p. 174). The following standard attributes exist (VAN DER AALST 2016, p. 131):

- $\#_{\text{activity}}(e)$ is the activity associated to event e.
- $\#_{\text{time}}(e)$ is the timestamp of event e.
- $\#_{\text{resource}}(e)$ is the resource associated to event e.
- $\#_{\text{trans}}(e)$ is the transaction type associated to event e, e.g., start and complete.

Table 2.2: A fragment of some event log: each line corresponds to an event (based on VAN DER AALST *2016, p. 129)*

		Attributes				
Case Id	Event Id	Timestamp	Activity	Resource	Cost	...
1	35654423	2010-12-30 11:02	register request	Pete	50	...
	35654424	2010-12-31 10:06	examine thoroughly	Sue	400	...
	35654425	2011-01-05 15:12	check ticket	Mike	100	...
	35654426	2011-01-06 11:18	decide	Sara	200	...
2	35654483	2010-12-30 11:32	register request	Mike	50	...
	35654485	2010-12-30 12:12	check ticket	Mike	100	...
	35654487	2010-12-30 14:16	examine casually	Pete	400	...
	35654488	2011-01-05 11:22	decide	Sara	200	...
	35654489	2011-01-06 12:05	pay compensation	Ellen	200	...
3	35654641	2011-01-06 15:02	register request	Pete	50	...
	35654643	2011-01-07 12:06	check ticket	Mike	100	...
...	...	...	...	...	...	...

Process discovery algorithms

This section focuses on the discovery task in the control-flow perspective, often referred to as *process discovery*. “A *process discovery algorithm* is a function that maps an event log *L* onto a process model *M* that is representative for the behavior seen in the event log *L*.” (VAN DER AALST 2016, p. 163) The challenge is to “create a process model that is consistent with the observed dynamic behavior” (VAN DER AALST & WEIJTERS 2004, p. 232). Four widely adapted quality performance metrics exist for assessing quality (cf. BUIJS et al. 2012; VAN DER AALST 2016):

1. “*Replay fitness* quantifies the extent to which the discovered model can accurately reproduce the cases recorded.” (BUIJS et al. 2012, p. 305)
2. *Simplicity*. “The complexity of a process model is captured by the simplicity dimension.” (BUIJS et al. 2012, p. 306)
3. “*Precision* quantifies the fraction of the behavior allowed by the model which is not seen in the event log.” (BUIJS et al. 2012, p. 306)
4. “*Generalization* assesses the extent to which the resulting model will be able to reproduce future behavior of the process.” (BUIJS et al. 2012, p. 306)

Many process discovery algorithms have been developed in the field of process mining[2]. Some important algorithms are briefly presented:

- *α-algorithm*. The α-algorithm (α) is one of the first process discovery algorithms. Basically, the α-algorithm constructs a Petri net from an event log using a directly-follows graph. The simplicity of the α-algorithm introduces limitations related to loops and duplicate activities. Many variants have been developed (e.g., α^+, α^{++}) to address those shortcomings. (LEEMANS 2017, pp. 60–62)
- *Heuristic miner*. The heuristic miner takes frequencies of events and paths into account when creating the model. Infrequent paths should not be included in the model. (VAN DER AALST 2016, p. 201) A directly-follows graph is constructed, and the activity relations are derived probabilistically. Nevertheless, no sound process model can be guaranteed. (LEEMANS 2017, p. 63)
- *Fuzzy miner*. The fuzzy miner focuses on complex, real-life processes with noise. Suitable abstractions of reality are created using (1) correlation and significance metrics, (2) edge filtering, and (3) activity aggregation and abstraction (GÜNTHER & VAN DER AALST 2007). Typically, important paths are highlighted (VAN DER AALST 2016, p. 44).
- *Genetic miner*. Genetic miners are evolutionary algorithms. Instead of relying on local information in the log, an iterative global search is applied. On the one hand, genetic miners are precise and robust to deal with noise and incomplete logs. For example, the *evolutionary tree miner* allows specifying the importance of each quality performance metric (BUIJS et al. 2012, p. 310). On the other hand, genetic miners are inefficient, resulting in high computation times for larger models and event logs. (cf. MEDEIROS et al. 2007; VAN DER AALST 2016)
- *Inductive miner*. Inductive mining techniques use process trees and a divide-and-conquer approach to create a sound process model. Therefore, infrequent behavior and very large event logs and models can be handled. (LEEMANS et al. 2014, 2018) Currently, the inductive miner is a leading process discovery algorithm (VAN DER AALST 2016, p. 222).

[2] BURATTIN (2013, pp. 41–53) presents a summary of the historical development. For further discussions of individual algorithms, please refer to BUIJS et al. (2014), DONGEN et al. (2009), LEEMANS (2017), VAN DER AALST (2016), & VAN DER AALST & WEIJTERS (2004).

Process models

Process discovery algorithms create process models in various perspective, semantic, and abstraction levels. A plethora of process model notations with different characteristics exist in industry and academia. (cf. BUIJS et al. 2012; VAN DER AALST 2016) Two important notations for process mining are briefly explained[3].

- *Petri nets*. A Petri net is a directed graph consisting of *places* and *transitions*. Petri nets are a simple and executable graphical notation. *WorkFlow-nets (WF-net)* are a subset of Petri nets that require a dedicated source (start) and sink (end) of the process. (VAN DER AALST 2016, pp. 59–65)
- *Business Process Modeling Notation (BPMN)*. In 2011, the *Object Management Group (OMG)* introduced BPMN 2.0, a widely used business process model standard (KALENKOVA et al. 2017, p. 1019). BPMN aims to provide a notation that is readily understandable by all business users (OMG 2011, p. 1). The BPMN notation models the process as a graph using standardized elements, such as activities and gateways, that cover different perspectives. Models related to process mining can be converted into Petri nets, and vice versa[4]. BPMN is very attractive for both process mining analysts and business users. Figure 2.3 shows an example BPMN process model.

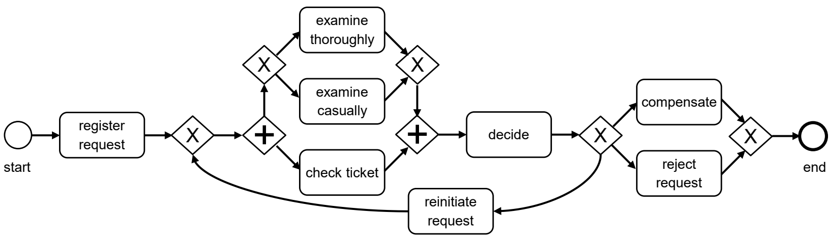


*Figure 2.3: Process model using the BPMN notation (*VAN DER AALST *2016, p. 69)*

[3] For an overview and discussion of notations (e.g., Causal nets, UML Activity Diagrams or Process Trees), please refer to BÖRGER (2012), RUSSELL et al. (2005), VAN DER AALST (2016), & VAN DER AALST et al. (2011).

[4] Please refer to KALENKOVA et al. (2017) for further discussion on the relation between BPMN 2.0, low-level models (e.g., Petri nets), and process mining.

2.3.3 Advanced concepts and methodologies

Firstly, multidimensional process mining and trace clustering are introduced. Secondly, methodologies are presented that demonstrate the applicability of process mining.

Multidimensional process mining

Process mining uses event data to extract process-related information. Unfortunately, "there are no process discovery techniques that produce overarching models able to relate and analyze different groups and process variants." (VAN DER AALST 2013, p. 1) Events and process models are organized into various dimensions using *process cubes* notation (cf. Figure 2.4). These dimensions can be analyzed separately to compare different process variants in terms of the fundamental of process mining[5]. (cf. BOLT & VAN DER AALST 2015; VAN DER AALST 2013)

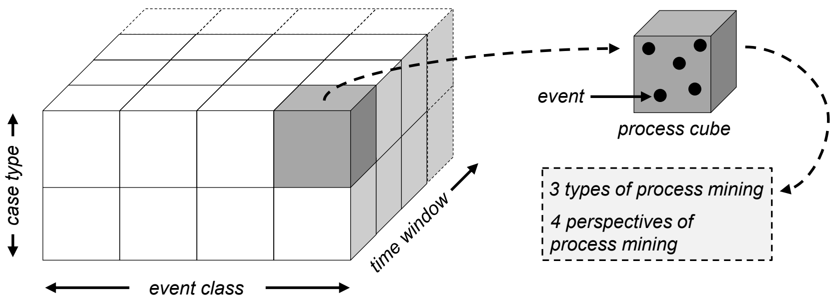


*Figure 2.4: The concept of process cubes (*VAN DER AALST *2013, p. 6)*

Process cubes allow organizing events in three dimensions:

- *Case type.* The case type is based on the attributes of the case as a whole, not on individual events (VAN DER AALST 2013, p. 6).
- *Event class.* This dimension is based on the attributes of individual events, e.g., activity name or resource (VAN DER AALST 2013, p. 6).
- *Time window.* The time window dimension uses timestamps, e.g., to cover process changes (cf. *concept drift*) (VAN DER AALST 2013, p. 17).

[5] Please refer to VOGELGESANG et al. (2016) for a review-based comparison of dimension classes, data requirements, and limitations of multidimensional process mining approaches.

Trace clustering

Trace clustering is a process mining technique that aims to identify groups of similar instances to reduce the complexity of the analysis (cf. Figure 2.5). In contrast to multidimensional process mining, clustering is typically used in an explanatory manner if groups are unknown. (VAN DER AALST 2016, p. 116) Therefore, clustering addresses issues related to less structured and more flexible processes with many process variants (cf. BOSE & VAN DER AALST 2010; DE WEERDT et al. 2013; SONG et al. 2009).

> **Definition.** *Trace clustering* splits an event log "into homogeneous subsets, and for each subset, a process model is created" (SONG et al. 2009, p. 109).

In general, clustering algorithms require a set of input features. Therefore, the event log is transformed into a set of input features (cf. *trace profile*). Typically, trace profiles map the *control-flow perspective* (BOSE & VAN DER AALST 2009, pp. 398–399):

- *Bag-of-activities.* For each trace, the frequencies of activities are mapped to a vector without taking the sequence into account.
- *k-gram model.* Trace fragments of *k* occurring activities are mapped (e.g., 2-gram refers to a pair of activities) to include this sequence.
- *Distance-based.* Distance-based functions, i.e., *hamming distance* or *edit distance*, evaluate the similarity of traces using distance functions.

Trace profiles can address the *case perspective*, including *performance*, *case attributes*, or *event attributes* (SONG et al. 2009, pp. 113–114). To evaluate the goodness of the clusters, established quality performance metrics (e.g., fitness) are evaluated for each cluster (BOSE & VAN DER AALST 2009, p. 397).

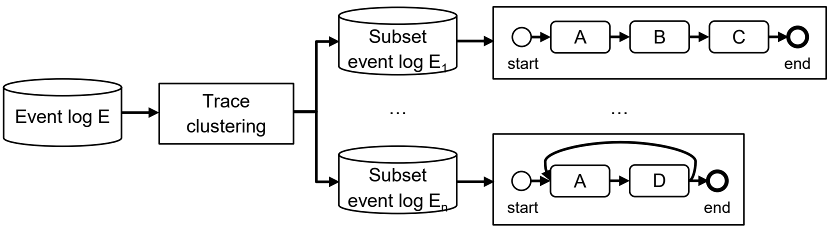


*Figure 2.5: The concept of trace clustering (*BOSE & VAN DER AALST *2010, p. 397)*

Process Mining Project Methodology (PM^2)

A range of process mining techniques and perspectives can be used to improve processes. However, ensuring practical support in real-world applications is far from trivial. Many theoretical methodologies exist, such as the *L* Life-cycle model*, and PM^2 can be seen as a comprehensive refinement. (VAN DER AALST 2016, p. 396)

PM^2 aims to improve the process performance or compliance to rules, and it covers a wide range of techniques suitable both for structured and unstructured processes. PM^2 supports an iterative execution of process mining. To ensure practical support, PM^2 focuses on (1) research questions, (2) performance findings, (3) compliance findings, and (4) improvement ideas. (ECK et al. 2015, p. 298)

In total, PM^2 includes six stages, specified with concrete tasks and outcomes (cf. Figure 2.6). The first two steps include (1) planning and (2) data extraction to initialize the project. Here, objectives are defined, and required event data and optional process models are extracted. In the third step, the data are (3) processed into event logs. The event log is created, enriched, and filtered. Domain ontologies can support these steps using domain-specific knowledge. (4) Process mining techniques are applied, and (5) findings are evaluated iteratively. Finally, (6) process improvements are implemented for operational support. (cf. ECK et al. 2015)

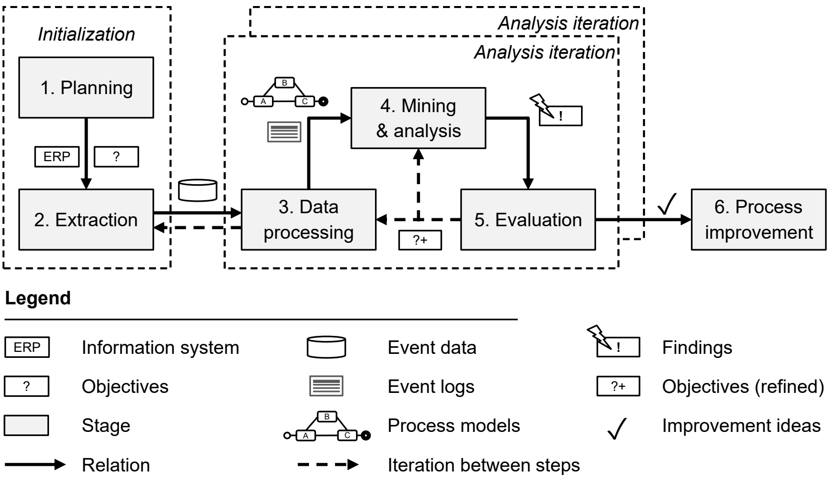


Figure 2.6: Process Mining Project Methodology (PM^2) (ECK et al. 2015, p. 299)

Ontology-based data extraction and preprocessing

It is a common misconception to think a project starts as soon as event logs are available (MURILLAS 2019). Theory states that creating event logs is far from trivial (VAN DER AALST & WEIJTERS 2004, p. 238), and sometimes significant effort is required (VAN DER AALST et al. 2012, p. 177); the effort to create event logs can be up to 80% of the time of a project (MURILLAS 2019). Possible challenges during extracting and preprocessing data relate to:

1. *Information systems*. Typically, many legacy information systems interact with each other. Identifying relevant systems and storage mechanisms can be challenging. (CALVANESE et al. 2016, p. 141)

2. *Data models*. Information systems do not record event logs explicitly (VAN DER AALST 2015, p. 105). Numerous data tables must be merged to correlate the data, and interesting data attributes must be precisely located in each data table (INGVALDSEN & GULLA 2008, p. 33).

3. *Abstraction*. The extraction spans several levels of abstraction, and there is no such notion for a single event log. The vocabulary used in the information systems and data models differs radically from domain knowledge, as, for example, in internal codes with implicit semantics. (CALVANESE et al. 2016, pp. 140–141)

4. *Scalability*. The volume of data created can be challenging for process mining (LEEMANS et al. 2018, p. 600). Furthermore, cases may have a lifetime that exceeds the time frame of the event log (VAN DER AALST 2016, p. 143).

If these time-consuming stages can be reduced, an impact in terms of time, cost, and quality can be created (MURILLAS 2019). Consequently, suitable data must be identified and extracted, and event logs must be created and enriched. Within the area of process mining, domain ontologies are frequently used to support these tasks.

Definition. "An ontology is an explicit specification of a conceptualization. [...] This set of objects, and the describable relationships among them, are reflected in the representational vocabulary with which a knowledge-based program represents knowledge." (GRUBER 1995, pp. 1–2)

Firstly, a set of relevant objects and properties enable efficient identification of necessary information systems, data tables, and columns (CALVANESE et al. 2016; INGVALDSEN & GULLA 2008). Secondly, domain ontologies include existing relationships between objects so that complex models can be flattened to an event log (INGVALDSEN & GULLA 2008). Although events and attributes are difficult to generalize, event logs can be enriched with concepts from domain ontologies to enhance the interpretation of results (JAREEVONGPIBOON & JANECEK 2013, p. 460).

Many concepts that use ontologies for data extraction and preprocessing refer to three stages (e.g., CALVANESE et al. 2016; INGVALDSEN & GULLA 2008; JAREEVONGPIBOON & JANECEK 2013; VAN DER AALST 2015):

1. *Ontology specification*. Create a shared understanding of domain-specific classes, object properties (relations), and data properties (attributes).

2. *Data extraction*. Identify application-specific information systems and underlying data models, including data tables and columns.

3. *Data processing*. Correlate events to cases and, subsequently, event logs. Enrich domain-specific attributes at the event, case, or event log level.

For example, CALVANESE et al. (2016) developed an annotation-based approach that allows domain experts to specify how to view the domain. In other words, events, traces and optional attributes are annotated in the ontology (cf. Figure 2.7).

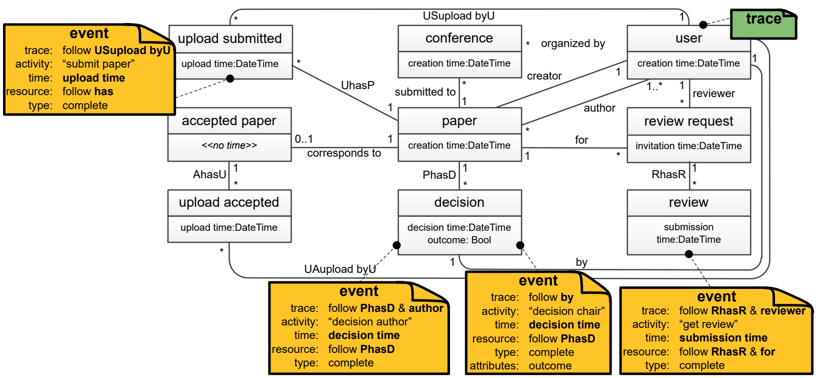


Figure 2.7: Domain ontology with annotations for ontology-based data extraction (CALVANESE et al. 2016, p. 105)

3 Literature review

This chapter identifies, discusses, and evaluates relevant literature contributing to the objectives of the thesis. A systematic literature review identified relevant process mining publications with applications in logistics and manufacturing (cf. Section 3.1). Relevant work is discussed and evaluated for the logistics (cf. Section 3.2) and the manufacturing industries (cf. Section 3.3) separately. A conclusive summary synthesizes the findings and outlines future research opportunities (cf. Section 3.4).

3.1 Systematic review approach

The systematic literature review provides a representative overview of the existing literature (cf. Figure 3.1). Each step is tailored based on the findings of three process mining literature reviews in healthcare (ROJAS et al. 2016), Supply Chain Management (SCM) (JOKONOWO et al. 2018), and business processes (DAKIC et al. 2018).

Stage	Step		Chapter
Review planning	I Specifying research questions		Chapter 1.3 (Objectives)
	II Defining unit, context, and evaluation of analysis		Chapter 3.1 (Approach)
Search and acquisition	III Searching		
	IV Delimiting		
	V Structuring		
Analysis and interpretation	VI Mapping and classifying	*For the application and methodological context*	Chapter 3.2 (Logistics)
	VII Critical assessment		Chapter 3.3 (Manufacturing)
	VIII Synthesis		Chapter 3.4 (Summary)

Figure 3.1: Approach for a systematic literature review of process mining in logistics and manufacturing (based on BOELL & CECEZ-KECMANOVIC *2014;* BRERETON *et al. 2007;* WEBSTER & WATSON *2002)*

Unit of analysis

The literature review includes relevant literature in the fields of logistics and manufacturing to enable value stream mapping for internal logistics using process mining (cf. Section 1.3). Integrating manufacturing allows a broad view of related applications and supports the identification of further research opportunities.

Classification and evaluation context

A concept-centric classification context can be formulated in terms of the addressed problem (*problem context*) or the applied methodology (*methodological context*). In practice, various process mining techniques and perspectives are combined. A review of the SCM literature shows that a "high number of the papers aim to indirectly contribute to all other types of process mining [than data preparation]." (JOKONOWO et al. 2018, p. 3633) DAKIC et al. (2018, p. 870) reported that 94% of the publications analyze the control-flow perspective, and 63% address the case/time perspective. In contrast, the problem context provides support for the practical application of process mining. For instance, a literature review in healthcare uses the process type to classify different hospital processes: "That way, process mining techniques and algorithms can be applied correctly and appropriately." (ROJAS et al. 2016, p. 228). However, a variety of processes with different characteristics exist in logistics and manufacturing. Thus, the problem context must be refined to the targeted industry to classify similar processes.

Consequently, the evaluation of the work is based on the problem context and a cross-analysis of the methodological context. The main findings are discussed in terms of the process types and the four stages of a process mining project: planning and data extraction, data preprocessing, mining, and analysis and evaluation.

Searching the publications

The publications were collected using the three scientific databases *Scopus®*, *Web of Science* and *Google Scholar*. A keyword search for *"process mining" AND (logistics OR manufacturing OR production)* was performed for each database. After an initial screening, the search was extended by specific terms such as *RFID* or *warehousing*. In total, after removing duplicates, 207 publications were considered.[1]

[1] The articles of KNOLL et al. (2017), REINHART et al. (2017), and KNOLL et al. (2019c) were excluded from the review.

Delimiting the publications

Both inclusion criteria (IC) and exclusion criteria (EC) were defined (based on BRERETON et al. 2007) to limit the total number of publications:

IC1. Publications explicitly using process mining techniques, algorithms, and concepts applied in the logistics or manufacturing domain.

IC2. Peer-reviewed publications and PhD theses in English.

IC3. Articles published before April 4, 2019.

EC1. Publications that do not include evidence of an application (neither real-world data nor simulation) of process mining in logistics or manufacturing.

EC2. Applications for non-material flow processes. For example, FAROOQUI et al. (2019) use process mining to analyze the operations of a robot.

The 207 publications were reviewed in terms of title, abstract, and keywords based on these criteria. Promising publications were evaluated in detail based on the full text and the same criteria. In this step, further literature was identified by selectively going forward and backward in the articles. The resulting 40 relevant publications were classified into seven industry categories (cf. Figure 3.2).

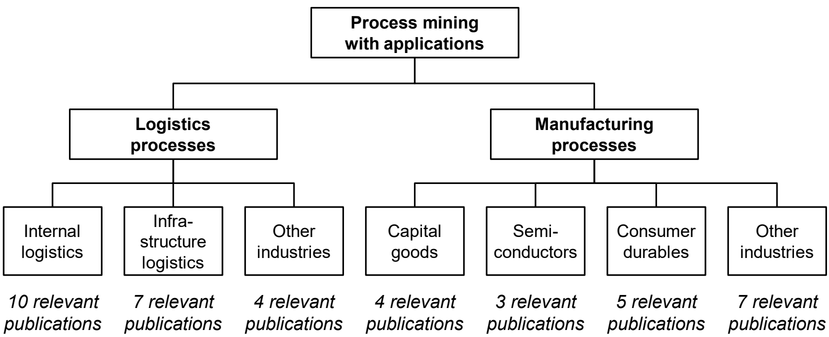


Figure 3.2: Classification of relevant process mining literature according to the domain and industry

3.2 Process mining in logistics

This section provides an overview of the major work in logistics. The work is classified into three applications: internal logistics (cf. Section 3.2.1), infrastructure logistics, including the dominant research stream of port logistics (cf. Section 3.2.2), and other applications (cf. Section 3.2.3). Afterward, the methodological context is analyzed (cf. Section 3.2.4). Section 3.2.5 concludes the literature in logistics.

3.2.1 Internal logistics

Internal logistics refers to the receipt of parts, warehousing (e.g., storing, sequencing), and line feeding through to line-side presentation, and can include further processing on the shop floor or of the finished goods. The activities can be classified into transport, buffer and store, collect and distribute, pick and sort, and quality checking. However, the occurrence of these activities, and the related manufacturing processes, varies across publications. The studies are clustered into three process types: (1) goods receiving to the manufacturing shop floor, (2) manufacturing shop floor, and (3) manufacturing shop floor to outgoing goods.

Goods receiving to manufacturing shop floor

ER et al. (2015a) developed a practical methodology and analyzed a process with two warehouses (cf. Figure 3.3). Within the analysis, the material flow was mined using process discovery. The results were combined with a performance analysis (e.g., duration) and rule-based checking of the conformance (e.g., First In - First Out (FIFO) principle). Various deviations from the reference process model (e.g., quality activities), long stock waiting times, and violations of the FIFO principle were identified. (cf. ER et al. 2015a)

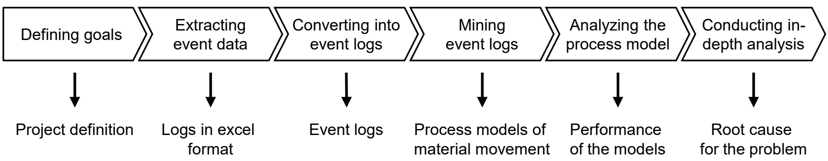


*Figure 3.3: Process mining methodology for analyzing a goods receiving process in the shoe manufacturing industry (*ER *et al. 2015a, p. 119)*

In ER et al. (2015b), the authors extended the case study with an in-depth analysis of the quality inspection. Interviews extended the understanding of the quality process, and multiple ERP data tables were needed to create the event logs. ER et al. (2015b) integrated information flow activities (e.g., *purchase order*). Process discovery identified issues related to the significantly higher duration of quality inspection for certain material types. (cf. ER et al. 2015b)

VAN CRUCHTEN & WEIGAND (2018) aimed to improve the data preprocessing for complex processes using domain knowledge. The domain knowledge was translated into rules to simplify the event log. By checking business constraints, invalid movements and locations were cleaned. In the case study, a business expert selected a process related to rework of defective materials. The process is potentially related to waste of inventory, as the blocked materials cannot be used for the *Material Resource Planning (MRP)*. For this reason, process discovery was combined with the duration and frequency of activities. Resulting inefficiencies due to blocked stock in the quality inspection and loops were uncovered. (cf. VAN CRUCHTEN & WEIGAND 2018)

Y. WANG et al. (2018) present a study in an electronic equipment manufacturer's complex manufacturing environment. A conformance checking analysis was carried out to discover the root causes of inventory differences. The answers to collected business questions identified various fault causes. For example, material issued to the production was sent back to different storages. Additionally, financial violations could be evaluated by including the value of the rejected parts in the analysis. (cf. Y. WANG et al. 2018)

Manufacturing shop floor

S.-k. LEE et al. (2013) developed a process mining methodology for transportation logs in a shipbuilding manufacturing process. The methodology focused on the identification of bottleneck activities, long waiting times, and, subsequently, the reduction of transport costs. The application showed that unplanned activities exist, and different blocks of a ship have unique characteristics that result in different transportation processes. As an example, the number of transportation activities varies from three to 37 activities based on the process variants. To overcome the product and process complexity, S.-k. LEE et al. (2013) applied hierarchical clustering to mine for unknown, local process variants (cf. Figure 3.4). Processing and waiting times were analyzed in detail for each of the four identified process variants. No process discovery and conformance checking techniques were used. (cf. S.-k. LEE et al. 2013)

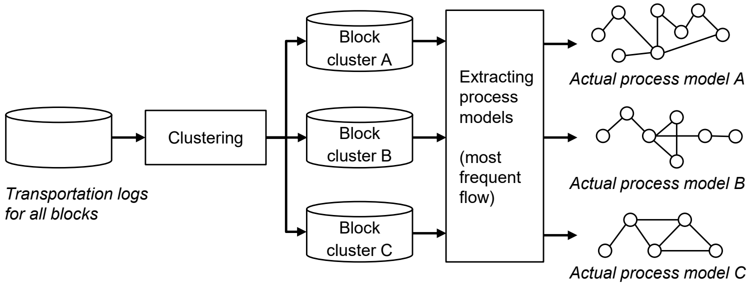


Figure 3.4: Trace clustering for process mining of transportation logs in a shipbuilding manufacturing process (S.-k. LEE *et al. 2013, p. 86)*

Similarly, BECKER & INTOYOAD (2017) applied k-medoids clustering to improve the results in heterogeneous process environments with many process variants, such as manufacturing and logistics, using context information. The paper used the frequency of a process and its overall cycle time for clustering. Based on the evaluation of six different data sets from manufacturing and logistics, the authors conclude that selecting the most frequent process variant can be used to reduce the complexity. The evaluation focused on the clustering approach, and no analysis of the process using process mining techniques was conducted. (cf. BECKER & INTOYOAD 2017)

In addition to these approaches evaluated with real-world data, two conceptual articles exist for this process type. BECKER et al. (2017) identified the issue that manufacturing and logistics processes are characterized by a high frequency of changes and heterogeneous information systems. The authors developed a concept to maintain processes using process mining and formulated "the need for a common information base in terms of an ontology" (BECKER et al. 2017, p. 78). For demonstration purposes, artificial data were used for process discovery. Notably, no data preprocessing or analysis has been completed. (cf. BECKER et al. 2017)

GLASCHKE et al. (2016) developed a concept to overcome heterogeneous application landscapes in an *Industrie 4.0 Laboratory* at the University of Potsdam. In this laboratory, a manufacturing process is simulated. Contrasting to all other publications in internal logistics, *Radio frequency identification (RFID)* is used as a data source. GLASCHKE et al. (2016) state that combining RFID with process mining facilitates a comprehensive look at a process. However, no analysis was completed. (cf. GLASCHKE et al. 2016)

Manufacturing shop floor to outgoing goods

PASZKIEWICZ (2013) evaluated the conformance of activities required to take finished mattresses from production and ship them to the client. The activities include the material flow (e.g., *on fork*) and information flow (e.g., *production finished*). PASZKIEWICZ (2013) state that a practical evaluation of conformance checking is still missing. Based on an interview with a warehouse manager, six conformance rules were collected and analyzed (cf. Figure 3.5). As an outcome, various violations (e.g., FIFO principle) were identified and addressed (e.g., worker training).

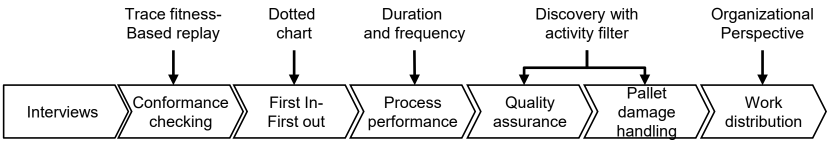


Figure 3.5: Conformance checking of an outgoing goods process in a mattress factory (own illustration, based on PASZKIEWICZ *(2013))*

Finally, LIIV & LEPIK (2014) analyzed a picking process used by a logistics warehousing service. The objectives of the work include both technical and business aspects. The business aspects focus on identifying deviations from the reference process and wastes of time. The authors describe the data extraction, preprocessing, discovery, and performance analysis steps of the process in detail. During the analysis, the duration and frequencies were combined with the mined process model. The transparency of the actual process enabled management to make further improvement plans.

3.2.2 Infrastructure logistics

The literature on infrastructure logistics can be broken down into two categories: port logistics and airport logistics.

Port logistics

A group of researchers developed various process mining techniques and evaluated them by examining Chinese ports. Only publications relevant to this thesis are presented here because the process types used to operate port logistics tend to differ in terms of a higher amount of activities.

Y. WANG et al. (2014a) is the earliest and most comprehensive study in this field. The authors aimed to enhance logistics process transparency, to strengthen the internal control of the company, and to improve performance. According to Y. WANG et al. (2014a), there is a lack of comprehensive methodologies to support practitioners of process mining in logistics. The authors developed a methodology for extracting, preprocessing, and evaluating performance and conformance (cf. Figure 3.6).

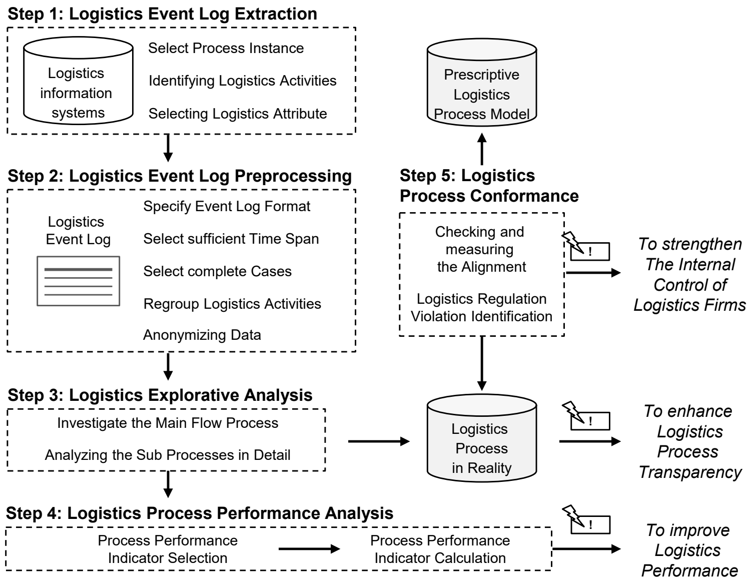


Figure 3.6: Process mining methodology for acquiring logistics knowledge in a port logistics process (Y. WANG et al. 2014a, p. 197)

The applied process mining techniques focus on the practical outcome, and the methodology covers many stages of process mining. Y. WANG et al. (2014a) emphasize the importance of experts when integrating knowledge of the material flow and resources. In contrast to the situation in internal logistics, the analyzed process for port logistics is comparatively complex. Further on, Y. WANG et al. (2014a) suggest using logistics attributes in the event log (e.g., cargo type) for the analysis. (Y. WANG et al. 2014a)

The same research group provided an extension of this work. As they identified a large set of variants in the process, Y. WANG et al. (2014b) applied trace clustering combined with domain knowledge (e.g., cargo type in the case perspective) for further analysis. After clustering the process variants, the correlation with available attributes was analyzed statistically. The complexity of process variants was reduced efficiently. Nevertheless, Y. WANG et al. (2014b) claim that the challenge lies in extracting a suitable set of case attributes. (cf. Y. WANG et al. 2014b)

Another issue in this context is the availability of similar activities for different locations (e.g., customs activities at different locations). Therefore, PULSHASHI et al. (2015) developed a multidimensional process mining approach to discover different process variants and measure the dependencies. (cf. PULSHASHI et al. 2015)

YAHYA et al. (2016) developed a process mining discovery algorithm to integrate expert domain knowledge. The authors state that most process mining research is related to general concepts of process mining, and only little focus has been put on domains. Therefore, they developed the proximity miner algorithm to integrate domain-specific constraints during process discovery (e.g., causality rules). The event logs of a transport process were mined to evaluate the approach. Additionally, a performance analysis created statistics about the duration and frequencies of events. (cf. YAHYA et al. 2016)

The presented approaches have developed or applied various process mining techniques to analyze processes. Other work has integrated process mining with other data mining techniques. After completing process discovery, J. WANG et al. (2016) integrated the organizational perspective of process mining with a graph-based network structure analysis. The importance (node centrality) and amount of work relations (edges) were calculated based on information about the process participants (case perspective). SUTRISNOWATI et al. (2015) developed an approach to predict the lateness of containers based on a *Bayesian network*. A process model based on the process discovery technique can be used to construct the Bayesian network. Notably, three articles in port logistics were not available in full text.

Airport logistics

One study focuses on airport logistics from a time perspective, which is in contrast to other articles aiming to understand different process variants in terms of the control-flow. DENISOV et al. (2018) argue that usually, the time-based metrics (e.g., duration) are aggregated over the time frame. Therefore, the performance spectrum pairs related process activities to visualize the variability of the duration over time (cf. Figure 3.6). The concept was evaluated using the baggage handling system of a major European airport. (cf. DENISOV et al. 2018)

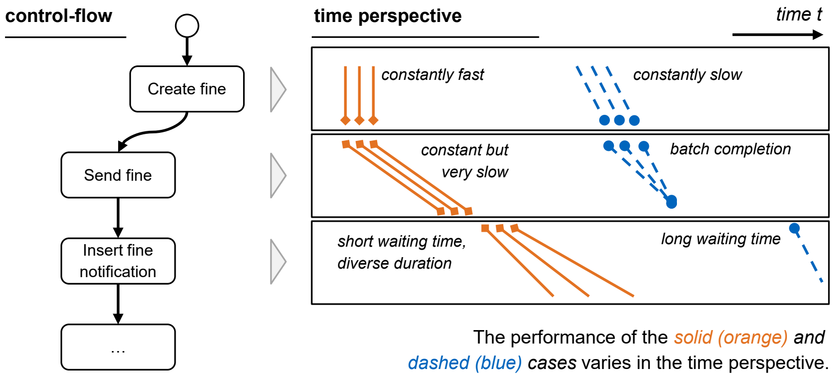


Figure 3.7: Performance analysis of time-dependent variability using the performance spectrum (illustration modified from DENISOV *et al. 2018, p. 140)*

3.2.3 Other industries

Distribution logistics

JAREEVONGPIBOON & JANECEK (2013) present a concept to improve the analysis results of process mining. The concept aims to enhance event logs with the semantics of an ontology. Included are steps for (1) examining event data, (2) defining ontologies, (3) creating and combining ontologies, and (4) mapping concepts from ontologies to event logs. The evaluation of this concept concentrated on a restocking process from warehouses to retail stores. In conclusion, the authors found that the discovered processes can be analyzed from different perspectives (e.g., product code in the case perspective) and aggregation levels. (cf. JAREEVONGPIBOON & JANECEK 2013)

Supply Chain Management (SCM)

In the context of SCM, GERKE et al. (2009) investigated the use of RFID data with process mining. The authors present an algorithm to prepare *EPCglobal data* into event logs. Extensive preprocessing was required, and various packaging and assembly operations made it difficult to follow a single process instance (GERKE et al. 2009, p. 286). KANG et al. (2013) adapted the work of GERKE et al. (2009) to analyze a supply chain of imported beef. Both evaluations were based on artificial data generated using simulations, and real-world applications were missing. Additional literature related to

SCM focuses on the cross-organizational perspective and is discussed in a literature review (cf. JOKONOWO et al. 2018).

Healthcare

Process mining is used to track the material flow of physical equipment, medical personnel and patients in healthcare using RFID data (ZHOU & PIRAMUTHU 2010a,b). A review of healthcare-related literature provides a broad overview (cf. ROJAS et al. 2016).

The articles in the review support the conclusion that process mining can be applied to analyze RFID data of material flow activities. The publications outline the challenges and steps required for preprocessing RFID data into event logs for process mining. However, no case study with a detailed process analysis exists. The feasibility of analyzing RFID data has been presented in the context of big data applications. ZHONG et al. (2015) processed RFID data within data warehouses to create a logistics trajectory. Later, ZHONG et al. (2016) developed a visualization concept and ZHONG et al. (2017) integrated physical resources. Notably, no process mining techniques were used.

3.2.4 Cross-analysis of the methodological context

Process mining has been applied and evaluated in different logistics industry sectors. The methodological context provides further insights across all publications in logistics. The literature review has identified two main types of research: articles related to the design and evaluation of concepts (*conceptual work*) and articles focusing on the practical application (*case study*). The characteristics of the methodological context vary depending on the research type.

Process types

Essentially, two generic types of processes exist: *lasagna processes* and *spaghetti processes*. Lasagna processes are well-structured and relatively simple, with a low number of activities. Spaghetti processes are unstructured and complex. Different process mining techniques can be applied to each process type. Theory claims that both types exist in the transportation industry. (VAN DER AALST 2016, p. 401)

The literature review confirms these theoretical findings as the number of activities analyzed in internal logistics varies from four to ten activities per process. If the activities are related to one or more locations such as storages, the complexity usually increases (cf. VAN CRUCHTEN & WEIGAND 2018; Y. WANG et al. 2018). Multiple publications have reported that many processes exist, either as process variants (e.g., BECKER & INTOYOAD 2017; S.-k. LEE et al. 2013) or as processes preselected by logistics experts (e.g., PASZKIEWICZ 2013; VAN CRUCHTEN & WEIGAND 2018). In infrastructure logistics for ports, by contrast, the number of activities ranges from ten to 37 activities, in addition to multiple process variants. Airport logistics may have up to 850 activities (DENISOV et al. 2018). The number of activities per process, events, and cases is reported to be high. For example, PASZKIEWICZ (2013) reported 87,660 cases and 554,745 events in a mattress factory, and VAN CRUCHTEN & WEIGAND (2018) analyzed a process with 4.2 million events in one year.

Planning and data extraction

Any process mining project starts with planning the objectives and questions and then extracting event data from information systems (VAN DER AALST et al. 2012, p. 177).

Conceptual work can be characterized by less-practical objectives and, typically, no analysis questions (i.e., BECKER & INTOYOAD 2017; Y. WANG et al. 2014b). The evaluation aims to verify that the concept (e.g., clustering techniques) can be applied. In contrast, the case studies have defined objectives and questions. However, the objectives and the processes selected for analysis are determined by the process expert's choice (e.g., ER et al. 2015a; PASZKIEWICZ 2013).

Due to the fact of heterogeneous information systems, the picture of event data is also sparse and fragmented. Except for S.-k. LEE et al. (2013), all publications with real-world data rely on transactional information systems (i.e., WMS or ERP). S.-k. LEE et al. (2013) refers to a manually recorded transportation history. Usually, multiple data tables, sometimes even across systems, must be extracted. ER et al. (2015b) claims that obtaining an event log is one of the main challenges. According to Y. WANG et al. (2014a), the identification of additional attributes is an important challenge in event log extraction and requires domain knowledge.

The concept of ontology-based data extraction and preprocessing is proposed to address this issue. BECKER et al. (2017) argue that upper ontologies should be used. JAREEVONGPIBOON & JANECEK (2013), on the other hand, state that event logs should be enriched using domain ontologies. Remarkably, only JAREEVONGPIBOON & JANECEK (2013) evaluated an ontology-based approach in distribution logistics.

Data preprocessing

Event data must be preprocessed into standardized event logs to apply process mining. Unfortunately, "the step to collect the event log used as input for process mining is far from trivial." (VAN DER AALST & WEIJTERS 2004, p. 238)

No strict distinction is made between the two steps because preprocessing may require an iterative step back to data extraction. However, the literature review revealed that preprocessing requires significant effort. For internal logistics, the majority of publications have explicitly described several steps related to filtering, renaming, merging, and enhancing to create usable event logs. VAN CRUCHTEN & WEIGAND (2018) developed a methodology for preprocessing for this purpose. LIIV & LEPIK (2014) reported that 90% of the project time (200 hours) was spent on data preprocessing. These challenges have rarely been reported in port logistics. Interestingly, in the context of SCM, GERKE et al. (2009) state that the case identifier must be reconstructed first, and the shift of states (e.g., from pallet to package) results in difficult relationships.

In conclusion, the preprocessed event logs can be characterized as follows. The case id varies but is always related to a traceable object (e.g., pallet or cargo id). The majority of event logs contain a start event and end event. The additional attributes are far from standard and vary across the papers. However, in more than one case, part-specific attributes (e.g., supplier), locations, and resources (e.g., workers) have been used.

Mining: Techniques, concepts, and methodologies

A variety of process mining techniques, concepts, and methodologies can be applied during a process mining project (cf. VAN DER AALST 2016).

The literature review in logistics confirms the findings in healthcare, SCM, and general business processes (cf. DAKIC et al. 2018; JOKONOWO et al. 2018; ROJAS et al. 2016). The most dominant technique employed on real-world data is the process discovery of the control-flow (13 publications). Typically, this is the starting point of the analysis. Closely related is the application of performance analysis (12 publications). Most frequently, the duration (also referred to as lead time) and the frequency of cases are analyzed (time perspective). Applications of conformance checking (six papers) and automated conformance checking (three papers) are described less frequently.

Advanced concepts have been developed and evaluated in addition to these frequently applied process mining techniques. Most importantly, different types of clustering techniques are used. For example, trace clustering (i.e., S.-k. LEE et al. 2013) is extended by domain knowledge of case attributes (i.e., Y. WANG et al. 2014b) or case-specific context information (i.e., BECKER & INTOYOAD 2017). In addition, domain knowledge is integrated into a process discovery algorithm using constraint rules (YAHYA et al. 2016). Less frequently, process mining is combined with advanced algorithms for inter-dependency (PULSHASHI et al. 2015), Bayesian networks (SUTRISNOWATI et al. 2015), or network analysis (J. WANG et al. 2016). Notably, case studies rarely reuse these techniques.

Analysis and evaluation

The challenge is to exploit event data meaningfully using event logs and process mining techniques (VAN DER AALST et al. 2012, p. 174).

Again, differences can be identified based on the research type. Conceptual work mostly focuses on a particular aspect when developing and evaluating the concept (e.g., clustering traces). The analysis of the process and the evaluation of the practical implications are mostly out of scope.

Case studies, in contrast, typically analyze processes holistically using multiple perspectives. Then, based on the objectives and questions, sufficient process mining techniques are used to achieve the results. The control-flow perspective is used most frequently. In internal logistics, process discovery is used to manually check non-value-added activities, i.e., quality or rework (cf. ER et al. 2015a; PASZKIEWICZ 2013). The control-flow perspective is often extended by the time perspective (frequency and waiting and processing time). Later, the metrics are used in an aggregated form (e.g., average duration), which is also referred to as performance analysis, or in a detailed analysis of cases using the dotted chart (ER et al. 2015a; PASZKIEWICZ 2013). Bottleneck analysis is used to identify long-running storage or quality-related activities. In contrast, the organizational perspective is rarely used in internal logistics.

After identifying deviations (“What happened?”), only a few publications have conducted an in-depth analysis (“Why does it happen?”). In the case perspective, process variants (e.g., quality-based cases) are linked with attributes (e.g., suppliers). Interviews are used to understand or verify the root causes (ER et al. 2015a). Notably, in time perspective, several publications refer to inventory as the root cause. However, none of the publications used process mining to analyze the inventory. Table 3.1 shows an overview of the literature.

Table 3.1: Evaluation of selected process mining publications in logistics: Internal logistics, infrastructure logistics, and others

	Internal logistics								Infrastructure				Others	
	ER et al. (2015a)	ER et al. (2015b)	VAN CRUCHTEN & WEIGAND (2018)	Y. WANG et al. (2018)	S.-k. LEE et al. (2013)	BECKER & INTOYOAD (2017)	PASZKIEWICZ (2013)	LIIV & LEPIK (2014)	Y. WANG et al. (2014a)	Y. WANG et al. (2014b)	PULSHASHI et al. (2015)	DENISOV et al. (2018)	GERKE et al. (2009)	JAREEVONGPIBOON & JANECEK (2013)
Process types														
Activities	◑	◔	◕	◑	◔	◑	◑	◑	◕	◕	◕	●	-	◔
Cases	-	◔	●	◕	◔	-	◕	◔	◑	◔	◔	◑	-	◔
Process variants	◔	◔	◔	◔	◑	◔	◔	◔	◔	◑	◑	◔	-	◔
Planning and extraction														
Business objectives	◕	◑	◑	◑	◑	◔	◕	◑	◑	◔	◔	◔	-	◑
Data identification	◔	◔	◑	◔	◔	-	◔	◑	◔	◑	◔	◔	◔	◕
Preprocessing														
Creating event logs	◑	◑	◕	◔	◔	-	◑	◑	◔	◔	◔	◔	●	◔
Filtering event logs	◔	◔	●	◔	◔	-	◔	◑	◕	-	◔	◔	-	◑
Enriching event logs	◔	◔	◕	◑	◑	-	◕	◑	◑	●	◕	◔	◔	●
Mining														
Process discovery	◕	◕	◑	◔	◑	-	◕	◑	◕	◑	◔	-	◔	◕
Performance analysis	◕	◕	◔	◔	◕	-	◕	◑	●	-	◔	●	-	◑
Conformance checking	◕	◑	-	◕	-	-	●	-	◕	-	-	-	-	-
Advanced concepts	◔	◔	◔	◔	◕	◕	◔	◔	◑	●	●	◕	-	◕
Analysis (perspectives)														
Control-flow	●	◕	◑	◑	◑	-	●	◕	◕	◑	◑	-	◔	◑
Time	◕	◕	◔	-	◑	-	◕	◑	●	-	-	●	-	◑
Case	◑	◑	-	-	◑	-	◑	-	◕	◑	◑	-	-	◕
In-depth analysis	◕	◑	-	-	-	-	◕	-	◕	-	-	-	-	◑

● Fully addressed, ◑ Partly addressed, - Not addressed

3.2.5 Conclusion

The literature review in logistics covers applications in internal logistics, infrastructure logistics, and other sectors. Based on the application, both simple processes with two warehouses (e.g., goods receiving and storage in internal logistics) and complex processes (e.g., port logistics) have been analyzed with process mining techniques.

The methodological context varies depending on the type of research. Conceptual literature usually does not define precise business objectives or analysis questions but proposes advanced concepts (e.g., clustering or ontologies). Case studies, in contrast, use experts to define precise objectives. Independent of the research type, the step of data extraction and preprocessing is highly time-consuming and challenging. Preparation of event logs is especially difficult. No ontology has been developed and applied for the context of internal logistics.

Different process mining techniques have been applied to different process types. Complex processes in port logistics mainly require advanced concepts of clustering to reduce the complexity of process variants. However, process discovery of the control-flow and performance analysis from the time perspective have been applied frequently. Conformance checking has been applied infrequently to identify deviations in the control-flow for simple process types. Differences between the research types also exist for analysis and evaluation. Case studies mainly try to answer the analysis questions, including in-depth analyses and evaluations with experts, using a variety of standard process mining techniques. Conceptual work aims to evaluate the applicability of the concept, but the practical benefit or evaluation with experts is mostly out of scope.

3.3 Process mining in manufacturing

This section provides an overview of the literature using process mining in manufacturing processes. Work in manufacturing is more fragmented than work in logistics. The publications can be categorized in terms of the industry: capital goods (cf. Section 3.3.1), semiconductors (cf. Section 3.3.2), consumer durables (cf. Section 3.3.3), and other industries (cf. Section 3.3.4). Afterward, the methodological context is discussed in Section 3.3.5, and the results of the review are summarized in Section 3.3.6.

3.3.1 Capital goods

Multiple articles have analyzed manufacturing processes in the shipbuilding industry as an example of capital goods. One case study reported on electrical equipment.

Shipbuilding

D. LEE et al. (2013) applied process mining to the assembly of ship blocks. The process is characterized by a multitude of process variants depending on the blocks to be manufactured. Therefore, hierarchical clustering was used based on (1) the activities, (2) the resources (workshops), and (3) a hybrid approach. The authors discovered a process model for each cluster to evaluate the results. D. LEE et al. (2013) concluded that the clusters represent reality more precisely than the planned models.

J. PARK et al. (2014) evaluated the performance of assembly in a shipbuilding block process. Again, the process variants compounded the analysis of discrepancies between the actual and the planned processing times. Therefore, J. PARK et al. (2014) developed a framework that utilizes k-means clustering to evaluate the performance of each process variant individually (cf. Figure 3.8). The authors conducted 30 interviews with experts to identify and prioritize performance metrics. Afterward, the authors identified inefficient blocks with unexpected deviations (e.g., waiting in the stockyard).

M. PARK et al. (2015) contribute a conceptual approach for a workload and delay analysis. The approach includes the degree of workload (cf. *resource perspective*) and the delay of activities (cf. *time perspective*).

Electrical equipment

Like ship block manufacturing, MEINCHEIM et al. (2017) state that the production of industrial control panels is highly customized and difficult to understand. While process discovery provided a holistic view of the process and showed unknown loops of activities, specific issues were still hidden. For this reason, MEINCHEIM et al. (2017) applied trace clustering. First, the authors clustered individual process variants to identify performance issues. The authors were faced with 170 process variants, and prioritization of the most frequent variant was required. The in-depth analysis highlighted that individual process variants could be characterized by different lead times. Bottleneck analysis was used to determine root causes and uncovered unnecessary waiting due to an unbalanced allocation of resources. (cf. MEINCHEIM et al. 2017)

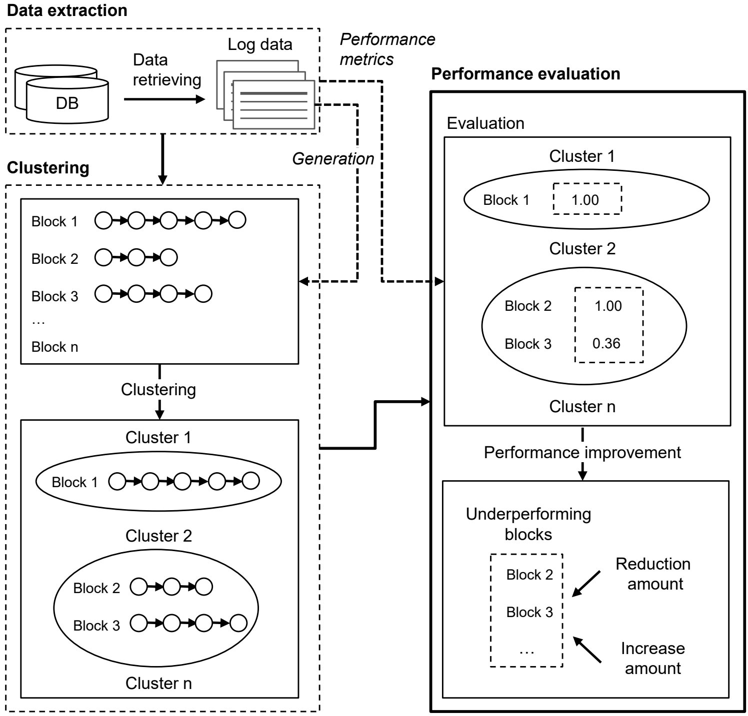


Figure 3.8: Framework for process mining of the block assembly process in the shipbuilding industry (J. Park et al. 2014)

3.3.2 Semiconductors

Rozinat et al. (2009) were the first to apply process mining techniques in manufacturing. The authors conducted an extensive analysis of a testing procedure of wafer scanners required to manufacture semiconductors. The process is extremely complex, with up to 16,250 events per case. The analysis was driven by two questions: "How are tests usually executed?" and "Where is the most time spent in the process?". After defining precise objectives, the event log was prepared to gain insights on performance metrics (e.g., frequencies and duration). Next, an iterative process discovery identified dominant feedback loops that required re-execution of already-completed testing sequences. Rozinat et al. (2009) applied basic filtering steps to reduce complexity. As the event log includes start and completion times, the analysis of testing and waiting times identified different patterns for individual activities. ROZINAT et al. (2009) stated that frequently applying process mining can enable a continuous improvement process. (cf. ROZINAT et al. 2009)

HSIAO et al. (2016) analyzed a chip probing process. However, in contrast to ROZINAT et al. (2009), the process was structured and comparatively simple (23 activities). HSIAO et al. (2016) developed a concept to predict the next activities using *Naive Bayes models*. The total costs were predicted in combination with activity-based costing, and the event log was annotated with cost information (cf. HSIAO et al. 2016). Additionally, VIALE et al. (2011) proposed a concept to align partial sequences of event logs with expert models. The authors stated that this concept is beneficial if many process variants exist. In contrast to conformance checking, the self-defined concept does not provide a quantified alignment. No results on real-world data were presented. (cf. VIALE et al. 2011)

In contrast to ROZINAT et al. (2009), HSIAO et al. (2016) and VIALE et al. (2011) did not analyze the process to identify potential for improvement. Neither process discovery nor conformance checking was applied.

3.3.3 Consumer durables

This section presents applications of process mining, focusing on textiles and household durables manufacturing processes.

Textiles

SAAD (2018) analyzed a textiles manufacturing process. The author reported that more than three months were required to extract and preprocess the data. Then, a process discovery and a performance analysis of bottlenecks were completed for different process variants. Although the process is comparatively simple (14 activities), a clustering technique with *Markov Chains* was applied to identify clusters. Afterward, similar analysis steps were repeated for selected clusters. However, no details about practical outcomes and improvement potentials were provided. (cf. SAAD 2018)

SATITCHAROENMUANG et al. (2018) applied process mining to delayed customer orders in a garment production process. To begin, the authors completed 25 interviews and recorded the paper-based documentation. The analysis focused on the control-flow and time perspective and showed that several activities were skipped. The authors concluded that the study is aligned with lean production theory as waste of time was reduced in each step. (cf. SATITCHAROENMUANG et al. 2018)

TU & SONG (2016) developed a method to analyze and predict the costs of a jeans manufacturing process. They utilized activity-based costing to enhance the costs of an activity. The work in progress and costs of events were used to predict the remaining time and total costs. This step was repeated for each trace to calculate statistical cost ranges. However, in contrast to HSIAO et al. (2016), no probabilities based on *Naive Bayes* were included. Critically, the authors did not report on practical implications. (cf. TU & SONG 2016)

Household durables

MUSIC & ROJEC (2012) analyzed a door side panel manufacturing process in a furniture factory. During the data extraction and preprocessing steps, additional attributes were integrated into the event log. An analysis of case frequencies identified that 98% of the cases were similar and simple. Consequently, cases with a long duration were removed. An initial process discovery determined that further classification of sub-groups was required. Suitable groups of products were identified based on an iterative exploration of additional attributes. Finally, the process model was extended with the time perspective. MUSIC & ROJEC (2012) reported that differences among product groups were not visible in the data directly due to the high number of different parts. However, the authors did not report practical implications or potential for improvements. (cf. MUSIC & ROJEC 2012)

BETTACCHI et al. (2016) completed a benchmark of five different process discovery algorithms in a coffee machine manufacturing process. During the preparation, the event logs were organized by product specifications (individual coffee machines). BETTACCHI et al. (2016) identified only a few non-standard traces explained by incorrect management, repair or replacements of defective components, and special customization. (cf. BETTACCHI et al. 2016)

3.3.4 Other industries

Two publications in the automotive industry and further unspecified processes or industries are discussed in this section.

Automotive industry

DIŠEK et al. (2017) present a case study focusing on data preprocessing in the automotive industry. The authors state that the processes are operated by many information systems, and significant effort is required for preprocessing data to apply process mining. DIŠEK et al. (2017) selected a transmission manufacturing process and technically described the data extraction and preprocessing steps. One month of effort was required to complete these steps. Notably, no methodological procedure is provided (e.g., data requirements). (cf. DIŠEK et al. 2017)

In the context of sustainability management, JO et al. (2014) developed a concept for improving a component manufacturing process. The authors integrated process mining to derive the current state and combined the results with simulation. In the evaluation, process mining was able to detect defective parts related to one specific machine. No further analysis of the process was reported. (cf. JO et al. 2014)

Unspecified processes, industries, or multiple case studies

YANO et al. (2013) developed an approach for data preprocessing and process analysis in the context of complex information systems. They developed a search algorithm to identify relations between database tables. Three patterns were used to identify exceptional cases: (1) direct repetition of the same activity, (2) going back to previous activities (loops), and (3) identifying violations of predefined business rules. Then, process discovery was used to investigate the exceptions. The evaluation was conducted on a manufacturing process with more than 70 activities. Interestingly, 60% of the cases were exceptional and related to a preparation and a testing procedure. Neither the three rules were evaluated nor were practical implications discussed in detail. (cf. YANO et al. 2013)

NATSCHLÄGER et al. (2017) developed a methodology to apply process mining in the manufacturing industry (cf. Figure 3.9). The authors highlighted the role of manufacturing experts and the required understanding of the production (e.g., plant visit). The methodology covers both the control-flow and time perspective. For example, infrequent paths and unexpected endings and absolute duration and standard deviations are considered. In the evaluation, two case studies on manufacturing processes were completed: a production with 21 different processes and 45.8 million events and a simple environment with two processes. Notably, neither the steps of methodology nor the results and practical implications were discussed. (cf. NATSCHLÄGER et al. 2017)

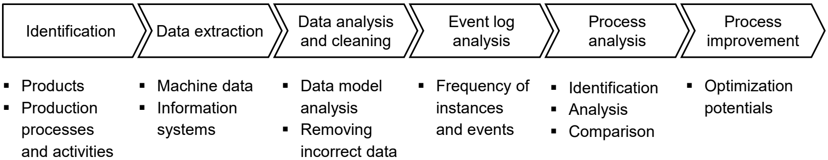


Figure 3.9: Methodology for process mining in the manufacturing industry (own illustration, based on NATSCHLÄGER *et al. (2017))*

NAGY et al. (2018) present a concept to relate defective products to the manufacturing process. The concept includes five self-developed algorithms to extract information about time and space from the process. As an example, one algorithm calculates the cumulative number of defective products per station. The evaluation showed how the concept could be applied to assembly line production with two lines, but no further process mining techniques were applied. (cf. NAGY et al. 2018)

INTAYOAD & BECKER (2018b) developed a concept to analyze the delay of orders under consideration of contextual information. *Naive Bayes models* were used to predict the delay. The authors extracted the number of concurrent events for a resource and the lead time of the previous case. The evaluation was conducted on three data sets of manufacturing companies, but a high degree of a relationship was reported in only one case. (cf. INTAYOAD & BECKER 2018b)

In relation to previous work on clustering, INTAYOAD & BECKER (2018a) developed an approach to integrate *Markov Chain clustering* before applying a process discovery. The authors state that real-world applications of process mining, which include complex and dynamic processes, were lacking support at the time of the study. The evaluation of the clustering technique was performed on a complex manufacturing process with 3,508 cases and 63,558 events. The clustering algorithm identified 50 process variants, and the evaluation showed that the fitness value of the discovered process model could be improved. (cf. INTAYOAD & BECKER 2018a)

Further applications in the manufacturing industry are related to conceptual work or other non-material flow processes. As an example, YANG et al. (2014) present a software architecture for manufacturing process mining. Furthermore, the production planning process (ER et al. 2018) and the failure diagnostics process of production shutdowns were analyzed (FEAU et al. 2016).

3.3.5 Cross-analysis of the methodological context

Similar to the findings in the methodological context in logistics, the literature review on manufacturing reveals further aspects of the methodological context. Again, the main findings are discussed in terms of process types, planning and data extraction, data preprocessing, process mining techniques and analysis and evaluation.

Process types

Compared to logistics, the manufacturing process types are less structured (and more spaghetti-like) in terms of activities, events, and especially, the number of process variants. Most publications emphasize that different product and part variants require different operations or sequences of operations and, consequently, activities. This fact is driven by the product and process complexity of the production system.

For example, in the shipbuilding industry, ship blocks are manufactured in a workshop production. Each of the 250 different blocks has a unique structure and requires different operations (J. PARK et al. 2014). In the semiconductor industry, processes are even more complex as they are characterized by the repetition of individual activities or even complete sequences of testing procedures. For example, ROZINAT et al. (2009) report up to 16,250 events per case, and VIALE et al. (2011) state that 1,000 different manufacturing processes with more than 50 modifications per week exist.

In contrast, the manufacturing process of coffee machines in the consumer durables industry is organized into two sub-assemblies and six assembly lines with five stations each, and the process includes six activities (BETTACCHI et al. 2016).

Planning and data extraction

Similar to case studies in logistics, case studies in manufacturing provide a reasonable explanation of the process and objectives. However, analysis questions are less frequent in the manufacturing industry. These studies aim to understand specific characteristics (e.g., lead times) that are not visible due to product and process complexity (e.g., J. PARK et al. 2014; ROZINAT et al. 2009). In this stage, the identification of manufacturing processes and products has required process experts (e.g., NATSCHLÄGER et al. 2017) and has been supported by interviews (e.g., J. PARK et al. 2014).

In contrast, conceptual literature mostly simplifies the tasks of planning and data extraction. Here, the focus is set on the evaluation of the developed approach and practical results and implications are rarely discussed. However, some case studies also neglect to discuss practical results (e.g., MUSIC & ROJEC 2012).

Typically, Manufacturing Execution Systems (MES) are used for data extraction. These information systems and the underlying databases are complex; they record massive amounts of data, and extracting all data is impractical. Furthermore, these systems do not record prepared event logs. (e.g., DIŠEK et al. 2017; J. PARK et al. 2014; YANO et al. 2013) Based on a valid process understanding and in combination with experts, relevant data can be extracted (e.g., NATSCHLÄGER et al. 2017; J. PARK et al. 2014). Nevertheless, the majority of publications do not report how the data is extracted, and if they do, they do not propose ontologies to systematically extract data.

Data preprocessing

The step of data preprocessing to create event logs in the manufacturing industry is comparatively simple. A few authors reported that cleaning of incorrect or incomplete data was required (e.g., DIŠEK et al. 2017; M. PARK et al. 2015). MEINCHEIM et al. (2017) stated that the cleaning had already been completed by the business analysts.

If reported, the order number was used as the case identifier. A few publications used an application-specific case identifier such as the ship block (e.g., J. PARK et al. 2014). Usually, no effort was reported for this step and, for instance, JO et al. (2014) stated that the MES already provided all the necessary information. Two notable exceptions exist. YANO et al. (2013) developed an algorithm to correlate events across multiple tables of an ERP system to create a case identifier. DIŠEK et al. (2017) reported that merging three information systems into one database took one month of effort.

Consequently, the event logs are simple, and only a few publications proposed additional attributes. Most publications referred to a complete start and end timestamp as well as the resources (e.g., machine). In contrast, additional attributes about the product (e.g., material) or the process (e.g., shift schedule) were rarely integrated (e.g., J. PARK et al. 2014). In addition, two approaches used activity-based costing to annotate each activity with costs (HSIAO et al. 2016; TU & SONG 2016).

Mining: Techniques, concepts, and methodologies

Process discovery and performance analysis are most frequently applied. Aside from conceptual work, almost every case study applied the process discovery technique. In combination with the process discovery, the performance analysis has been used to calculate statistics about frequencies (e.g., case frequencies) and time metrics (e.g., waiting, lead times). To identify relevant performance metrics, M. PARK et al. (2015) carried out an extensive survey with 30 experts and TU & SONG (2016) used the cost-annotated event logs to calculate the costs of each case.

Conformance checking with predefined models is rarely used in the manufacturing industry (e.g., D. LEE et al. 2013; NATSCHLÄGER et al. 2017). To partially evaluate the conformance, VIALE et al. (2011) aligned sequences of the event logs with expert models and YANO et al. (2013) suggested specifying business rules to identify deviations. However, both approaches have not been evaluated. Additionally, further metrics are derived from pattern extraction. As an example, YANO et al. (2013) proposed rules to calculate repetitions, loops, and violations of business rules. Other patterns are related to defective parts and machines (e.g., NAGY et al. 2018).

Many researchers combine process mining techniques with advanced concepts in the manufacturing industry. Clustering is suitable when many process variants exist (e.g., MEINCHEIM et al. 2017; J. PARK et al. 2014). The clustering techniques use trace information, case attributes (e.g., resource), or contextual information (e.g., concurrent activities on the same resource) (e.g., INTAYOAD & BECKER 2018b; D. LEE et al. 2013). Furthermore, two approaches aim to predict future states of processes (e.g., times or costs) (HSIAO et al. 2016; TU & SONG 2016) and JO et al. (2014) combine process mining with simulation.

Analysis and evaluation

The literature review in the manufacturing industry shows differences between the two research types. Conceptual literature without practical objectives rarely analyzes processes in detail. Typically, clustering is applied at the beginning to derive clusters that can be analyzed afterward. In contrast, case studies focus on the analysis with simple techniques. Basic statistics of the processes are often analyzed first to support the process understanding (e.g., MUSIC & ROJEC 2012; ROZINAT et al. 2009). Based on this, further iterative analysis steps, such as filtering, are combined with process discovery in the control-flow perspective. In particular, the frequencies of process variants are used for decision making. However, no explicit recommendations are made about removing exceptions (MUSIC & ROJEC 2012) or analyzing exceptions in detail to discover new knowledge (YANO et al. 2013). Other case studies emphasize the importance of experts for analysis and evaluation (e.g., ROZINAT et al. 2009).

The control-flow and time perspective are dominant in analysis. As conformance checking has rarely been applied, most deviations have been derived manually using process discovery. For example, ROZINAT et al. (2009) manually identified loops of repeating activities and idle times. If applied, conformance checking is used to evaluate the performance of the clustering technique (D. LEE et al. 2013). For both research types, the time perspective (i.e., waiting times or processing times) has been analyzed more often (e.g., MEINCHEIM et al. 2017; J. PARK et al. 2014). In the case perspective, derived clusters are mainly used for segmentation. Also, product-related attributes of the event log are used to manually build groups (MUSIC & ROJEC 2012). Cost information is rarely analyzed, even though it may exist in the event log (e.g., TU & SONG 2016). An overview of relevant articles is provided in Table 3.2.

3.3.6 Conclusion

The literature review in the manufacturing industry identified a variety of applications for different production systems (e.g., workshop and assembly line production). Complex processes with numerous activities and low structures are dominant. Case studies focus on creating a process understanding of different process variants. Usually, simple event logs are created using MES, and no significant effort is reported.

However, the complexity of processes and process variants shows that the analysis must be structured because no technique provides overarching results. Therefore, both simple and iterative "trial-and-error" filtering techniques, and advanced concepts of clustering, can be used to derive different clusters. This approach is often combined with process discovery and performance analysis. In contrast, conformance checking is only applied infrequently. Furthermore, existing domain knowledge about predefined processes or manufacturing operations is rarely integrated.

Again, the analysis strongly depends on the type of research. Both top-down and in-depth analyses have been conducted. These approaches are non-exclusive: the performance of the time perspective can be combined with the control-flow of the process variants to analyze different clusters in detail. Case studies emphasize the importance of process understanding and expert knowledge to derive improvement potentials.

Table 3.2: Evaluation of selected process mining publications in manufacturing: Capital goods, semiconductor, consumer durables, and other industries

	Capital goods				Semiconductor			Durables			Others			
	D. Lee et al. (2013)	J. Park et al. (2014)	M. Park et al. (2015)	Meincheim et al. (2017)	Rozinat et al. (2009)	Viale et al. (2011)	Hsiao et al. (2016)	Music & Rojec (2012)	Bettacchi et al. (2016)	Tu & Song (2016)	Yano et al. (2013)	Natschläger et al. (2017)	Intayoad & Becker (2018b)	Dišek et al. (2017)
Process types														
Activities	◑	◔	●	◕	●	●	◑	◕	●	◔	◕	◑	◑	●
Cases	◔	◔	◑	◕	◔	-	◑	◕	◕	◔	◕	●	◑	◔
Process variants	◑	◑	◔	◕	●	●	◑	◑	-	◔	◑	◕	◑	◑
Planning and extraction														
Business objectives	◔	●	◑	◑	●	◑	◔	◑	◔	◔	◔	◔	-	◔
Data identification	◑	●	●	◔	◑	◑	◔	◔	◔	◔	◕	◑	-	◑
Preprocessing														
Creating event logs	◔	◔	◔	◔	◔	◔	◔	◔	◔	◔	●	◔	◔	●
Filtering event logs	◑	-	◑	-	◑	-	-	-	-	-	-	◑	-	●
Enriching event logs	◑	◑	◕	-	-	-	◑	●	-	◑	-	◔	◑	●
Mining														
Process discovery	●	◑	-	●	●	◑	-	●	-	◑	●	●	-	●
Performance analysis	◑	●	●	◕	◕	-	◑	◕	◔	◕	◑	◑	◑	◕
Conformance checking	◑	-	-	-	-	◑	◑	◑	-	-	◑	◑	-	-
Advanced concepts	●	●	◑	◕	-	◕	◕	◔	-	◕	◑	-	◕	-
Analysis (perspectives)														
Control-flow	◔	◔	-	◑	●	◕	◑	◕	◔	◔	◑	◑	-	◑
Time	-	●	●	●	●	-	◑	◔	-	◔	-	◑	-	◑
Case	◑	●	◑	◑	◑	-	◑	●	-	◔	◔	◔	-	◔
In-depth analysis	-	●	◑	◕	●	-	-	◔	-	-	-	◔	-	◔

● Fully addressed, ◑ Partly addressed, - Not addressed

3.4 Summary and research opportunities

The literature review in the logistics and manufacturing industry provides a comprehensive overview of the application and methodological context. In the following section, the findings are summarized and discussed in terms of the objectives of the thesis.

Generally speaking, the literature review shows that process mining is capable of creating transparency and supporting the analysis of processes in logistics and manufacturing. Both process mining and value stream mapping reveal the current state of a process and identify potential for improvement. However, process mining provides support to cover process complexity and dynamics. Process mining addresses dynamics by creating precise and sound process models of material and information flow activities based on historical event data. Furthermore, complex processes with many activities, events, and process variants can be successfully discovered and analyzed.

From an application viewpoint, no work in internal logistics in the context of a mixed-model assembly line production exists. The effects of product and process complexity and dynamics are mostly neglected in publications about internal logistics. The following research opportunities would provide support for the objectives of the thesis and its research questions in the context of internal logistics.

O1. Supporting the planning and data preparation

Theory states that any process mining project starts with planning: defining objectives and questions and extracting event data from information systems (VAN DER AALST et al. 2012, p. 177). The literature review shows that this step is often neglected. Only a few publications have defined precise objectives and analysis questions. If reported, the practical benefit of the objectives and expected outcomes mostly remain unclear.

Notably, even though lean production is the de facto standard, none of the publications utilize lean production theory to derive objectives and analysis questions. However, reported objectives and findings are partially aligned with lean production theory (e.g., reduction of waiting times). Nevertheless, the planning is highly application-specific and relies on the expert's choice (e.g., selection of the process).

> **Research opportunity.** Supporting the definition of objectives and analysis questions in a process mining project based on lean production theory.

Process mining theory states that data extraction can be challenging. Therefore, the concept of ontology-based data extraction and preprocessing is proposed (cf. Section 2.3.3). The literature review confirms previous findings about complex and heterogeneous information systems in manufacturing and, in particular, in logistics. Two concepts address this challenge by using ontologies for data extraction and enrichment. However, no domain ontology for internal logistics has been developed or evaluated.

The step of data identification and standardization is rarely reported in the articles. Most publications focus on the technical perspective (e.g., database tables). The articles show that a variety of technical and domain-specific terminology is used. Systematic identification of relevant objects, object properties, and their relations can be enabled using ontologies but has not been applied yet.

> **Research opportunity.** Developing a domain ontology for internal logistics to support the identification, extraction, and standardization of data.

In the field of process mining, a variety of data imperfection patterns exist (e.g., SURIADI et al. 2017). However, process mining applications in manufacturing and logistics rarely focus on data validation. In contrast, value stream mapping is applied on the shop floor, e.g., by manually recording processes or conducting interviews with workers. Therefore, existing event data must be validated on the shop floor to enable value stream mapping using process mining.

> **Research opportunity.** Developing a practical guideline for event data validation in internal logistics.

Process mining theory claims that significant effort may be required to correlate events belonging to the same process instance (VAN DER AALST et al. 2012). The literature review confirms this fact. Several publications in the field of logistics have reported significant effort to create event logs based on transactional ERP systems. None of the publications covers product complexity while preprocessing. Additionally, literature in the field of SCM identified challenges caused by logistics operations that can modify the state (e.g., a split of a pallet shifts the case identifier). These challenges have not yet been solved for internal logistics.

From a lean production perspective, the holistic view of a value stream contains all the activities from the supplier to the customer, including the supplier, the material flow (e.g., logistics operations), inventories, and customer demand. Furthermore, underlying resources (e.g., packaging) are also required. However, most publications in process mining do not enrich event logs with these attributes.

> **Research opportunity.** Providing algorithms for creating and enriching event logs for internal logistics to enable a holistic value stream perspective.

O2. Mapping the value stream using process mining

Many process mining techniques, algorithms, and concepts exist in the field of process mining theory (cf. Section 2.3). The literature review elucidates that process discovery and performance analysis are frequently applied in the field of manufacturing and logistics using existing process discovery algorithms. These algorithms are capable of creating process models that cover process complexity and dynamics. Performance analysis is mostly used to calculate frequencies and time measurements. Less frequently, conformance checking is applied to measure the alignment between the planned process model and the actual behavior. In addition, a wide range of advanced concepts (e.g., trace clustering) has been developed.

However, the practical value of deriving process improvements is rarely reported, and existing domain knowledge is mostly neglected. Again, the product complexity and the holistic perspective of value streams are not covered. In particular, no work has been done on inventory profiles (e.g., saw tooth diagram) in the field of process mining.

> **Research opportunity.** Combining state-of-the-art process mining techniques with logistics domain knowledge to cover product and process complexity and dynamics to provide a holistic view of the value stream.

O3. Supporting the analysis according to lean production theory

The challenge is to exploit event data meaningfully using event logs and process mining techniques (VAN DER AALST et al. 2012). The literature review confirms this challenge. If objectives and analysis questions are not defined, the analysis of the process tends to be less detailed, lacking an in-depth evaluation from a practical perspective. Subsequently, the practical support for process improvement is missing. Furthermore, as the analysis is not aligned with lean production theory, a systematic identification of waste is lacking. In practice, the analysis depends on the experts' abilities to align process mining with domain knowledge.

From a manufacturing perspective, process mining theory is often technical, and the language differs from the manufacturing and logistics domain. Consequently, no support is provided for (1) when to apply which process mining technique, (2) which practical support (e.g., types of waste) can be created, and (3) which potential issues (e.g., lessons learned) must be considered.

The literature review also shows that different process types, objectives, and analysis questions require different process mining techniques and, subsequently, affect the analysis. Therefore, an iterative analysis is required rather than a sequential, step-by-step procedure. These challenges are strengthened in the context of product and process complexity as well as dynamics. An effective analysis can be impossible when a system has dozens of individual value streams with their own characteristics. Therefore, different perspectives (e.g., control-flow, time) are required.

Finally, even though process mining theory claims that the practical evaluation and operational support is a necessary step of process mining, the literature review reveals that this step is often neglected. Practical outcomes in terms of process improvements or the existence of practical constraints are rarely integrated or discussed. Both conceptual work and case studies tend to see process mining as a singular project instead of a continuous tool. Time-dependent analyses and effects are often neglected, even though theoretical concepts could provide support.

> **Research opportunity.** Providing practical support to systematically analyze value streams (e.g., types of waste) using process mining techniques in the context of product and process complexity and dynamics.

4 Conceptual design of the approach

As a first major part of the *prescriptive study* (cf. Section 1.4), this section compromises the conceptual design of the approach. The overarching goal of the thesis is to *enable an effective and efficient application of value stream mapping in internal logistics using process mining* (cf. Section 1.3). Therefore, the research streams of value stream mapping and process mining are integrated in terms of (1) requirements (cf. Section 4.1), (2) assumptions (cf. Section 4.2), and (3) concept (cf. Section 4.3). In Section 4.4, the methodology for the industrial application is presented.

4.1 Requirements

Requirements of value stream mapping

R1. *Creating a holistic view of the value stream using process mining*. The goals of value stream mapping are to observe the flow across the whole value stream and to identify the waste within the process (cf. ROTHER & SHOOK 1999). When enabling value stream mapping using process mining, these goals should be seen as an overarching objective. Suitable process mining techniques (e.g., process discovery) must be selected and tailored to internal logistics or developed (e.g., inventory profiling) if required.

R2. *Scaling to cover product and process complexity*. Today, products contain hundreds of parts that follow different paths and processes. In this case, value stream mapping can be seriously challenging or can even break down (cf. BRAGLIA et al. 2006; FORNO et al. 2014). In industry, product and process variety is the most frequently reported challenge (SPATH 2010, p. 68). For internal logistics, each product variant has its own value stream: i.e., customer demands, material flows, inventories, and suppliers (KNOLL et al. 2019c). Consequently, to provide support, the approach must scale to cover product and process complexity.

R3. *Capturing dynamics*. The static paper-and-pencil tool does not capture dynamics. If processes are not stable or frequently change, the current state map provides only a limited snapshot or is obsolete (cf. FORNO et al. 2014; SPATH 2010). In particular, time and quantity data measurements are impractical (FORNO et al. 2014, p. 781). Consequently, the approach must capture time-dependent dynamics and enable continuous recording of value streams.

R4. *Reducing manual effort*. The time spent collecting the data and constructing the current state map is frequently reported as the costliest stage (cf. FORNO et al. 2014; SHOU et al. 2017). The approach must reduce this manual effort by the use of process mining.

Requirements of process mining

R5. *Supporting the planning stage according to lean production theory*. Process mining theory identified that defining concrete objectives and analysis questions is important for a successful process mining project (ECK et al. 2015, p. 300). Meanwhile, the literature review reveals that this step is often neglected. Therefore, the approach must support the definition of objectives and analysis questions according to lean production theory.

R6. *Providing a domain ontology for internal logistics*. In the context of heterogeneous information systems data extraction can be challenging. To overcome these challenges, process mining theory and applications in the field of logistics suggest supporting the data extraction and preprocessing using a domain ontology. The concept must support the data identification, extraction, and standardization of the taxonomy using an internal logistics ontology.

R7. *Providing algorithms for creating and enriching event logs for internal logistics*. Process mining theory claims that many information systems do not record event logs explicitly. The literature review confirms this challenge for internal logistics. To mine for value streams using process mining, algorithms for creating event logs that can scale to cover the product and process complexity and dynamics must be provided. Event logs must be enriched by attributes identified using the ontology to enable a holistic view of the value stream.

R8. *Supporting the analysis according to lean production theory*. The challenge is to exploit event data meaningfully using event logs and process mining techniques.

Therefore, “the diagnostic should be simple, accurate, and suggestive for the next, more detailed step in the analysis” (GRAVES 1981, p. 664). Process mining must be linked with lean production to provide practical support. Subsequently, practical guidelines must be developed to systematically analyze value streams (e.g., types of waste) in internal logistics. This requires considering different perspectives and iterations.

4.2 Assumptions

This section briefly describes the underlying assumptions of the concept. This is essential to set the scope and outline the strengths and existing limitations.

A1. *Lean production and lean logistics*. It is assumed that the existing production and internal logistics systems are designed according to lean production principles. In particular, logistics must be operated based on predefined and standardized logistics processes (cf. *logistics reference process*) and activities.

A2. *Product and process complexity and dynamics*. It is assumed that the approach will be applied in suitable application scenarios in which existing limitations of value stream mapping are significant. In the case that there is no product and process complexity or dynamics in the logistics system, value stream mapping without process mining might be more economical.

A3. *Data availability*. It is assumed that the physical logistics processes are operated by information systems and that these information systems create event data during the operation of logistics. If the process is not operated by information systems, the methodology cannot be applied.

A4. *Data reliability*. It is assumed that the logistics processes and activities create reliable data, that no activities record data infrequently, and that the master data (e.g., supplier specification) is reliable.

A5. *Interdisciplinary project team*. It is assumed that the required competencies and roles are available. According to ECK et al. (2015), members of process mining project teams should have different backgrounds. Logistics experts (*business experts*) and process analysts are frequently required. The logistics management (*business owners*) and software engineers must be available for specific tasks.

4.3 Overview

This section presents the concept for value stream mapping for internal logistics using process mining[1]. The concept includes a methodology for an industrial application and four main research modules. The methodology for the industrial application consists of four consecutive steps and enables value stream mapping for internal logistics using process mining. The four main research modules describe the theoretical development (e.g., underlying assumptions or literature-based development) and the research results (e.g., algorithm specification). The research results of this thesis are required as input to execute the methodology. Figure 4.1 shows an overview of the concept.

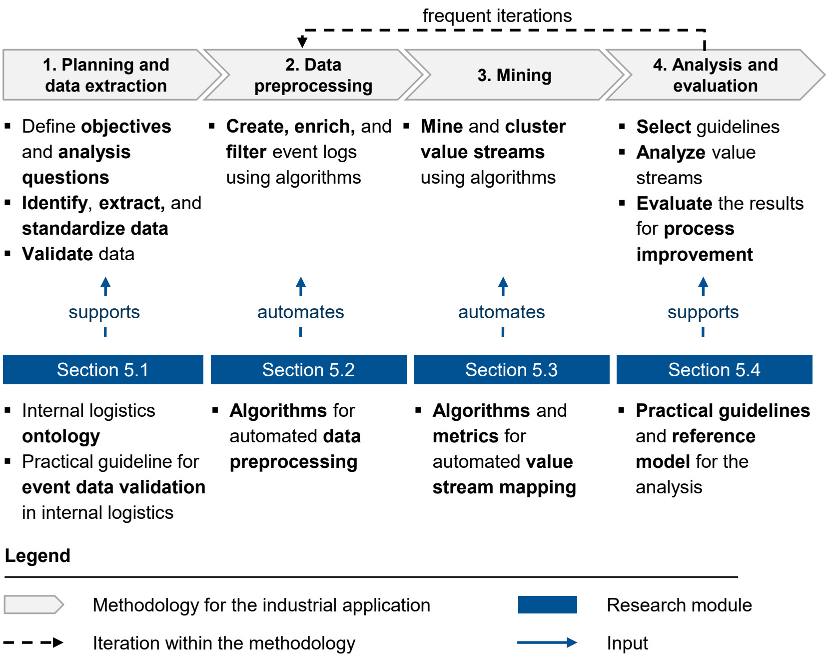


Figure 4.1: Conceptual design of value stream mapping for internal logistics using process mining: a methodology and four research modules

[1] The concept has been published within KNOLL et al. (2019b,c). The first step (*Planning and extraction*) has also been referred to as *Modeling internal logistics* and has been refined as the concept integrates the ontology-based extraction presented in KNOLL et al. (2019b).

Methodology for the industrial application

The methodology for practitioners aligns and integrates the research results to enable value stream mapping for internal logistics. Thereby, the methodology adapts PM^2, which is a generic process mining methodology that covers the necessary steps of a process mining project (cf. Section 2.3.3).

The first step covers planning and data extraction to ensure that objectives and analysis questions are defined and that data is extracted and validated. These manual tasks are supported by the internal logistics ontology and the practical guideline for event data validation. In the second step, the extracted data is processed into enriched event logs. Then, in the third step, the enriched event logs are used to mine and cluster value streams. The second and third steps are performed automatically for each value stream using algorithms. An initial understanding of data preprocessing and mining is required to implement the algorithms in practice. The fourth step focuses on the analysis and evaluation of the results for process improvement. Further support is provided by the practical guidelines for the analysis that integrate process mining with lean production theory. Iterations are possible during the analysis. In Section 4.4, the methodology and its relationship to each research result are presented.

Main research modules

The four main research modules describe the theoretical development and research results.

- Section 5.1 describes the literature-based development of the internal logistics ontology and the practical guideline for event data validation in internal logistics.
- Section 5.2 describes the development of three algorithms used for preprocessing the raw data into enriched event logs for process mining.
- Section 5.3 describes six process mining techniques used for mining and clustering value streams, including the adaption of existing techniques to internal logistics (e.g., multidimensional process mining or process discovery) and the development of new techniques (e.g., inventory profiling).
- Section 5.4 describes the literature-based development of eight practical guidelines and the reference model for the analysis, each focusing on the integration of process mining and lean production theory.

4.4 Methodology for the industrial application

4.4.1 Planning and data extraction

The first step of the methodology aims (1) to define objectives and analysis questions, (2) to identify, extract and standardize data, and (3) to validate data. The outcome of this step is a set of standardized and validated data that is required for data preprocessing.

Defining objectives and analysis questions

Any process mining project starts with defining objectives and analysis questions. According to ECK et al. (2015, p. 231), "various case studies showed the importance of defining concrete research questions for a successful process mining project." In contrast, Chapter 3 shows that this step is often neglected when applying process mining in the manufacturing and logistics industry. In particular, if no concrete objectives and analysis questions exist, the practical benefit and impact remain unclear.

The overarching objective can be derived by lean production theory: eliminate waste and increase efficiency to improve processes (cf. OHNO 1988). In the field of internal logistics, a variety of application-specific objectives can be addressed, for instance, to reduce lead times by eliminating inventory in a block storage. Therefore, the seven types of waste found in any process (cf. Section 2.1.2) can be used to define objectives and analysis questions. This task is driven by both the logistics expert and management. The practical benefit must be evaluated for each analysis question. An ideal business case scenario can be calculated to support this application-specific step. As an outcome, a set of prioritized analysis questions is defined and documented.

Identifying, extracting, and standardizing the data using the ontology

Data extraction can be challenging in complex and heterogeneous information systems, such as manufacturing and logistics. In practice, numerous information systems with technical data models consisting of dozens of data tables, attributes, and relationships exist. Domain ontologies can be used to identify, extract, and standardize data for process mining (cf. Section 2.3.3). In contrast to technical data requirements, a domain ontology provides a shared understanding of relevant classes and object properties (relationships) and data properties (attributes). Consequently, ontologies reduce the time to extract the required data.

The team uses the analysis questions and the internal logistics ontology (cf. Section 5.1.1) to identify the required data. In the ontology, a generally valid set of required classes for value stream mapping using process mining is annotated (cf. Figure 4.2).

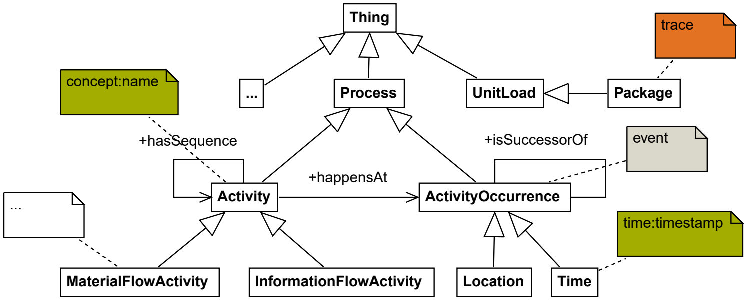


Figure 4.2: Example extract of the internal logistics ontology with annotations for process mining (based on KNOLL *et al. 2019b)*

Firstly, the logistics expert identifies or extends the required classes and data properties in the ontology for each analysis question. Secondly, the corresponding information systems and data tables must be identified. Thirdly, the feasibility and complexity of each analysis question must be evaluated by the process analyst. Therefore, the number of necessary classes and data properties in the ontology and the data availability (e.g., number of information systems and data tables) must be considered. Fourthly, beneficial and feasible analysis questions must be prioritized. These tasks highlight the importance of an interdisciplinary team: logistics experts cannot assess the feasibility of the analysis, and process analysts cannot assess the practical benefit. Fifthly, the necessary data must be extracted from the information systems, which may require the support of software engineers to transform the data tables and columns into the standardized taxonomy of the ontology. Finally, the extracted data must be stored in the schema of the input data for data preprocessing (cf. Section 5.2).

Validating the data

A variety of data imperfection patterns exist in process mining (e.g., SURIADI et al. 2017). Before using the extracted data for process mining, an initial validation of the data is required. The purpose of this task is to compare the existing event data with the reality on the shop floor at the production plant. This comparison is crucial for further improvement initiatives.

To validate the data on the shop floor, the logistics expert and the process analyst use the practical guideline for event data validation in internal logistics (cf. Section 5.1.2). During the data validation, the initial understanding of the application will be enhanced. Subsequently, the feasibility of the analysis questions can be re-evaluated. If the extracted data cannot be used to answer the analysis questions, an iterative step back to the extraction or the definition of objectives and analysis questions is required.

As an outcome, beneficial and feasible analysis questions are selected, and required data is extracted, standardized, and validated. Furthermore, the interdisciplinary team has gained a shared understanding of internal logistics.

4.4.2 Data preprocessing

The second step of the methodology preprocesses the extracted data into enriched event logs. Algorithms are applied (1) to create event logs, (2) to enrich event logs, and (3) to filter event logs. The outcome of this step is an event log for each part-specific value stream that is ready to use for mining.

Creating event logs

According to VAN DER AALST et al. (2012, p. 174), “all process mining techniques assume that it is possible to sequentially record events such that each event refers to an activity (i.e., a well-defined step in some process) and is related to a particular case (i.e., a process instance)”. However, process mining theory states that creating event logs is far from trivial, and sometimes significant effort is required (cf. Section 2.3.3). While business processes are controlled by workflow systems, internal logistics does not record high-quality event logs explicitly. Instead, to operate internal logistics, a WMS creates transfer orders that integrate the material and information flow to supply production (cf. Section 2.1.3). Each transfer order holds information about the logistics process, including (1) the part (e.g., variant of a part, or sub-assembly and quantity), (2) the location (source and destination), and (3) time of occurrence are recorded. (cf. KNOLL et al. 2019c)

The transfer orders are processed and transformed using a *Breadth-First Search (BFS)* algorithm to create the event logs. The algorithm connects individual transfer orders belonging to a specific package (e.g., batch number), reflecting the material flow within the process from goods receiving through to assembly. The algorithm also covers logistics operations, in particular, the shift from a pallet to packages, and repeats this procedure for each package of a part-specific value stream. An event log is created for each part-specific value stream separately that contains a set of cases (packages). (cf. KNOLL et al. 2019c)

For an industrial application, the software engineer must implement Algorithm 1 (cf. Section 5.2.1) once in a software environment.

Enriching event logs

So far, the event logs contain basic information about cases, activities (e.g., movements between storage locations), and timestamps. However, they do not provide any further process context, which is needed to correlate specific process and event characteristics (e.g., resources) with a specific behavior (LEONI et al. 2014, p. 252). Using the *Extensible Event Stream (XES)*[2], the de facto standard for event logs, attributes can be enriched using the extracted data. Using the internal logistics ontology for data extraction ensures that relevant context information is available and can be enriched.

For an industrial application, the software engineer must implement Algorithm 2 (cf. Section 5.2.2) once in a software environment.

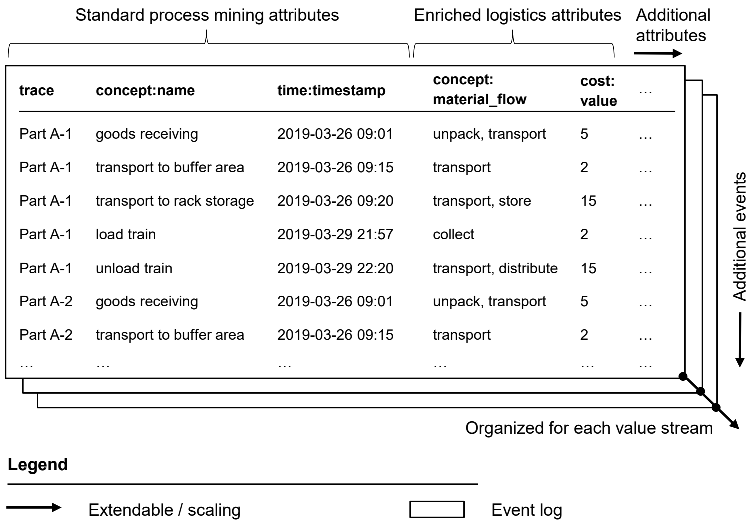
Filtering event logs

Filtering the event log aims to create the correct view and to reduce complexity (ECK et al. 2015). Filtering removes irrelevant events, cases, or attributes from the event log. Depending on the scope of the analysis, filtering can be done iteratively.

To apply filtering, the team specifies a list of attributes with allowed or forbidden values. This list of *key-value pairs* $\langle \delta_{1,k,v}, \ldots, \delta_{n,k,v} \rangle$ is used as an input for the algorithm. For example, product components, suppliers, time frames, or personalized attributes (e.g., names) can be filtered. For an industrial application, the software engineer must implement Algorithm 3 (cf. Section 5.2.3) once in a software environment.

An outcome of this step is an enriched and filtered event log for each part-specific value stream (cf. Figure 4.3).

[2] In the XES standard, the following nomenclature for data storage is used: trace refers to case identifier, concept:name refers to the activity and time:timestamp refers to the timestamp. For consistency in the thesis, the terms of a case, activity and timestamp are used.



trace	concept:name	time:timestamp	concept: material_flow	cost: value	…
Part A-1	goods receiving	2019-03-26 09:01	unpack, transport	5	…
Part A-1	transport to buffer area	2019-03-26 09:15	transport	2	…
Part A-1	transport to rack storage	2019-03-26 09:20	transport, store	15	…
Part A-1	load train	2019-03-29 21:57	collect	2	…
Part A-1	unload train	2019-03-29 22:20	transport, distribute	15	…
Part A-2	goods receiving	2019-03-26 09:01	unpack, transport	5	…
Part A-2	transport to buffer area	2019-03-26 09:15	transport	2	…
…	…	…	…	…	…

Figure 4.3: Example set of enriched event logs (based on KNOLL *et al. 2019b,c)*

4.4.3 Mining

The third step of the methodology mines and clusters the value streams using six process mining techniques. A value stream can be mined for each part using the event logs and multidimensional process mining. The outcome of this step is a holistic view, including a process model, an inventory profile, and related metrics of each value stream.

Process discovery

Process discovery takes an event log to create a process model without using any a priori information (VAN DER AALST et al. 2012, p. 175). The result is a process model similar to the current state map of the value stream, including the occurring activities and the control-flow in reality. However, process discovery provides three benefits:

1. *Process complexity*. Process discovery algorithms are capable of covering complex processes with many activities and different flows and can learn the best fitting model that represents reality. Consequently, process discovery is more accurate and less subjective than value stream mapping. (KNOLL et al. 2019c)

2. *Dynamics*. Process discovery algorithms take the event log of a specific time frame. Therefore, process discovery enables long-term observation and clearly shows temporal stages (e.g., changes in the process). In contrast, filtering enables an iterative analysis of specific time frames. (KNOLL et al. 2019c)

3. *Manual effort*. The process discovery algorithms create the process model automatically. Because they only rely on ad hoc filtering of the event log, the manual effort is significantly lower. (KNOLL et al. 2019c)

Process discovery is the most frequently used process mining technique (cf. Chapter 3), and numerous algorithms exist (cf. Section 2.3.2). This research module covers the selection of suitable process discovery algorithms (cf. Section 5.3.1).

For an industrial application, the software engineer must implement the inductive miner algorithm (cf. Section 2.3.2) once in a software environment.

Conformance checking

Conformance checking evaluates if reality, as recorded in the event log, conforms to the model, and vice versa (VAN DER AALST et al. 2012, p. 175). Similar to process discovery, conformance checking focuses on the control-flow of the process. The result is a quantified alignment between the process model and the event log. Deviations of value streams can be measured using reference process models. The algorithm evaluates all reference process models for each value stream to capture dynamics (e.g., concept drifts of processes). This procedure identifies and selects the best fitting process model and its alignment. (cf. KNOLL et al. 2019c)

For an industrial application, the software engineer must implement Algorithm 4 (cf. Section 5.3.2) once in a software environment.

Activity mapping

Activity mapping evaluates material and information flow activities independently of reference processes and value streams. Here, both the average and variance waiting and processing times and frequencies of individual events are aggregated statistically. This aggregation enables evaluation of the stability of activities, and value-added and non-value-added activities can be identified. (cf. KNOLL et al. 2019c)

For an industrial application, the software engineer must implement the Algorithm 5 (cf. Section 5.3.3) once in a software environment.

Inventory profiling

Inventory profiling creates the actual inventory profile of a value stream based on the event log. Like process discovery, the inventory profile is created without any a priori information. Therefore, the algorithm mines the inventory levels, the demand, and the deliveries. The inventory profile algorithm can identify both absolute quantities and packages (inventory on a case level) to cover the product complexity and variety. With the resulting inventory profile, the conformance of the actual behavior can be compared with the inventory control policy.

For an industrial application, the team must define the time-interval k (e.g., daily level). However, k can be adjusted depending on the analysis questions. The software engineer must implement Algorithm 6 (cf. Section 5.3.4) once in a software environment.

Performance analysis

Performance analysis provides an aggregated view of all value streams by aggregating the event log and the results of other process mining techniques statistically. In contrast to process discovery and conformance checking, performance analysis is more domain-specific than a process mining standard. An initial set of metrics can be proposed, but the performance measurement and its metrics always depend on the nature of the production system.

- *Non-financial efficiency metrics* include the lead time, inventory aggregated to average, and variance values. The metrics are normalized on the case level or time level (e.g., demand per day) or provided as absolute numbers.
- *Non-financial effectiveness metrics* include the conformance checking result and the non-value-added activities of value streams. Example quality-related activities may be summarized depending on the activity categories. The metrics are presented in absolute numbers and normalized numbers on the case level.
- *Financial cost metrics* include the activities (e.g., transportation, handling) and the inventory as the main cost drivers. Activity-based costing and inventory costing are applied to determine the costs.

For an industrial application, the logistics expert and the process analyst must tailor the proposed metrics (cf. Section 5.3.5) to the objectives and analysis questions. The software engineer must implement the metrics once in a software environment.

Clustering

Clustering aims to identify process variants of similar value streams (groups of instances) to reduce the complexity of the analysis. The concept includes two types of clustering: trace clustering and value stream clustering. Trace clustering is beneficial for process-specific deviations independent of the part-specific value stream. Value stream clustering supports the identification of groups of value streams and takes the results of conformance checking and performance analysis as input.

A reference process must be selected to apply trace clustering. A list of value streams must be defined for value stream clustering. The clustering algorithm cannot be determined in advance because performance depends on the application-specific data. Due to its robustness, the k-means algorithm with the gap statistics method can be used to start. For an industrial application, the software engineer must implement both types of clustering (cf. Section 2.3.3 and Section 5.3.6) once in a software environment.

An outcome of this step is the mining of a holistic value stream for each part (cf. Figure 4.4), and similar value streams are clustered.

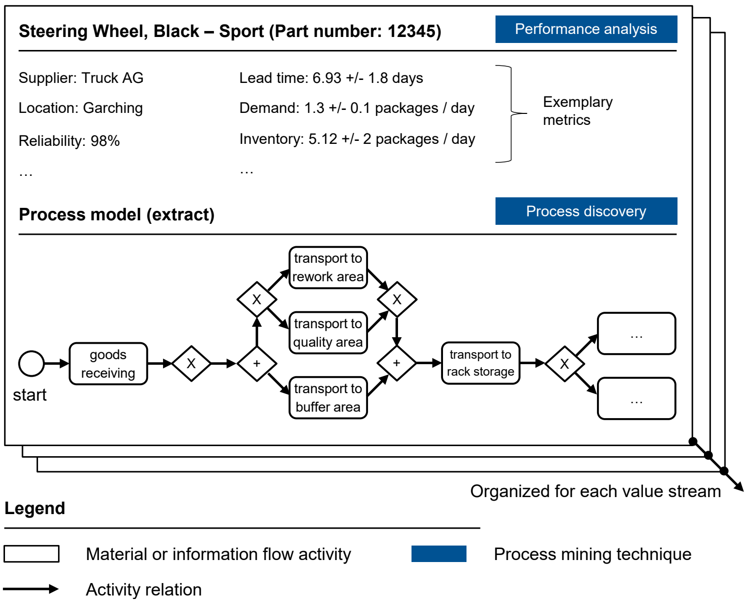


Figure 4.4: Example extract of mined value streams (based on KNOLL *et al. 2019c)*

4.4.4 Analysis and evaluation

The fourth step focuses on the analysis and evaluation of the results for process improvement. This step includes (1) selecting practical guidelines, (2) analyzing value streams according to the guidelines, and (3) evaluating the results for process improvement. The outcome of this step is a set of concrete and evaluated improvement ideas.

Selecting practical guidelines for the analysis

Analysis becomes increasingly challenging as product and process complexity and dynamics increase. However, due to the application-specific objectives and analysis questions, no prescriptive step-by-step analysis is possible[3].

To support the analysis, (1) eight practical guidelines and (2) a reference model for the analysis are presented in Section 5.4. Both focus on the integration of process mining with lean production theory and the main objective of eliminating waste.

Each practical guideline provides an analysis objective, a link to lean production (e.g., types of waste), the process mining technique(s), the analysis description, potential issues and lessons learned, and the relation to other practical guidelines. Because of the modular and iterative character of the analysis, the reference model for the analysis is modeled as an *Activity-based Design Structure Matrix (DSM)*[4]. In the Activity-based DSM, the relation between the rows and the columns indicates the flow. According to BROWNING (2001), reading down a column reveals input sources, while reading across a row indicates output sinks. In the reference model for the analysis, the rows and columns reflect the practical guidelines, and the relation specifies the flow. For example, *Filtering "reduces the complexity (for the)" process discovery*.

The logistics expert and the process analyst simulate the analysis in the reversed direction to select guidelines. If possible, the team selects the type(s) of waste based on the objectives and analysis questions. Then, the team selects the relevant guideline(s) by reading across the row(s). For each selected guideline, the team scans down the column(s) to identify further relations, then scans the related guideline(s) in the row.

[3] Please refer to Section 5.4 for a detailed discussion of this aspect.

[4] A DSM is a square matrix with identical row and column labels that displays the relations between the elements. The Activity-based DSM is used to model processes or activity networks based on their dependencies (BROWNING 2001, pp. 292–293).

This procedure yields an ordered set of guidelines that can be applied during the analysis. Finally, the team discusses the selected guidelines (e.g., analysis description and lessons learned) and verifies that the expected results contribute to the objective(s) and analysis question(s). An illustration of the procedure is shown in Figure 4.5.

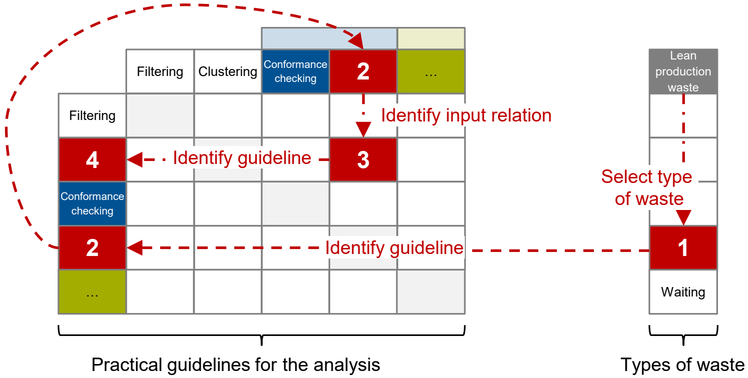


Figure 4.5: Illustration of the procedure to select suitable guidelines in the reference model for the analysis (e.g., to identify waste)

Analyzing value streams according to the practical guidelines

The process analyst performs the analysis and frequently discusses the results with the logistics expert. Even though the practical guidelines support the analysis, this task requires experience and iterations. Promising results (e.g., unexpected transport activities) are used for the evaluation.

Evaluating the results for process improvement

The results of the analysis must be related to the objectives and improvement ideas to provide practical support (Eck et al. 2015). For each analysis question, the team must evaluate the results in terms of the practical benefit and reliability (e.g., data quality). Based on the results, the team can develop ideas to improve the current state. Afterward, the improvement ideas must be validated on the shop floor.

As an outcome of this step, a set of concrete and evaluated improvement ideas are defined for implementation. The improvements can be monitored, and further improvement potential can be identified. This methodology supports the continuous improvement of value streams.

5 Detailed design of the approach

5.1 Planning and data extraction

5.1.1 Internal logistics ontology for process mining

This section describes the internal logistics ontology that is used for data extraction. Firstly, the literature-based development of the ontology is described in Section 5.1.1.1. Secondly, an overview of developed ontology is provided in Section 5.1.1.2. Thirdly, the classes are explained in detail (cf. Sections 5.1.1.3 to 5.1.1.7).

5.1.1.1 Literature-based development of the internal logistics ontology

The *Ontology Development Guide* by NOY & MCGUINNESS (2001) is used (cf. Appendix A.2.1.1) to develop the internal logistics ontology in this thesis.

Step 1: Determining the domain and scope

The objectives of the thesis (cf. Section 1.3) and ontology-based data preprocessing (cf. Section 2.3.3) are matched to determine the domain and scope. The ontology must create a shared understanding of the process perspective of internal logistics, and required concepts of process mining (e.g., case identifier) must be annotated. In addition, related attributes to enrich the event logs (e.g., costs) must be defined. Four competency questions are defined to support this step (KNOLL et al. 2019b):

- Which logistics activities are related to the material flow and information flow?
- Which resources and actors are required to fulfill these activities?
- How can the transition of objects be described regarding the time and location?
- Which specifications are required to characterize parts and processes?

Step 2: Considering reusing existing ontologies

According to NOY & MCGUINNESS (2001), it is almost always worth considering reusing existing ontologies. Therefore, ontologies in the field of internal logistics are reviewed. The review approach (e.g., keywords) is described in Appendix A.2.1.1[1].

In total, 14 publications are related to internal logistics. The process and resource perspectives are used to classify the publications (cf. NEGRI et al. 2017). Table 5.1 shows the evaluation of relevant work for developing the internal logistics ontology.

Table 5.1: Evaluation of relevant work for developing the internal logistics ontology

	Process					Resource			Others					
	P. LIAN et al. (2007)	D. PARK et al. (2008)	LIBERT et al. (2010)	HOXHA et al. (2010)	ZHANG & TIAN (2010)	HIMOFF et al. (2006)	LI et al. (2014)	NEGRI et al. (2017)	LORENZ et al. (2005)	MERDAN et al. (2008)	BONFATTI et al. (2010)	JINBING et al. (2008)	KOWALSKI & QUINK (2013)	K. M. d. OLIVEIRA et al. (2013)
Scope														
Internal logistics	◕	●	●	◔	◑	◔	◑	●	◔	◑	◔	◑	◔	-
Concepts														
Process	●	●	◕	◑	◑	◔	-	-	◔	◔	-	-	◔	◔
Resource	-	-	◑	◔	-	◑	◑	●	-	◑	◔	◔	●	◔
Unit load	-	◔	◑	-	◔	◔	◑	-	-	◔	-	◑	◔	-
Actor	-	-	◑	●	◑	◔	-	-	-	◔	◔	-	-	-
Customer order	◑	-	◕	◑	-	◑	-	-	-	◔	-	-	◔	-

● Fully addressed, ◑ Partly addressed, - Not addressed

The first group of ontologies focuses on the process perspective. In this group, the ontologies include the process and a set of activities. Here, LIBERT et al. (2010) developed the most comprehensive ontology. The authors formalized the functions and information required for the material flow of internal logistics. Consequently, the

[1] Note, the development of the ontology as well as the ontology for internal logistics presented in this section have been published in KNOLL et al. (2019b).

different perspectives of the material flow cover the process, the resource, and the actors. Furthermore, the relationships between the classes and a set of initial data properties are included. However, the ontology is not complete; the material flow activities, for example, only include buffer, store, and transfer. Other material flow activities, such as picking and distributing, are not included. Similarly, ZHANG & TIAN (2010) and HOXHA et al. (2010) modeled a holistic picture of internal logistics and existing relationships on an abstract level. In contrast, D. PARK et al. (2008) and P. LIAN et al. (2007) modeled a precise picture of the process and its activities, but other relevant classes (e.g., resources) are missing.

The second group of ontologies focuses on the resources of internal logistics. Many classes are modeled, including data properties. In contrast, the relations (object properties) between the classes are not in the scope. In this group, NEGRI et al. (2017) developed the most comprehensive ontology. The authors formulated a set of nine sub-classes of the class component, such as storage and transporter. For each class, additional sub-classes and data properties are provided (NEGRI et al. 2017). Notably, the unit load describes a product that is not further described using sub-classes. The work of NEGRI et al. (2017) is an extension of the *Manufacturing Systems Ontology*, an upper ontology developed by FUMAGALLI et al. (2014). The other two publications modeled the resources on an abstract level (HIMOFF et al. 2006; LI et al. 2014).

The third group summarizes publications that focus on certain aspects of internal logistics, for instance, packaging (KOWALSKI & QUINK 2013) or transport (MERDAN et al. 2008). Partial aspects are modeled with sub-classes and data properties from a micro-perspective. For example, KOWALSKI & QUINK (2013) defined ten classes that describe packaging, packaging goods (parts), unit loads, and underlying standards, including instances (e.g., DIN ISO). Subsequently, a precise separation between products and packages, and packaging, is given. However, existing relationships between the classes and the holistic perspective of internal logistics have been neglected (e.g., BONFATTI et al. 2010; JINBING et al. 2008).

The review outlines the opportunity to reuse existing ontologies and suggests four improvement directions. Firstly, most existing ontologies do not integrate the process and resource perspective. The relations between classes are often neglected, and no holistic picture of internal logistics is created. Secondly, as the ontologies have different purposes, the ontologies are modeled with a different level of abstraction. Ontologies with explicit formalization and data properties (e.g., NEGRI et al. 2017) can be used to enrich event logs. In contrast, other ontologies are abstract and do not specify properties. Thirdly, no standardized taxonomy exists; MERDAN et al. (2008), for example, use the term *pallet* while other ontologies refer to *unit load*. Fourthly, existing upper ontologies are often neglected. In particular, the process is often modeled using concepts that are not compatible with the process mining perspective. (KNOLL et al. 2019b)

Step 3: Enumerating important terms

Table 5.2 presents an overview of the enumerated (main) terms of the internal logistics ontology based on the review. The count describes the number of occurrences within the reviewed ontologies. Frequent terms are used to define the hierarchy of top- and sub-classes. The representative ontologies provide the basis for modeling, e.g., to reuse classes, object properties (relations), and data properties (attributes).

Table 5.2: Main terms of the internal logistics ontology based on the review

Class	Exemplary term(s)	Count	Representative ontologies
Resource	Storage, transporter	17	• NEGRI et al. (2017)
Process	Activity, time	14	• BOCK & GRUNINGER (2005) • LIBERT et al. (2010)
Actor	Supplier, customer	11	• HOXHA et al. (2010)
UnitLoad	Product, package	9	• PANETTO et al. (2012)
Customer Order	Transfer order	7	• OBITKO et al. (2010) • LIBERT et al. (2010)

Steps 4-6: Define the classes, properties, and facets

The ontology is modeled in the fourth, fifth, and sixth steps. If possible, concepts of existing domain ontologies and upper ontologies, such as *Process Specification Language (PSL)*, are integrated, supported by fundamental concepts of internal logistics.

5.1.1.2 Overview of the internal logistics ontology

The internal logistics ontology consists of five top classes: *CustomerOrder*, *Process*, *UnitLoad*, *Resource*, and *Actor* (cf. Figure 5.1). The focus of the internal logistics ontology is set on the process (cf. *Process*). A process consists of a sequence of activities (cf. *Activity*) covering the material (cf. *MaterialFlowActivity*) and information flow (cf. *InformationFlowActivity*) of internal logistics. Every activity happens at an activity occurrence (cf. *ActivityOccurrence*) specifying the time (cf. *Time*) and location (cf. *Location*). Actors (cf. *Actor*) and resources (cf. *Resource*) are required to operate this process. The customer (cf. *Customer*) generates a customer order (cf. *CustomerOrder*) that triggers the process, resulting in transfer orders (cf. *TransferOrder*) for internal logistics. A transfer order contains one or many parts (cf. *Part*), instantiating product components (cf. *ProductComponent*) that are stored as packages (cf. *Package*) on unit loads (cf. *UnitLoad*). During the operation of this process, the transfer orders, including activity occurrences, are stored as information objects (cf. *InformationObject*). The ontology with all classes and properties is published in KNOLL et al. (2019b).

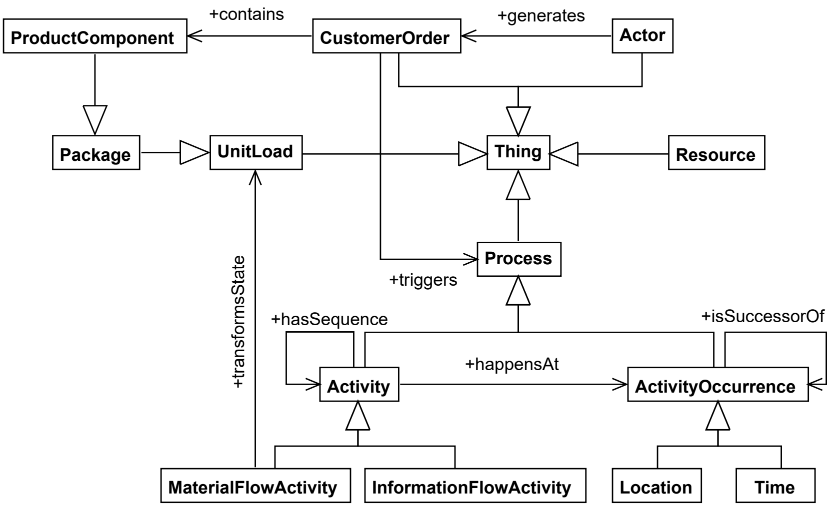


Figure 5.1: Overview of the top classes and relations of the internal logistics ontology (based on KNOLL *et al. 2019b, p. 430)*

5.1.1.3 Customer Order

The customer order (cf. *CustomerOrder*) describes the market requirement of products (OBITKO et al. 2010, p. 322). The demand planning process uses actual orders of customers (cf. *Customer*) and predicted orders based on historical statistics to create customer orders. The master production planning process aggregates the customer orders to a production schedule with production orders (cf. *ProductionOrder*). (cf. SCHUH & P. STICH 2012) Then, production orders are decomposed into work orders (cf. *WorkOrder*) for production and manufacturing processes and transfer orders (cf. *TransferOrder*) for internal logistics processes (LIBERT et al. 2010, p. 82). A transfer order contains one or many parts (cf. *Part*) and triggers the internal logistics process (cf. *Process*) on the shop floor (ER et al. 2015a; KNOLL et al. 2019c; LIIV & LEPIK 2014; TEN HOMPEL & SCHMIDT 2010), including an activity (cf. *Activity*) and activity occurrence (cf. *ActivityOccurrence*) related to a specific time (cf. *Time*) and location (cf. *Location*) (cf. Section 5.1.1.4). Figure 5.2 shows the customer order.

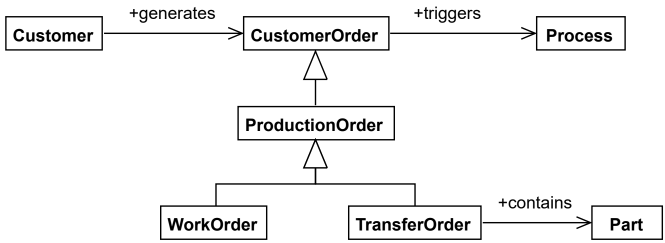


Figure 5.2: The class CustomerOrder of the internal logistics ontology (based on KNOLL *et al. 2019b, p. 430)*

Annotations for process mining

The transfer order takes on a key role in supporting value stream mapping using process mining. The transfer order is the trigger for any process and activity in internal logistics (cf. Section 2.1.3). If started and completed, a transfer order is confirmed, as is the activity, including the activity occurrences (events). Transfer orders, including the activity occurrences, are stored as information objects in information systems. The transfer order holds the raw data for event logs (KNOLL et al. 2019c).

> A transfer order triggers the process and activities that transform the state of the unit load and stores related activity occurrences (events).

5.1.1.4 Process

A process is a set of specific and ordered activities across time and place, with a beginning and an end, intended to reach a specific goal (cf. Section 2.1). For internal logistics, the logistics process ensures the availability of the right product, in the right quantity, and the right condition, at the right place, at the right time, for the right customer, at the right cost (RUTNER & LANGLEY 2000, p. 73).

The upper ontology PSL is used to model the process (cf. *Process*) in the internal logistics ontology (cf. Figure 5.3). The PSL defines an ordered process with the main concepts of activities (cf. *Activity*) and occurrences (cf. *ActivityOccurrence*): (1) an activity is defined as “a class or type of action” (SCHLENOFF & GRUNINGER 2000, p. 16) and (2) an activity occurrence as “an event or action that takes place at a specific place and time” (SCHLENOFF & GRUNINGER 2000, p. 16). Every activity occurrence is linked to a given activity and includes a specific location (cf. *Location*) and time (cf. *Time*) at which an activity begins and ends (SCHLENOFF & GRUNINGER 2000).

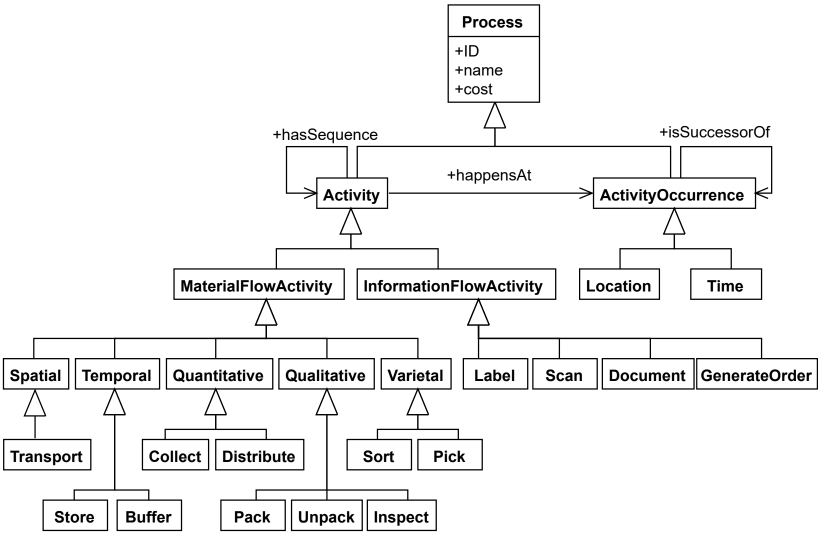


*Figure 5.3: The class Process of the internal logistics ontology (*KNOLL *et al. 2019b)*

During tailoring, the activities are classified into material flow (*MaterialFlowActivity*) and information flow activities (*InformationFlowActivity*) and further specified into nine generic activity classes (cf. GÜNTHNER & BOPPERT 2013; KNÖSSL 2015). Furthermore, an activity can be classified as a value-added, non-value-added but required, or non-value-added activity (DURCHHOLZ 2014, p. 52). A schema with five categories is predefined to instantiate non-value-added activities in the application: (1) quality, (2) rework, (3) replenishment, (4) urgent order, and (5) repack.

Annotations for process mining

The process represents the fundamental concept of process mining: activities with activity occurrences (events). “Each sequence of primitive activity occurrences is a possible execution trace, and all sequences together represent everything of concern that can possibly happen at runtime.” (BOCK & GRUNINGER 2005, p. 213) The internal logistics ontology is aligned with process mining theory: (1) an event refers to an activity, (2) the time of an event defines the timestamp, (3) events can be linked to a predecessor and/or successor, and (4) a (predefined) sequence of activities reflects a process model. However, the nature of internal logistics introduces two challenges if the activities are instantiated. (1) *Location-specific activities*: The generic activities can be fundamentally different depending on the context, e.g., a transfer activity is related to resources foreseen for a specific path between two locations. The location of an occurrence further specifies activities in internal logistics. (2) *Synchronization errors*: In internal logistics, material flow activities can be executed independently of information flow activities. Then, multiple material flow activities may occur before an information flow activity completes a transfer order or vice versa.

5.1.1.5 Unit Load

A unit load (cf. *UnitLoad*) is the basic handling unit for internal logistics and is defined as “the means used to move and handle one or more workpieces at one time.” (NEGRI et al. 2017, p. 24) A unit load includes one or many packages (cf. *Package*) (ARNOLD et al. 2010, p. 703). A package is defined as a packaging good, i.e., a product variant or sub-assembly, with a specific quantity and packaging (cf. *Packaging*) (DIN EN 55405 2014; KOWALSKI & QUINK 2013). Hence, a unit load, or package, refers to a unique batch of a specific order (cf. Figure 5.4). The abstract sub-class of the product component (cf. *ProductComponent*) is introduced according to the upper ontology *Product-driven ONTOlogy for Product Data Management (ONTO-PDM) interoperability within manufacturing process environment* (PANETTO et al. 2012) to model the nature of product variants or sub-assemblies. The review on multi-criteria inventory classification of KABIR & HASIN (2013) is reused and extended with fundamental literature on internal logistics (e.g., GÜNTHNER & BOPPERT 2013; NYHUIS et al. 2008; NYHUIS & WIENDAHL 2009) to specify relevant data properties of a part (cf. *Part*) for internal logistics.

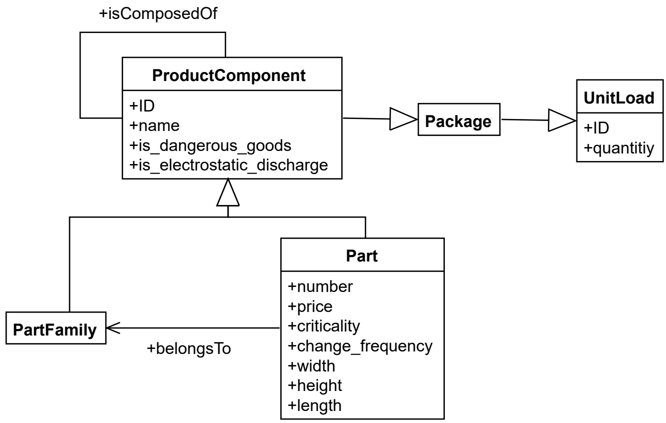


*Figure 5.4: The class UnitLoad of the internal logistics ontology (*KNOLL *et al. 2019b)*

Annotations for process mining

The unit load enables the creation of event logs and provides domain-specific attributes to be enriched for each value stream. Firstly, the unit load, or package, provides a traceable object that is transformed by material flow activities. The state of the unit load can be modified depending on the type of material flow activity. Consequently, the package ensures a unique case identifier for process mining. Secondly, the data properties of parts and product components classes enhance the case perspective.

5.1.1.6 Resource

To operate the process, the material flow and information flow activities require resources (cf. *Resource*). In total, the resource includes five sub-classes (cf. Figure 5.5). Similar to the activities, the resources are separated into material flow (cf. *MaterialFlowResource*) and information flow resources (cf. *InformationFlowResource*).

The material flow resource describes the resources required to enable the material flow activities: the transporter (cf. *Transporter*), the storage (cf. *Storage*), the load carrier (cf. *LoadCarrier*), the packaging (cf. *Packaging*), and the order picking (cf. *Order-Picking*). Supporting resources such as straps, tools, and foam material are summarized as aid (cf. *Aid*). The transporter and the storage resource are based on NEGRI et al.

(2017) and are classified into the continuous (cf. *ContinuousTransporter*) and discrete transporters (cf. *DiscreteTransporter*), and similarly, storages (cf. *ContinuousStorage*, *DiscreteStorage*). The information flow resources cover the acquisition, processing, and storage of information. An abstract information object (cf. *InformationObject*) is introduced to cover the heterogeneous information systems (JÜNEMANN & BEYER 1998). The infrastructure (cf. *Infrastructure*), energy, and human elements have been modeled abstractly.

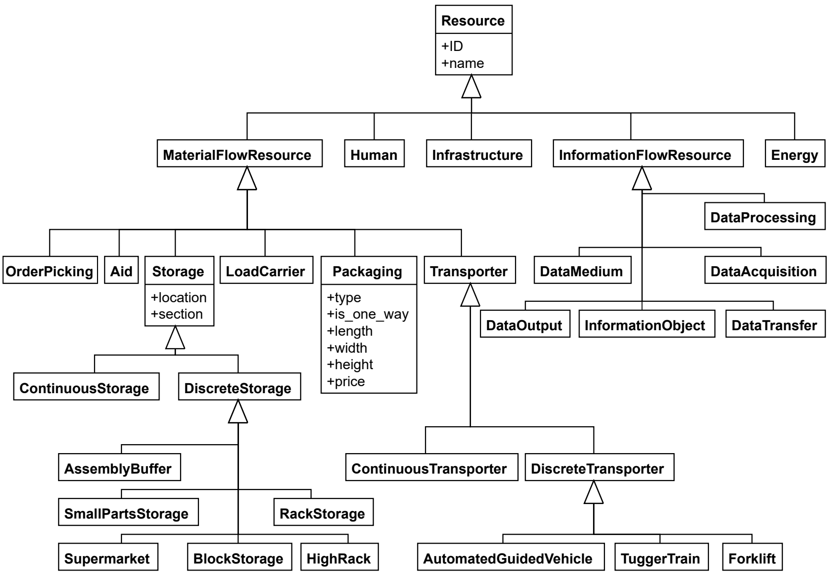


*Figure 5.5: The class Resource of the internal logistics ontology (*KNOLL *et al. 2019b)*

Annotations for process mining

The resource provides domain-specific attributes to enrich the event log. Firstly, the data properties of the packaging and storage classes enhance the case perspective. They cover the product and the resulting packaging complexity within the analysis and evaluation of value streams (e.g., spatial restrictions). In addition, the storage section can be used to differentiate ingoing, internal, and outgoing storages, which is required for the inventory profiling algorithm. Secondly, the sub-classes of storages and transporters can be used to instantiate the master data in the application.

5.1.1.7 Actor

The actor (cf. *Actor*) covers the actors required to operate internal logistics (cf. Figure 5.6). According to HOXHA et al. (2010), the customer (cf. *Customer*), the supplier (cf. *Supplier*), and the manufacturing company (cf. *Manufacturer*) are necessary. For internal logistics, the customer is categorized as an external (cf. *ExternalCustomer*) or internal customer (cf. *InternalCustomer*), e.g., the assembly line. To operate the process, the supplier delivers the parts, and the manufacturer fulfills the customer orders.

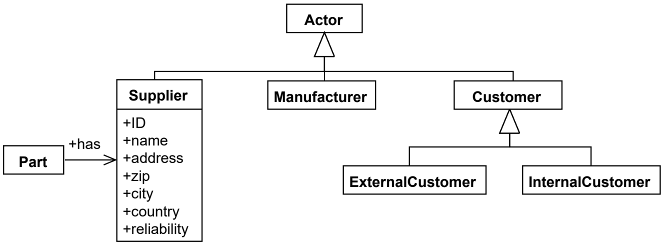


*Figure 5.6: The class Actor of the internal logistics ontology (*KNOLL *et al. 2019b)*

Annotations for process mining

The supplier provides domain-specific attributes that are enriched for each value stream. They include suppliers' static data properties (e.g., city and country) and the actual performance and reliability (e.g., risk of shortages). These data and attributes support analysis and decision-making about processes and inventory on hand, and the supplier enhances the case perspective.

5.1.2 Practical guideline for event data validation in internal logistics

This section provides a practical guideline for validating event data in internal logistics before data processing. The practical guideline aims to identify quality issues related to the event data in internal logistics[2]. The development includes three steps. Firstly, generally valid quality issues of event data described in process mining theory are briefly

[2] To improve the quality of event logs, research proposes guidelines for logging (e.g., VAN DER AALST 2016). To identify quality issues of non-event data, e.g., master data, please refer to data mining literature (cf. CHU et al. 2016; KIM et al. 2003; P. OLIVEIRA et al. 2005).

presented. Secondly, domain-specific data quality issues within internal logistics (e.g., case studies) are evaluated. Thirdly, the practical guideline is formulated.

Related work on quality issues of event data

According to VAN DER AALST et al. (2012, p. 179), the resulting quality of process mining depends on the quality of the input event data. Therefore, the authors define four criteria to judge the quality of event logs: trustworthy, complete, semantics, and safe. Then, VAN DER AALST et al. (2012) derive five maturity levels of event logs and discuss them with practical examples (e.g., types of information systems).

In contrast to these five rough maturity levels, BOSE et al. (2013) provide a comprehensive quality classification framework for event logs. The authors define four categories to assess the quality of the event log: missing data, incorrect data, imprecise data, and irrelevant data. In combination with process characteristics, BOSE et al. (2013) derive 27 classes of quality issues. Timestamps, for instance, can be missing completely or be incorrect (e.g., the difference between the event in reality and the documentation in the information system). Many authors use this framework to assess the quality of event logs in process mining in different domains, such as healthcare (e.g., ALHARBI et al. 2017; ALVAREZ et al. 2018; ROJAS et al. 2017).

In between the range of five maturity levels and 27 precise classes of quality issues, a variety of research on the quality of event logs exist (cf. review of SURIADI et al. 2017). Even though an overlap between quality issues and dimensions of event logs exist, less attention is spent on the raw event data extracted from information systems. To address this issue, SURIADI et al. (2017) adapted the work of BOSE et al. (2013) to develop 11 data imperfection patterns that have been evaluated in a user study with 15 researchers and five practitioners. Recent work focuses on initial approaches for automatically detecting imperfection patterns using algorithms (e.g., ANDREWS et al. 2018).

Evaluation of quality issues of event data in internal logistics

The domain-specific quality issues of event data within internal logistics are derived from the 11 data imperfection patterns (SURIADI et al. 2017). The characteristics of transfer orders (cf. Section 5.1.1.3) and the findings of the case studies are discussed and evaluated for each data imperfection pattern (cf. Chapter 3).

1. *Form-based Event Capture*. This pattern states that single events overwrite all data associated with an updated timestamp (SURIADI et al. 2017, p. 140). In internal logistics, a transfer order contains one or many parts that trigger individual activities. For example, depending on the resources, parts can be delivered separately (e.g., tugger train) or as a whole unit load (e.g., forklift). Therefore, this pattern must be checked in the application.

2. *Scattered Event*. Scattered events describe additional events (e.g., different life cycles) that can be extracted from the event data (SURIADI et al. 2017, p. 140). This pattern received the second-highest importance rating in the user study of SURIADI et al. (2017). In internal logistics, a transfer order includes a start and a completion timestamp. Thus, two different events can be derived. The majority of case studies report two timestamps. However, exceptions, including only one timestamp, exist (e.g., ER et al. 2015b). This pattern must be integrated into the data preprocessing and checked in the application.

3. *Elusive Case*. Elusive cases occur if events are not explicitly linked to their respective case identifiers (SURIADI et al. 2017, p. 140). SURIADI et al. (2017) showed that this pattern received the highest importance rating of all patterns. In internal logistics, transfer orders do not include a case identifier. Therefore, the case identifier must be constructed during data preprocessing.

4. *Scattered Case*. A scattered case includes missing activities that can be retrieved from different information systems (SURIADI et al. 2017, p. 141). The literature review highlighted heterogeneous information systems in logistics (cf. Chapter 3). This imperfection pattern can occur in the application depending on the material and information flow of the physical logistics process. Internal logistics offers an additional challenge because material flow activities can be executed without any information flow. None of the case studies reported this pattern explicitly.

5. *Collateral Events*. Here, multiple events refer to one particular process step, e.g., trivial low-level activities that do not contribute much to the analysis (SURIADI et al. 2017, p. 142). For internal logistics, again, this pattern can occur depending on the material and information flow and the related resources. An automated conveyor line, for example, might trigger multiple events for controlling and monitoring the equipment. This situation implies that the number of activities and events does not necessarily correlate with the physical process or effort.

6. *Synonymous Labels*. This pattern refers to labels that are syntactically different but semantically similar, e.g., the same real-world activity with different labels (SURIADI et al. 2017, p. 144). The case studies in internal logistics did not identify this pattern explicitly (cf. Chapter 3). However, this pattern occurs frequently if multiple information systems are merged (SURIADI et al. 2017, p. 144). In that case, the pattern must be checked within the application.

7. *Homonymous Labels*. Here, an activity is repeated multiple times, and the interpretation of the activity differs across the occurrences (SURIADI et al. 2017, p. 144). For internal logistics, this pattern has not been reported as the standardized activities refer to the (same) material flow activity. However, the process complexity (process types) identified in the literature review is comparatively low (cf. Chapter 3). The activity occurrence (event) must be enriched with the location to address process complexity (cf. Section 5.1.1.4).

8. *Polluted Label*. A polluted label refers to activities that are structurally the same but tailored to the event, for example, by appending event-specific information to the label (SURIADI et al. 2017, p. 143). For internal logistics, the literature review identified standardized activities that are predefined in the information system. However, this pattern can occur in the application.

9. *Unanchored Event*. An unanchored event refers to different formats of values that are not compatible with each other (SURIADI et al. 2017, p. 139). Many cleaning steps during the data preprocessing have been reported to address these issues in internal logistics. However, the prevalence of this pattern heavily depends on the application scenario, e.g., if multiple information systems must be merged.

10. *Inadvertent Time Travel Description*. Here, the events are recorded with an erroneous timestamp that is caused by manual data entry failures (SURIADI et al. 2017, p. 138). For internal logistics, this pattern is not relevant as the transfer orders are created using an information system (e.g., WMS or ERP). Furthermore, no case study has reported on this specific pattern (cf. Chapter 3).

11. *Distorted Label*. This pattern refers to labels that have strong similarities but do not exactly match, caused by manual data entry failures, for instance (SURIADI et al. 2017, p. 143). For internal logistics, this pattern is not relevant as the event data is created using transfer orders.

In conclusion, the evaluation and discussion shows that nine patterns can possibly occur in internal logistics (cf. Table 5.4). In particular, three patterns (cf. *Scattered Event*, *Elusive Case* and *Homonymous Labels*) relate to the universal nature of transfer orders and must be addressed during the data preprocessing. However, most imperfection patterns are application-specific and must be validated before further work takes place. In addition, many imperfection patterns are related to merging event data of multiple information systems.

Table 5.3: Evaluation of imperfection patterns of event data in internal logistics

		Nature		Information system(s)		
-	Imperfection pattern	Universal	Application	Single	Multiple	Examplary root cause
1	Form-based Event Capture		x	x		Parametrization
2	Scattered Event	x	(x)	x		Transfer order update
3	Elusive Case	x	(x)	x		Unit load & batch ID
4	Scattered Case		x		x	Missing bar code scan
5	Collateral Events		x		x	Level of abstractions
6	Synonymous Labels		x		x	Non-standardized label
7	Homonymous Labels	x	(x)			Distributed activities
8	Polluted Label		x		x	Parametrization
9	Unanchored Event		x		x	Different data models
10	Inadvertent Time Travel					-
11	Distorted Label					-

Practical guideline for event data validation in internal logistics

The practical guideline aims to support practitioners with five principles to identify quality issues of event data on the shop floor.

1. *Observe the process on the shop floor.* An essential requirement is to observe the process on the shop floor. Special attention must be paid to the activities related to the information flow that generate event data, for example, manual bar code scans, mobile data terminals, or automated conveyor lines[3].

[3] Advanced concepts to model the material, information and data flow are referred to MEUDT et al. (2017).

2. *Record your own data for each process.* Along with observation, sample data must be recorded for each reference process and activity. For instance, the actual processing times of activities can be compared to the measured duration of activities. If the effort is too high, the main processes and activities (e.g., frequencies) must be prioritized.

3. *Talk to people who execute the process every day.* Interviews with workers on the shop floor are required to validate the data quality and potential weaknesses of the processes. In particular, the validation requires understanding when the data is generated in the process. For example, is the bar code confirmation scan executed at every step or only at the end of each shift?

4. *Compare the findings with existing documentation.* Findings made on the shop floor must be compared to the existing documentation. The existing documentation of internal logistics, i.e., reference processes and activities, and information technology, i.e., underlying information systems and data models, must be analyzed. The latter is very important as multiple imperfection patterns are caused by the heterogeneity of information systems. For each deviation, further interviews are required to derive the root causes and to understand the actual behavior.

5. *Compare the findings with the event data.* Finally, the findings made and recorded on the shop floor must be compared with the extracted event data. Here, the nine relevant imperfection patterns must be checked based on the findings.

5.2 Data preprocessing

This section describes the development of the algorithms for creating (cf. Section 5.2.1), enriching (cf. Section 5.2.2), and filtering event logs (cf. Section 5.2.3). Consequently, the flattened data[4] that is extracted using the internal logistics ontology (cf. Section 5.1.1) is preprocessed into enriched event logs.

For each algorithm, the preliminary declarations and the flattened input data are specified, linking the algorithm's input data with the internal logistics ontology. The algorithm is explained using pseudo code.

Figure 5.7 shows the relationship between the input data, the algorithms, and the preprocessed data for process mining as a *Data Flow Diagram (DFD)*[5]. The preprocessed data include an enriched event log for each value stream and the predefined reference process models suitable for multidimensional process mining.

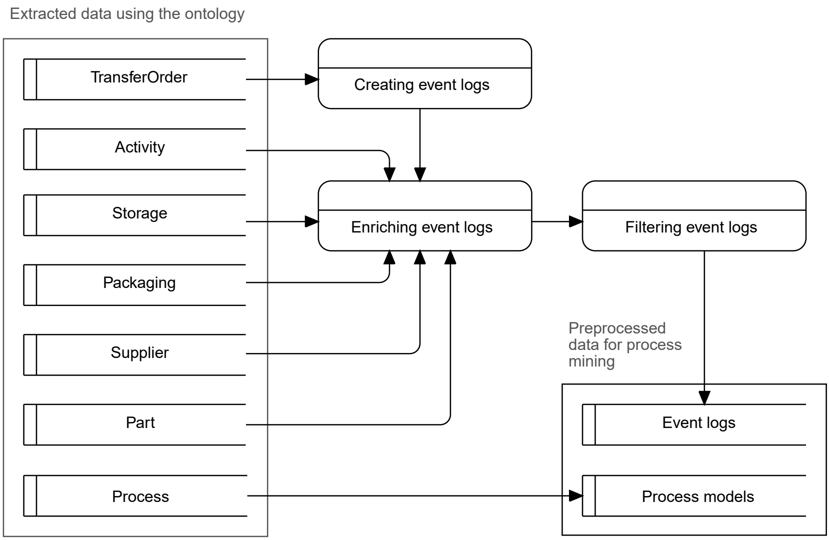


Figure 5.7: Data Flow Diagram (DFD) for preprocessing event logs

[4] To flatten implies to aggregate an existing data model. It is like a tabular view of the complete data set (VAN DER AALST 2016, p. 160).

[5] The DFD models a system as a network of transformations linked by paths of data (GANE & SARSON 1979).

5.2.1 Creating event logs

Enabling process mining requires event logs with a case identifier, an activity, and a timestamp (cf. Section 2.3.2). In contrast, internal logistics does not record an event log explicitly; hence, the event log must be created (cf. KNOLL et al. 2019c).

Preliminary declarations

In internal logistics, the unit load consists of one or many packages that reflect the material flow from goods receipt through to assembly. The unit load provides the basis for the case identifier in internal logistics. Due to the nature of internal logistics, a variety of material flow activities exist. These activities can change the state of the unit load, potentially affecting the composition of the unit load (cf. Section 5.1.1.2). Consequently, the package is used as the traceable object to correlate the event log. An event log is provided for each value stream to adapt multidimensional process mining for internal logistics. (cf. KNOLL et al. 2019c)

> **Definition**. Let the *case identifier* of the event log L be the smallest unit load of a single package for one part (KNOLL et al. 2019c, p. 134).

A transfer order triggers the process and activities that transform the state of the unit load and stores related activity occurrences (events). Both a defined start and completion exist, each with a specific time and location. Consequently, an activity is a class or type of action triggering a collection of material and information flow activities between a specified source and destination location (cf. Section 5.1.1.4).

> **Definition**. Let the *activity* of the event log L be the transformation of a unit load triggering a collection of material and information flow activities between a specified source and destination location (based on KNOLL et al. 2019c).

The time of the activity occurrence (events) is used to specify the timestamp for process mining (cf. Section 5.1.1.4). As every transfer order stores the activity occurrences, both the start and end timestamp can be mapped to the standard transactional life-cycle model of process mining: *start* and *complete*. Further activity occurrences can be extracted if they are available, e.g., the *schedule* event. (VAN DER AALST 2016, p. 131)

> **Definition**. Let the *timestamp* of the event log L be the specific timestamp that the event takes place (based on KNOLL et al. 2019c).

Flattened input data specification

Let the input data λ_{TO} for the algorithm be a tabular representation of the transfer orders including the relationships to (1) the process, (2) the activities and activity occurrences (events), and (3) the unit load, or package, with the part (cf. Table 5.4). The following nomenclature is used to link the flattened input data with the internal logistics ontology: *Class* or *Class_relationType_ClassOrProperty*.

Table 5.4: Flattened input data λ_{TO} of transfer orders

Column	Attribute	Internal logistics ontology
1	transfer_order_id	TransferOrder_has_ID
2	activity_id	Activity_has_ID
3	transfer_order_item	TransferOrder_contains_Part
4	unit_load_batch_id	UnitLoad_has_BatchID
5	part_number	Part_has_Number
6	part_quantity	UnitLoad_has_PartQuantity
7	location_source	Activity_happensAt_ActivityOccurrence
8	location_destination	Activity_happensAt_ActivityOccurrence
9	time_start	Activity_happensAt_ActivityOccurrence
10	time_complete	Activity_happensAt_ActivityOccurrence

A transfer order has a unique identifier (cf. *Column 1*), contains one or many packages enumerated as transfer order items (cf. *Column 3*) and is associated with a specific unit load (cf. *Column 4*). Each transfer order refers to a unique activity identifier that describes a set of material and information flow activities (cf. *Column 2*). A specified source and destination location and a start and complete timestamp exist for each transfer order (cf. *Columns 7-10*). As the traceable unit load, or package, can be correlated, transfer orders also can be correlated. Consequently, a unique identifier is described using the part (cf. *Column 5*), the unit load (cf. *Column 4*), and the source and destination location (cf. *Columns 7-8*). (KNOLL et al. 2019c)

Algorithm specification

In view of the fact that internal logistics has many value streams, the algorithm is designed for multidimensional process mining (cf. Algorithm 1). For this reason, the transfer orders are split into groups according to part numbers. All transfer orders without a successor (e.g., assembly line) are used as a starting point. For each starting point, a *BFS* identifies all leaves in the graph in linear time (KOZEN 1992, p. 19). The path for each leaf to the root reflects the material flow and information flow of an individual package. The event log can be constructed and flattened into the defined case identifier schema using the paths. This reversed-direction search offers the potential to connect any transfer order without setting explicit starting points (e.g., goods receiving). Then, the available life-cycle events are extracted, e.g., start and complete. As a result, an event log is created for each value stream. (KNOLL et al. 2019c, p. 134)

Algorithm 1 Creating event logs (based on KNOLL et al. 2019c, p. 134)

Input: λ_{TO}... Transfer orders

Output: $\langle L_1, ..., L_N \rangle$... Event logs (for N value streams)

procedure CREATEEVENTLOGS
    $\lambda_{TO}(s\_id) \leftarrow \lambda_{TO}(location\_source, unit\_load\_batch\_id, ...)$
    $\lambda_{TO}(d\_id) \leftarrow \lambda_{TO}(location\_destination, unit\_load\_batch\_id, ...)$
    $\lambda_{TO}(item\_count) \leftarrow group(\lambda_{TO}, transfer\_order\_id)$
    $P \leftarrow distinct(\lambda_{TO}(part\_number))$
    for all p in P **do**
        $C \leftarrow filter(\lambda_{TO}, part\_number = p)$
        $case\_id \leftarrow 1$
        for $i \leftarrow 1, filter(C, d\_id = NULL)$ **do**
            $node\_id \leftarrow 1$
            BFS ▷ BFS tree from C(i) where edge (u,v) if $C(u, d\_id) = C(v, s\_id)$
            for all leaf in BFS **do**
                $L_p(case\_id, node\_id) \leftarrow path(leaf, root)$ ▷ path returns visited activities in C
                $node\_id \leftarrow node\_id + 1$
            end for
            $case\_id \leftarrow case\_id + 1$
        end for
        $enumerate(L_p)$ ▷ enumerate *case_ids*
        $lifecycle(L_p)$ ▷ extract available life-cycle events
    end for
    return $\langle L_1, ..., L_N \rangle$ ▷ grouped by value streams
end procedure

5.2.2 Enriching event logs

An event log L can be enriched by creating or computing additional attributes (based on the event log itself) or by attributes derived using external (data) sources using the internal logistics ontology (cf. ECK et al. 2015; KNOLL et al. 2019b).

Preliminary declarations

Enriching event logs always depends on the objectives and analysis questions in the application. Presented attributes are not always required and must be further extended on request. Three steps are required to extend the attributes. Firstly, the internal logistics ontology must be extended, including classes, object properties, and data properties. The object properties specify the relationship within internal logistics, the underlying information systems, and the event log. Secondly, the input data, including an attribute to merge the event log, must be specified. This ensures that the attribute is given both in the event log and in the information system. Thirdly, the algorithm must be extended based on the updated input data.

Flattened input data specification

To specify the input data, a generic set of attributes for the enrichment is clustered according to the top classes of the ontology.

Process. Let the input data λ_A for the algorithm be a tabular representation of the activity (cf. Table 5.5). The unique activity (cf. *Column 1*) can be enriched by a name (cf. *Column 2*), e.g., to include source and destination location. The material flow (cf. *Column 3*) and information flow (cf. *Column 4*) attribute represent the collection of the activities required on the shop floor, reflecting the sub-classes of an activity (cf. *MaterialFlowActivity*, *InformationFlowActivity*). The proposed classification (e.g., rework) is used to differentiate between value-added, non-value-added but required, and non-value-added activities (cf. Section 5.1.1.4).

The cost value (cf. *Column 6*) and the currency are specified (cf. *Column 7*), e.g., monetary or non-monetary effort, to evaluate an activity's effort. For the assessment of the cost value, Activity-based Costing (ABC) or time-driven ABC can be used (VAN DER AALST 2016, p. 86). As a transfer order contains one or multiple packages, the effort must be split and allocated to each individual package. The enumerated number of packages is used for this purpose.

Table 5.5: Flattened input data λ_A of activities

Column	Attribute	Internal logistics ontology
1	activity_id	Activity_has_ID
2	activity_name	Activity_has_Name
3	activity_material_flow	MaterialFlowActivity
4	activity_information_flow	InformationFlowActivity
5	activity_category	Activity_has_Category
6	activity_cost_value	Activity_has_CostValue
7	activity_cost_currency	Activity_has_CostCurrency

Resource. Let the input data for the algorithm be a tabular representation of the storage λ_{ST} (cf. Table 5.6) and the packaging λ_{PG} (cf. Table 5.7) resource. For internal logistics, a storage has a unique identifier (cf. *Column 1*) with a specific location (cf. *Column 2*). One or multiple storage locations can be aggregated into a storage section (cf. *Column 3*). (KNOLL et al. 2019c, p. 133)

Table 5.6: Flattened input data λ_{ST} of storages

Column	Attribute	Internal logistics ontology
1	storage_id	Storage_has_ID
2	storage_location_id	Resource_has_LocationID
3	storage_name	Storage_has_Name
4	storage_section	Storage_has_Section

For internal logistics, each part has its individual characteristics and requires suitable packaging (cf. *Column 1*). The packaging has a unique identifier (cf. *Column 2*) with a set of characteristics (cf. *Columns 3-5*). The flattened input data includes a list of parts, including the packaging specifications. (KNOLL et al. 2019a, p. 576)

Table 5.7: Flattened input data λ_{PG} of packaging

Column	Attribute	Internal logistics ontology
1	part_number	Part_uses_Packaging
2	packaging_id	Packaging_has_ID
3	packaging_name	Packaging_has_Name
4	packaging_type	Packaging_has_Type
5	packaging_size	Packaging_has_Size

Actor. Let the input data λ_{SU} for the algorithm be a tabular representation of the supplier (cf. Table 5.8). For internal logistics, every part is delivered from a supplier that produces the part (cf. Section 5.1.1.7). Furthermore, the supplier has a set of characteristics (cf. *Columns 2-7*).

Table 5.8: Flattened input data λ_{SU} of suppliers

Column	Attribute	Internal logistics ontology
1	part_number	Part_has_Supplier
2	supplier_ID	Supplier_has_ID
3	supplier_name	Supplier_has_Name
4	supplier_address	Supplier_has_Address
5	supplier_zip	Supplier_has_Zip
6	supplier_city	Supplier_has_City
7	supplier_reliability	Supplier_has_Reliability

UnitLoad. Let the input data λ_{PT} for the algorithm be a tabular representation of the part (cf. Table 5.9). For internal logistics, every part can be identified using a unique identifier (cf. *Column 1*). Furthermore, the part has a set of characteristics (cf. *Columns 2-3*). These characteristics are defined for each part individually or inherited from the product component (cf. *ProductComponent*). In addition, a part belongs to a part family (cf. *Column 4*) and has a predefined reference process (cf. *Column 5*) that specifies the sequence of activities (cf. Section 5.1.1.4).

Table 5.9: Flattened input data λ_{PT} of parts

Column	Attribute	Internal logistics ontology
1	part_number	Part_has_Number
2	part_name	Part_has_Name
3	part_value	Part_has_Value
4	part_family_name	Part_belongsTo_PartFamily
5	part_reference_process	Part_has_Process

Algorithm specification

The algorithm uses the event log L and the flattened input data λ_A, λ_{ST}, λ_{PG}, λ_{SU}, λ_{PT} to enrich the event log (cf. Algorithm 2). As the algorithm is designed for multidimensional process mining, the procedure to enrich the event log is applied for each value stream, or part number, separately. The procedure merges the flattened input data with the event log L using the primary attribute, calculates additional attributes, and returns the enriched event log L_e. (cf. KNOLL et al. 2019b,c)

Algorithm 2 Enriching event logs (based on KNOLL et al. 2019b,c)

Input: $\langle L_1, ..., L_N \rangle$... Event logs
Input: λ_A... Activity
Input: λ_{ST}... Storage
Input: λ_{PG}... Packaging
Input: λ_{SU}... Supplier
Input: λ_{PT}... Part
Output: $\langle L_{e,1}, ..., L_{e,N} \rangle$... Enriched event logs

procedure ENRICHEVENTLOGS
  for all L in $\langle L_1, ..., L_N \rangle$ **do**
    $E \leftarrow L(E)$ ▷ set of all events of the event log L
    $part\_number \leftarrow E(part\_number)$
    $E \leftarrow merge(E, \lambda_A, activity\_id)$
    $E(cost\_value) \leftarrow E(cost\_value)/E(item\_count)$ ▷ calculate shared cost ratio
    $E \leftarrow merge(E, \lambda_{ST}, storage\_id)$
    $E \leftarrow merge(E, \lambda_{PG}, part\_number)$
    $E \leftarrow merge(E, \lambda_{SU}, part\_number)$
    $E(supplier\_distance) \leftarrow distance(\lambda_{SU}(part\_number))$
    $E \leftarrow merge(E, \lambda_{PT}, part\_number)$
    $L_e \leftarrow update(L, E)$ ▷ update event log
  end for
  return $\langle L_{e,1}, ..., L_{e,N} \rangle$
end procedure

5.2.3 Filtering event logs

Filtering the event log aims to create the correct view and reduce complexity (ECK et al. 2015). Therefore, irrelevant events, cases, or attributes are removed from the event log. Any attribute available in the event log L_e can be used to apply filtering, and a set of *key-value pairs* $\langle \delta_{1,k,v}, ..., \delta_{n,k,v} \rangle$ is defined in the industrial application.

Preliminary declarations

In contrast to ad hoc filtering using process mining software (cf. Section 5.4.3.1), this section focuses on two aspects of filtering: (1) selecting a sufficient time frame and (2) anonymizing data. For process mining, a sufficient time frame of the event log is required. "The larger the number of records used, the higher the process model's fidelity." (RUSCHEL et al. 2018, p. 6) However, the trade-off between a short and long time frame must be considered. Long-running time frames can reduce the trace fitness and the classification result of reference processes because of concept drifts. To anonymize data, any personal data, such as logistics operators, must be filtered. (KNOLL et al. 2019c, p. 134) Further aspects of data privacy challenges are discussed in the process mining theory (cf. MANNHARDT et al. 2018; PETERSEN et al. 2018).

Algorithm specification

The procedure to filter event logs is shown in Algorithm 3. An extract of the *XES Standard Definition 2.0*[6] for the enriched event log L_e is shown in Table 5.10. Please refer to Appendix A.2.2.1 for additional attributes.

Algorithm 3 Filtering event logs (based on KNOLL et al. 2019c)

Input: $\langle L_{e,1}, \ldots, L_{e,N} \rangle$... Enriched event logs
Input: $\langle \delta_{1,k,v}, \ldots, \delta_{n,k,v} \rangle$... Key-value pairs
Output: $\langle L_{e,1}, \ldots, L_{e,N} \rangle$... Enriched event logs (filtered)

procedure FILTEREVENTLOGS
  for all L_e in $\langle L_{e,1}, \ldots, L_{e,N} \rangle$ **do**
    for all k,v in $\langle \delta_{1,k,v}, \ldots, \delta_{n,k,v} \rangle$ **do**
      $E \leftarrow filter(L_e(E), k = v)$ ▷ filter based on key-value pairs
      $L_e \leftarrow update(L_e, E)$ ▷ update event log
    end for
  end for
  return $\langle L_{e,1}, \ldots, L_{e,N} \rangle$
end procedure

[6] Available at: http://xes-standard.org/_media/xes/xesstandarddefinition-2.0.pdf, requested on May 24, 2019.

Table 5.10: Extract of the enriched event log L_e (Extensible Event Stream (XES) Standard Definition 2.0)

Extension	Level	Key	Type	Description
concept	event	event_id	string	A unique transfer order number, item (part), and batch.
concept	event	activity_id	integer	Activity id.
concept	event	activity_name	string	Activity name including the source and destination location.
concept	event	activity_material_flow	list	A list of material flow activities.
concept	event	activity_information_flow	list	A list of information flow activities.
concept	event	activity_category	string	Value-added or non-value-added activity category.
lifecycle	event	transition	string	Life-cycle of each activity occurrence (event).
time	event	timestamp	date	Date and time of the activity occurrence (event).
cost	event	value	float	Value of a cost.
cost	event	currency	string	Currency of a cost.
packaging	trace	name	string	Name of the packaging.
packaging	trace	type	string	Type of the packaging.
supplier	trace	name	string	Name of the supplier.
supplier	trace	distance	float	Distance of the supplier to the plant.
supplier	trace	reliability	float	Reliability of the supplier.
part	trace	number	string	Unique number of the part.
part	trace	name	string	Name of the part.
part	trace	value	float	Value of the part.

5.3 Mining

This section describes the development of the framework for mining and clustering value streams. The framework is organized into six process mining techniques. In general, the framework requires the results of the data preprocessing (cf. Section 5.2). Depending on the technique, the results of other techniques can be required. For each technique, preliminary declarations are formulated based on the theory of process mining and internal logistics and the requirements of the approach (cf. Section 4.1). Finally, the resulting algorithms are explained using pseudo code.

Figure 5.8 shows the relationship between the preprocessed data for mining, the techniques, and the mined data for the analysis.

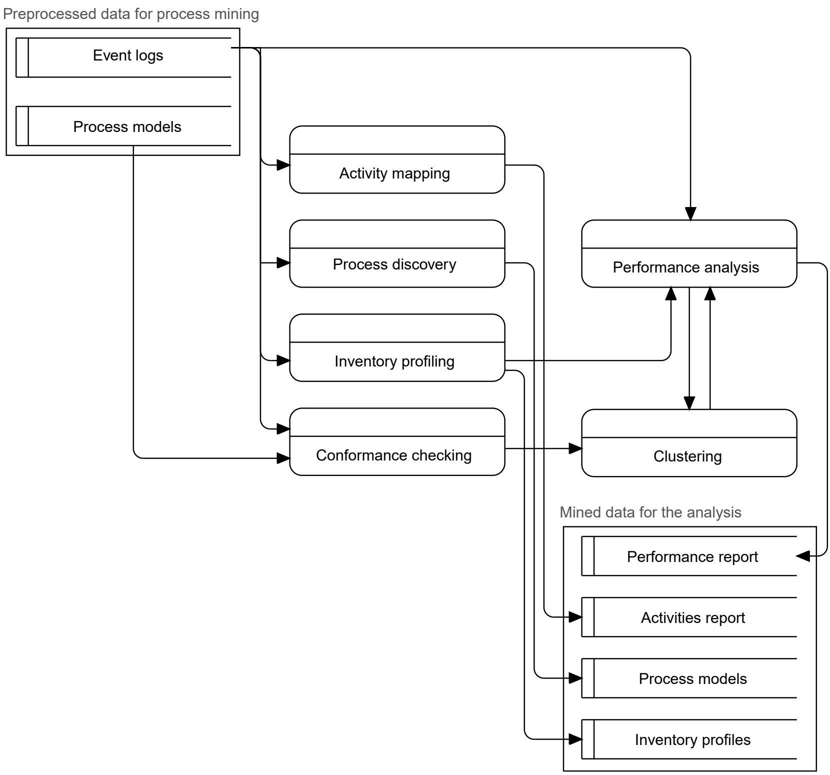


Figure 5.8: Data Flow Diagram (DFD) for mining and clustering value streams

Different process mining techniques, characterized by different maturity levels (cf. Chapter 3), are required to contribute to the overarching goal of the thesis (cf. Section 1.3). Firstly, this work contributes to the literature by adapting multidimensional process mining (cf. Section 2.3.3) to mine each value stream separately. Secondly, this work contributes the following outcomes to the literature:

1. *Process discovery* is the most frequently used process mining technique (cf. Chapter 3), and numerous process discovery algorithms with different characteristics exist (cf. Section 2.3.2). Section 5.3.1 contributes a literature-based evaluation and selection of process discovery algorithms in the context of internal logistics to the literature.

2. *Conformance checking* is another elementary process mining technique (cf. Section 2.3.2). However, conformance checking typically evaluates one event log with one process model. Section 5.3.2 contributes to the literature by developing an algorithm to align and classify part-specific event logs with multiple (reference) process models.

3. *Activity mapping* is a pen-and-paper-based method of lean production introduced by JONES et al. (1997). Section 5.3.3 contributes to the literature by developing an algorithm and selecting metrics to characterize activities.

4. *Inventory profiling*. Process mining has not been used to analyze inventory profiles (cf. Chapter 3). Section 5.3.4 contributes to the literature by developing an algorithm for inventory profiling.

5. *Performance analysis* is another frequently used process mining technique (cf. Chapter 3). In contrast to process discovery and conformance checking, the performance analysis is rather domain-specific than a process mining standard. Section 5.3.5 contributes a literature-based selection of performance metrics to the literature.

6. *Clustering* is an advanced process mining technique (cf. Section 2.3.3), and many applications in the field of logistics and manufacturing have been reported (cf. Chapter 3). Section 5.3.6 contributes to the literature by specifying relevant input features for value stream clustering.

5.3.1 Process discovery

Within process discovery, the process model is derived from the event log without any a priori information about the process (KNOLL et al. 2019c, p. 135).

Preliminary declarations

Process discovery of the control-flow is similar to drawing the current state map in value stream mapping. Both approaches focus on the actual behavior of the process, its activities, and their ordering. Consequently, the current state map can be created using process discovery to identify potential for improvement. (cf. KNOLL et al. 2019c)

> **Practical benefit**. Process discovery enables an in-depth analysis of the value stream, including both value-added and non-value-added activities and their ordering.

From the perspective of value stream mapping, the first step is to choose a part family (ROTHER & SHOOK 1999). In contrast to manufacturing, value streams in internal logistics can be highly individual for each product variant and sub-assembly (cf. Chapter 1). Process discovery implements multidimensional process mining to create a process model for each value stream individually (KNOLL et al. 2019c, p. 135).

Evaluating and selecting process discovery algorithms

Much progress in developing new algorithms has been made in the field of process mining. However, according to VAN DER AALST & WEIJTERS (2004, p. 239), "there is a strong relation between the mining algorithm and the type of problems that can be successfully handled by that algorithm."

Quality performance metrics[7] are used (cf. Section 2.3.2) to evaluate and select suitable process discovery algorithms. For instance, DONGEN et al. (2009) discuss the common assumptions and shortcomings of the algorithms in five categories. Advanced approaches use regression models to evaluate, compare, and rank algorithms (J. WANG et al. 2013) or include the dimensions of the event log to the benchmark (WEBER et al.

[7] An overview of existing metrics in the field of process mining can be found at ROZINAT et al. (2007, p. 9). For further discussions of individual algorithms, please refer to BUIJS et al. (2014), DONGEN et al. (2009), LEEMANS (2017), VAN DER AALST (2016), & VAN DER AALST & WEIJTERS (2004).

2013). However, according to J. WANG et al. (2013), no widely accepted standard to benchmark algorithms exists.

The review of process mining applications in manufacturing and logistics extends process mining theory (cf. Chapter 3). Based on this work, existing process types are characterized, and applied process discovery algorithms are evaluated. Firstly, the cross-analysis of the methodological context in both fields shows a wide range of process types. In internal logistics, analyzed processes include up to ten activities. Furthermore, the product and process complexity result in up to 4.2 million events in one year. In contrast, process types in the manufacturing industry are more complex, including up to 16,250 events per case. Secondly, the case study articles report about numerous algorithms. Most frequently, the heuristic miner is applied. Other publications include the fuzzy miner, the inductive miner, or self-defined algorithms. MEINCHEIM et al. (2017), for example, applied the inductive miner due to its flexibility and scalability. This fragmented picture can be confirmed for both the manufacturing and logistics industries. An exception is BETTACCHI et al. (2016), who completed a benchmark analysis of five process discovery algorithms in the context of the manufacturing industry. To assess the algorithms, BETTACCHI et al. (2016) extended the four quality dimensions of BUIJS et al. (2014) with complexity metrics, e.g., the number of nodes. BETTACCHI et al. (2016) concluded that the inductive miner and the evolutionary tree miner are the most suitable algorithms, and the low computation time of the inductive miner is superior.

The cross-analysis of the review provides three findings. Firstly, a variety of discovery algorithms can be applied for various process types. Secondly, less attention is spent on the selection and evaluation of algorithms. Thirdly, BETTACCHI et al. (2016) propose the inductive miner due to the highest fitness and precision values and high performance.

Consequently, the cross-analysis confirms the findings of process mining theory. In general, no algorithm is suitable for every process type. However, the inductive miner demonstrated its suitability within multiple studies. Due to its robustness and ability to handle large, incomplete event logs with much infrequent behavior (VAN DER AALST 2016, p. 222), the inductive miner is recommended for process discovery in internal logistics (KNOLL et al. 2019c). If required, advanced approaches can be applied to benchmark different algorithms. An example of a value stream mined using process discovery is presented in the industrial application (cf. Figure 6.3).

5.3.2 Conformance checking

Conformance checking evaluates if reality recorded in the event log conforms to the model, and vice versa (VAN DER AALST et al. 2012, p. 175). Deviations of value streams can be measured using reference process models (KNOLL et al. 2019c).

Preliminary declarations

Conformance checking requires the application of one or many reference process models (*de jure models*). It is assumed that a set of reference process models $\langle M_1, ..., M_n \rangle$ exists that can be aligned with activities recorded in the event log L_e. In the following section, three suitable metrics to align and classify an event log L_e with a process model M are proposed and explained (KNOLL et al. 2019c).

> **Practical benefit**. Conformance checking quantifies the alignment between the reference process and the actual behavior of a value stream.

The *fitness* "quantifies the extent to which the process model can accurately reproduce the cases recorded in the event log." (BUIJS et al. 2014, p. 309) "A model has a perfect fitness [equals 1] if all traces in the log can be replayed by the model from beginning to end." (BUIJS et al. 2014, p. 309) Fitness is the most important metric for the algorithm. To illustrate fitness, an event log L with three different traces σ_1, σ_2, σ_3 and a process model M are shown in Figure 5.9. For $\sigma_1 = \langle a, b, c \rangle$, the *fitness*$(\sigma_1, M)$ equals 1.0 because all events of the trace can be replayed on M. For $\sigma_2 = \langle a, b \rangle$, the *fitness*$(\sigma_2, M)$ equals 0.8 because activity c of the process model M is not consumed in the log. For $\sigma_3 = \langle a, b, d \rangle$, the *fitness*$(\sigma_2, M)$ equals 0.67 because in addition to σ_2, the event d is missing in the process model M.

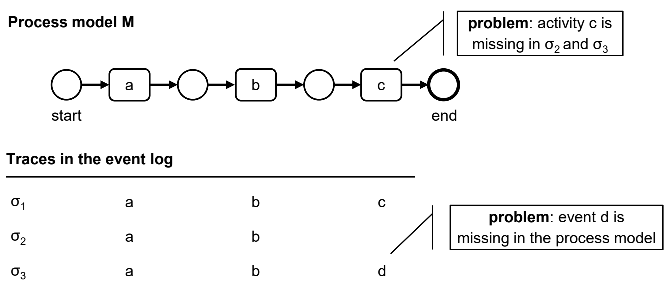


Figure 5.9: Illustration of conformance checking on process model M

Precision "quantifies the fraction of the behavior allowed by the model which is not seen in the event log." (Buijs et al. 2012, p. 306) If all paths in the model can be observed in the event log, the precision equals 1. Assuming that models describe activities of reference processes, precision is the second-most important metric for the algorithm. The *generalization* reflects the likelihood of overfitting. If paths are visited infrequently, the generalization is low (Buijs et al. 2012, p. 309). The generalization is the third most important metric to extend the algorithm.

Algorithm specification

The algorithm uses a set of event logs $\langle L_1, ..., L_N \rangle$ and a set of process models $\langle M_1, ..., M_n \rangle$ to align and classify the best-fitting process model for each value stream. The three metrics are compared for each process model M, and the maximum value is selected (cf. Algorithm 4). The definition of the metrics is based on process mining theory (cf. Appendix A.2.3.1). The temporary results for each value stream (c_f, c_p, c_g) are also used as input for value stream clustering (cf. Section 5.3.6).

Algorithm 4 Aligning and classifying event logs (based on Knoll et al. 2019c, p. 136)

Input: $\langle L_{e,1}, ..., L_{e,N} \rangle$... Event logs (enriched)
Input: $\langle M_1, ..., M_n \rangle$... Process models
Output: $\langle L_{e,1}, ..., L_{e,N} \rangle$... Event logs (enriched, aligned, and classified)

procedure AlignAndClassifyValueStreams
  for all L_e in $\langle L_{e,1}, ..., L_{e,N} \rangle$ **do**
    for all M in $\langle M_1, ..., M_n \rangle$ **do**
      $c_f(M) \leftarrow fitness(L_e, M)$
      $c_p(M) \leftarrow precision(L_e, M)$
      $c_g(M) \leftarrow generalization(L_e, M)$
    end for
    $i_{max} \leftarrow argmax(c_f, c_p, c_g)$ ▷ ordered by c_f then c_p then c_g
    $E(M) \leftarrow (M(i_{max}), c_f(i_{max}))$
    $L_e \leftarrow update(L_e, E)$ ▷ update event log
  end for
  return $\langle L_{e,1}, ..., L_{e,N} \rangle$
end procedure

5.3.3 Activity mapping

Activity mapping aims to analyze occurring activities, both material and information flow, independently of reference processes and value streams (KNOLL et al. 2019c).

Preliminary declarations

JONES et al. (1997) developed a general approach to analyze activities to eliminate unnecessary activities and simplify others to reduce waste. The authors manually recorded activities, including a set of relevant metrics, e.g., total time taken or the type of activity (operation, transport) (JONES et al. 1997, p. 162). The proposed approach supports these steps using process mining (KNOLL et al. 2019c).

> **Practical benefit**. Activity mapping analyzes every activity occurrence to identify value-added and non-value-added activities across processes and value streams.

Activity mapping proposes a set an initial set of metrics (KNOLL et al. 2019c, p. 133):

- *Frequency* is the number of activity occurrences of an activity within a specific time frame (KNOLL et al. 2019c, p. 133).
- *Processing time* is the difference between the start and completion of an activity. The life-cycle attribute that distinguishes the start from completion and the associated timestamps are required to measure the duration of activities (VAN DER AALST 2016, p. 135).
- *Waiting time* is the time required for a resource to become available and begin the activity (VAN DER AALST 2016, p. 86). The completion time of the predecessor activity occurrence is required to measure the waiting time. If no predecessor exists, the waiting time is zero.

If further details are required, in particular about material flow activities, activity mapping can be extended. For this, KNOLL et al. (2019c) propose five additional metrics to characterize the material flow. The modification of part quantities of a unit load, for instance, is used to differentiate between collect and distribute activities. Then, KNOLL et al. (2019c) mapped the metrics against generic material flow activities (cf. Section 5.1.1.4). Please refer to KNOLL et al. (2019c, pp. 133–134) for the specification of the additional metrics.

Algorithm specification

The algorithm uses a set of event logs $\langle L_{e,1},\dots,L_{e,N}\rangle$ to map the activities. The processing and waiting times are calculated on an event log level. This calculation is necessary to determine the predecessor, if available. Then, activities $\langle A_1,\dots,A_n\rangle$ in the event universe E of all event logs are processed separately. These events are removed to avoid double counting of duplicate events introduced during the creation of event logs. Finally, the values are reduced to average and variance for the activities report (cf. Algorithm 5).

Algorithm 5 Activity mapping (based on KNOLL et al. 2019c, p. 134)

Input: $\langle L_{e,1},\dots,L_{e,N}\rangle$... Event logs (enriched)
Output: $\langle A_1,\dots,A_n\rangle$... Activities

procedure MAPACTIVITIES
  for all L_e in $\langle L_{e,1},\dots,L_{e,N}\rangle$ **do**
    $E \leftarrow L_e(E)$ ▷ set of all events of the event log L_e
    $E(processing) \leftarrow E(complete) - E(start)$ ▷ timestamps
    if predecessor **then**
      $E(waiting) \leftarrow E(start) - E_{pre}(complete)$ ▷ timestamps
    else
      $E(waiting) \leftarrow 0$
    end if
    $L_e \leftarrow update(L_e, E)$ ▷ update event log
  end for
  $E \leftarrow \langle L_{e,1},\dots,L_{e,N}\rangle$ ▷ set of all events of all event logs
  for all A in E **do**
    $E_A \leftarrow filter(E, activity = A)$
    $E_A \leftarrow remove\_duplicates(E_A)$ ▷ remove duplicate events
    $\delta_A \leftarrow reduce(E_A(processing), E_A(waiting))$ ▷ average and variance
    $A \leftarrow length(E_A), \delta_A$
  end for
  return $\langle A_1,\dots,A_n\rangle$
end procedure

5.3.4 Inventory profiling

Inventory profiling creates the actual inventory profile of a value stream based on the event log. Like process discovery, the actual behavior of the inventory is modeled without any a priori information.

Preliminary declarations

Many inventory models designed to reduce inventory have been established in theory and industry. What they have in common is modeling the inventory history for each part over time (e.g., NYHUIS & WIENDAHL 2009). In industry, where thousands of parts have individual value streams (cf. Chapter 1), modeling the actual inventory (i.e., not assumed inventory) can be challenging. The proposed approach aims to create the inventory profile of a value stream based on the event log.

> **Practical benefit**. Inventory profiling enables an in-depth analysis of the actual inventory history over time.

It is assumed that any activity available in the event log can be classified into (1) a *goods receiving activity* that increases the inventory, (2) an *internal logistics activity* not affecting the inventory, and (3) an *outgoing goods activity* that decreases the inventory. Furthermore, any event includes the actual part quantity (cf. Section 5.1.1.4).

It is assumed that an event log with a fixed time window exists, and events outside the time window can occur (cf. Section 2.3). Then, the event log can be discretized in k time-intervals $\delta t_1, ..., \delta t_k$. To determine k, the first and last event and the required precision (e.g., 1 day) are used. Thereupon, the cases can be classified into four scenarios:

1. *Missing goods receiving activity*. The start event of a case is not available. It is assumed that the case (package) entered the logistics system before the start date.
2. *Complete case*. The start and end event of a case are available. It is assumed that the complete case is observed within the event log.
3. *Missing outgoing goods activity*. The end event of a case is not available. It is assumed that the case (package) remains in the logistics system.
4. *Hidden case*. The scenario that both the start and end events are outside the time frame, before or after, is not considered.

The part quantities or cases in the event log can be used to create the inventory profile.

- *Quantity level*. This perspective uses relative inventory movements: quantities of incoming goods are added, and quantities of outgoing goods are subtracted. While the computation is simple, the absolute level of inventory remains unknown.
- *Case level*. This perspective evaluates the number of active cases for each discretization step. A case is active as long as the case is not completed by an end event. The absolute measurement of inventory levels can be enabled.

The inventory profile uses the case level. However, three limitations remain:

- *Discretization error*. In general, a case is active for the complete time-interval δt, e.g., from 00:00 to 23:59 for $\delta t = 1 day$. This error exists for all k resulting in δt larger than the precision of the timestamp (e.g., 1 second). However, the discretizing event logs simplify the procedure and (process) model (TSAI et al. 2010, p. 57). Therefore, a simplification is implemented: a case is active for δt of the goods receiving activity and inactive for δt of the outgoing goods activity.
- *Hidden cases*. If no start and end events exist, no active case can be created artificially, even if a package might be on stock. Using a sufficient time frame (e.g., several months) and evaluating value streams with few events in detail is recommended.
- *Simplified logistics system*. Inventory profiling aggregates multiple storage locations to one logistics system. This aggregation helps to assess the required inventory, but process-related restrictions must be considered (e.g., required buffers that introduce additional inventory).

Algorithm specification

The algorithm uses a set of event logs $\langle L_{e,1}, ..., L_{e,N} \rangle$ to create the inventory profile IP for each value stream (cf. Algorithm 6). Firstly, the *quantity statement* is calculated for each unit load received at goods receiving. For internal logistics, the state of the unit load can be modified by material flow activities, e.g., splitting a unit load into smaller packages (cf. Section 5.2.1). Consequently, active cases can include different sizes (e.g., pallet and package). Therefore, all cases must be normalized to the smallest unit load of a single package. Secondly, *artificial cases* are created for the remaining quantities to normalize cases. An artificial case includes a start and an end event. The start is inherited from the event related to the goods receiving activity, and the end event is set to the end of the event log. Subsequently, every case in the event log reflects the smallest unit load of a single package. Thirdly, to address incomplete cases, *artificial events* are created to complete cases. An artificial start event (cf. Scenario 1) or an end event (cf. Scenario 3) is created for each incomplete case. Scenario 2 does not require further modifications. Subsequently, every case in the event log is complete. Fourthly, the *actual inventory profile* is calculated. The event log is transformed into an empty matrix where: (1) the rows reflect the total number of cases, and (2) the columns reflect the k time-intervals. For each case, the matrix elements of the discretized start event δt_{start} and end event δt_{end-1} are set to 1, including the range between the events. Finally, the inventory profile IP is the column sum for each $\delta t_1, ..., \delta t_k$. Algorithms to create the demand profile DP and goods receiving profile RP are shown in the Appendix A.2.3.2.

Algorithm 6 Creating the inventory profile

Input: $\langle L_{e,1}, ..., L_{e,N} \rangle$... Enriched event logs
Input: k... Time-intervals
Output: $\langle IP_1, ..., IP_N \rangle$... Inventory profiles

procedure CREATEINVENTORYPROFILE
  for all L_e in $\langle L_{e,1}, ..., L_{e,N} \rangle$ **do**
    $C \leftarrow group(L_e(case\_id, date), min, max)$
    $C(offset\_start) \leftarrow C(min - min(L_e(date)))$ ▷ based on k
    $C(offset\_end) \leftarrow C(max(L_e(date)) - max))$ ▷ based on k
    for all e in filter($L_e, category = goods\_receiving$) **do**
      $q = e(quantity) - sum(filter(L_e, outgoing\_goods), quantity)$ ▷ calculate the remaining part quantity of a unit load
      if q > 0 **then**
        $C \leftarrow artificial\_cases(q)$ ▷ add artificial cases
      end if
    end for
    $A \leftarrow matrix\_zeros(len(C), k)$
    for all c in C **do**
      if unable to find start event in C **then**
        $c \leftarrow artificial\_event(min(L_e(date))$ ▷ based on k
      end if
      if unable to find end event in C **then**
        $c \leftarrow artificial\_event(max(L_e(date))$ ▷ based on k
      end if
      $A(c, c(offset\_start, offset\_end - 1)) \leftarrow 1$ ▷ including the steps in between
    end for
    $IP \leftarrow column\_sum(A)$
  end for
  return $\langle IP_1, ..., IP_N \rangle$
end procedure

5.3.5 Performance analysis

Performance analysis provides a holistic view of all value streams. The event log and the results of other process mining techniques are aggregated statistically.

Preliminary declarations

Performance measurement is the process of quantifying the efficiency and effectiveness of action using metrics (NEELY et al. 1995, p. 80). Measurement is important to identify success, whether the customer needs are met, to identify problems and waste, to ensure fact-based decisions, and that improvements actually happen (PARKER 2000, p. 63).

> **Practical benefit**. Performance analysis uses the results of process mining techniques to create an aggregated and holistic picture of all value streams.

Process mining applications in manufacturing and logistics demonstrate the benefits of performance analysis. However, the extent of the analysis and the set of metrics is far from standard (cf. Chapter 3). In contrast, value stream mapping provides a set of frequently applied metrics (ROMERO & ARCE 2017; SHOU et al. 2017). Furthermore, performance metrics have been extensively discussed in the literature (e.g., CAPLICE & SHEFFI 1994; GUNASEKARAN & KOBU 2007). These research streams are briefly discussed and summarized to propose an initial set of metrics (cf. Table 5.11).

The literature review of SHOU et al. (2017) identified 36 metrics frequently used when applying value stream mapping. Most frequently, the cycle time, lead time, and inventory are applied. In general, 19 of the 36 metrics relate to production efficiency. The review of ROMERO & ARCE (2017, p. 1078) confirms these findings and highlights the lead time. Further metrics related to internal logistics include the processing time, waiting time, transportation, and rework and defects (non-value-added activities). Second most, financial metrics are used, e.g., the non-value-added cost. These metrics focus on the process and day-to-day perspective. (SHOU et al. 2017, p. 3911)

The literature review of GUNASEKARAN & KOBU (2007) identified 27 key performance metrics and the authors conclude that there is no shortage of performance metrics. Time and productivity dimensions have significant weight. “While financial performance measures are important for strategic decisions, day-to-day control of manufacturing and distribution operations is better handled with non-financial measures.” (GUNASEKARAN & KOBU 2007, p. 2828) A study with 121 manufacturing executives confirms the importance of non-financial metrics (FULLERTON & WEMPE 2009, p. 232). Non-financial metrics are an integral component of a lean production system (DURDEN et al. 1999). Nevertheless, a balanced presentation of both financial and operational measures can be useful (KAPLAN & NORTON 1992, p. 71). The literature review of SANTOS et al. (2016, p. 339) identified the key financial metrics of transportation, inventory, storage or material handling costs, and administrative costs for logistics. Useful performance metrics depend on the nature of the production system and must be tailored to individual organizations (GUNASEKARAN & KOBU 2007).

Table 5.11: Relevant performance metrics in the context of internal logistics (based on GUNASEKARAN *&* KOBU *2007;* ROMERO *&* ARCE *2017;* SANTOS *et al. 2016;* SHOU *et al. 2017)*

Nature of measurement	Category	Metric
Non-financial	Efficiency	Lead time
Non-financial	Efficiency	Inventory
Non-financial	Efficiency	Processing time
Non-financial	Efficiency	Waiting time
Non-financial	Effectiveness	Conformance to specifications
Non-financial	Effectiveness	Transportation
Non-financial	Effectiveness	Rework
Non-financial	Effectiveness	Defect
Financial	Cost	Transportation costs
Financial	Cost	Inventory costs
Financial	Cost	Storage / handling costs
Financial	Cost	Scrap / defect costs
Financial	Cost	Administrative costs

In contrast, process mining applications have rarely integrated these findings and performance metrics. Typically, the frequencies and lead times (duration) of processes and activities have been analyzed (cf. Chapter 3). Existing articles focused on the technical perspective (e.g., number of cases or fitness value) without relating the findings to the business. Consequently, a gap exists between applied metrics in the field of process mining and established performance metrics.

Performance metrics can be calculated or aggregated on the activity level (e.g., duration of an individual activity), case level (e.g., cost of a case), and event log level (e.g., number of cases in a specific time frame). The average (mean), variance (standard deviation), median, and minimum and maximum values can be used to aggregate the metrics. Performance metrics can also be absolute (e.g., number of cases) or relative (e.g., ratio of quality activities).

Non-financial efficiency metrics

- The *lead time* (duration) is the total time from the creation of the case to its completion (VAN DER AALST 2016, p. 86). The lead time is collected for each case and aggregated on the event log level for each value stream.
- The *processing time* of a case is the sum of the processing times for all activities (cf. Section 5.3.3). The processing time is collected for each case and aggregated on the event log level for each value stream.
- The *waiting time* of a case is the sum of the waiting times for all activities (cf. Section 5.3.3). Thus, the waiting time is collected for each case and aggregated on the event log level for each value stream.
- *Demand* is the number of cases within a normalized time-interval (e.g., one day). The demand is calculated for each time-interval and aggregated (e.g., mean) for each value stream. (KNOLL et al. 2019c, p. 135)
- *Delivery* (frequency) is the number of cases entering the system within a normalized time-interval (e.g., one week). Similar to the demand, the deliveries are summarized on the event log level for each value stream.
- *Inventory*. The number of active cases reflects the inventory on stock. In general, inventory can be separated into cycle-stock and safety stock. To evaluate the safety stock, absolute inventory, and relative inventory metrics, i.e., range on the delivery day to cover the upcoming demand, are used. To evaluate the cycle-stock, the ordered quantities Q can be compared to JIT ($Q = 1$), which results in waste of $Q/2 - 1/2$. The inventory metrics are collected for each time-interval and aggregated on the event log level for each value stream.

Non-financial effectiveness metrics

- *Conformance checking*. The (highest) trace fitness is used to measure deviations from the reference process (cf. Section 5.3.2). If required, the fitness related to other reference processes can be evaluated, e.g., to separate concept drifts from systematic failures. Then the trace fitness is provided for each value stream.

- *Non-value-added activities*. The activity categories are used to determine the root causes of deviations. Relative and absolute activity occurrences can be calculated for each case in each activity category. Then the metrics are aggregated for each activity category and on the event log level for each value stream.

Financial cost metrics

- *Activity costs*. The activity costs reflect the effort to complete an activity. ABC or time-driven ABC can be used to assess the costs (cf. Section 5.2.2).
- *Inventory costs*. The inventory costs reflect all costs to hold the inventory, e.g., the capital costs or storage space costs.

5.3.6 Clustering

Clustering aims to identify groups of similar instances to reduce the complexity of the analysis. In this section, *value stream clustering* is proposed to identify groups of value streams, e.g., those with high costs due to rework activities.

Preliminary declaration

Value stream clustering is a domain-specific extension that covers product and process complexity. It is assumed that this complexity prevents analysis of each value stream separately, e.g., performing process discovery.

> **Practical benefit**. Clustering provides support for the analysis to identify systematic issues related to both (reference) processes and value streams.

The review identified a variety of modifications of trace clustering (cf. Chapter 3), including the time perspective (e.g., cycle time), the organizational perspective (e.g., workshop resources), or the case perspective (e.g., cargo types). These modifications demonstrate the benefits of domain-specific characteristics for clustering in the field of manufacturing and logistics. Value stream clustering aims to identify domain-specific groups of value streams in internal logistics. Therefore, value stream clustering maintains the relationships of value streams and event logs.

Definition. Let a value stream profile be a set of features $\langle f_1, ..., f_n \rangle$ that maps the characteristics of a value stream.

It is assumed that the results of performance analysis provide a set of suitable metrics to create value stream profiles. Hence, the proposed metrics are discussed in terms of value stream clustering.

- *Non-financial efficiency metrics*. Lead time, demand, and inventory can be used to separate value streams. Those established metrics of value stream mapping provide a set of initial metrics. Additional metrics can be specified in the application, such as minimum, average, and maximum inventory.
- *Non-financial effectiveness metrics*. Conformance checking and non-value-added activities are both suitable for separating value streams. Conformance checking findings for the three quality performance metrics are used (cf. Section 5.3.2) for value stream clustering. Notably, multiple values of each metric (*top-n*) can be integrated, e.g., the highest three fitness values (*top-3 fitness*). Then, different types of deviations can be separated (e.g., systematic failures from concept drifts). Relative occurrences of non-value-added activities are used to separate the underlying root causes (e.g., to derive a rework cluster).
- *Financial cost metrics*. The financial cost metrics provide an extension to both efficiency and effectiveness metrics. If combined, the economic impact of deviations can be used to focus on costly clusters.

In any case, clustering algorithms require comparable features, so normalization of the input features $\langle f_1, ..., f_n \rangle$ is required. On the one hand, this affects dynamics over time, e.g., normalize the total quantity in a specific period to a quantity per day. On the other hand, absolute values must be normalized to relative values, e.g., the maximum is reduced to 1.

Algorithm specification

Numerous clustering algorithms exist in the data mining field. The *k-means* algorithm is frequently used because of its robustness and simplicity. Many methods can be used (e.g., *elbow method* or *gap statistics*) to determine the number of clusters. (cf. KODINARIYA & MAKWANA 2013) A set of value stream profiles is created and used as input features for the clustering algorithm.

5.4 Analysis and evaluation

This section describes the reference model and the eight practical guidelines that support the analysis (cf. Section 4.4.4). Firstly, the literature-based development of the analysis is described in Section 5.4.1. Secondly, the reference model for the analysis is presented in Section 5.4.2. Thirdly, the eight practical guidelines for the analysis are explained in detail (cf. Section 5.4.3).

5.4.1 Literature-based development of the analysis

The literature-based development of the analysis is conducted in four steps. Firstly, the preliminary declarations outline how support can be provided. Secondly, the reference model for the analysis is developed. Thirdly, a generic set of properties to model the guidelines is defined. Fourthly, the eight guidelines are modeled in detail.

Step 1: Outlining preliminary declarations

The analysis is problem-, objective-, and application-specific. The scope may be introduced by what it is not and how practical support can be provided. Firstly, the analysis always depends on the analysis questions and objectives (e.g., types of waste); it should not be a prescriptive, step-by-step procedure. The practical guidelines must be loosely coupled and can be iteratively combined or skipped. Secondly, the analysis cannot be complete. The reference model for the analysis must be set up initially and must be capable of evolving over time as new information is acquired. Thirdly, the analysis does not aim to identify the most wasteful value streams (e.g., accumulating different types of waste) but instead aims to identify the potential for process improvement. Assuming that different types of waste are introduced by different causes, the guidelines must address different types of waste and causes separately. In conclusion, the analysis cannot be too prescriptive and must be flexible and extendable.

The review reveals research opportunities (cf. Section 3.4). In general, the integration of process mining (e.g., techniques) and lean production theory (e.g., types of waste) is required. In addition, the synthesis of lessons learned (e.g., potential issues) increases support. Standardizing the practical guidelines with reusable properties (e.g., objectives) helps to ensure that the analysis will be beneficial.

> **Practical benefit**. The reference model and the practical guidelines for the analysis provide support by integrating process mining with lean production theory and the main objective of eliminating waste.

Step 2: Developing the reference model for the analysis

Relevant articles were selected based on the evaluation in the review (cf. Chapter 3) to develop the *reference model for the analysis*. The steps suggested in the articles were extracted, mapped, and clustered into *practical guidelines for the analysis*. Theoretical process mining perspectives were used as main categories (e.g., time perspective) to guide this procedure, and the variety of analysis steps was reduced according to their added value and frequencies of occurrence. The mapping of 12 resulting articles to the guidelines can be found in Appendix A.2.4.1. Next, the established types of waste were mapped to the practical guidelines based on the case studies, process mining theory, and logical reasoning. The relationships between the practical guidelines were defined to complete the reference model. The reference model is defined as an Activity-based DSM that can be extended at any time to ensure flexibility. The reference model for the analysis consists of eight practical guidelines and is presented in Section 5.4.2.

Step 3: Defining a generic set of guideline properties

Before the practical guidelines for the analysis are modeled in detail, generic guideline properties are defined. The initial set of six properties provides the structure for each practical guideline in Section 5.4.3. This initial set can be extended depending on the requirements in the application, for example, by adding organizational properties.

- *Objective: "What is the objective of the guideline?"* The objective property ensures that every analysis has a clear objective that provides a practical benefit. A generic formulation should be preferred, e.g., identify value streams with oversized inventories, to ensure the re-usability of a practical guideline.

- *Lean production: "How is the guideline related to lean production?"* The lean production property links the practical guideline to lean production theory. Consequently, the property extends the objective with established types of waste (e.g., waste of inventory). Based on this property, application-specific analysis questions can be mapped to the practical guidelines.

- *Process mining: "Which process mining perspectives, techniques, and metrics are applied?"* The process mining property links the practical guideline to process mining theory. This includes the process mining perspective (e.g., control-flow), techniques (e.g., conformance checking), and metrics (e.g., trace fitness). Aside from the control-flow and time perspective, the case perspective enhances the understanding of any analysis, at least in theory. Therefore, the case perspective will not be specified in detail. Please refer to the internal logistics ontology (cf. Section 5.1.1).

- *Description: "Which steps are performed during the analysis?"* The description property specifies instructions about steps that can be conducted during the analysis. In particular, this includes top-down prioritization rules according to metrics (e.g., first quartile of the trace fitness) or an in-depth analysis (e.g., a discovered process model of a specific value stream). The description property helps to ensure the analysis is standardized and repeatable.

- *Potential issues: "Which potential issues should be taken into account?"* This property addresses potential issues of the practical guideline and the analysis and reflects lessons learned and issues from previous case studies.

- *Continue with: "What are the next steps?"* This property proposes the next steps after completing the analysis using the practical guideline. In addition to the reference model, this property focuses on evaluating the findings, for instance, with further validation steps on the shop floor.

Step 4: Modeling the practical guidelines for the analysis

Twelve articles and personal experiences of the author of this thesis were used to model the eight practical guidelines in detail. The practical guidelines developed for the analysis are presented in Section 5.4.3.

5.4.2 Reference model of the analysis

The reference model for the analysis consists of eight practical guidelines. The rows and columns reflect the practical guidelines, and the relation specifies the flow: *Practical guideline* "*type of relation*" *Practical guideline* (cf. Figure 5.10). For instance, *Filtering "reduces the complexity (for the)" process discovery.*

			Control-flow perspective		Time perspective				
	Filtering	**Clustering**	**Conformance checking**	**Process discovery**	**Lead times / frequencies**	**Bottleneck analysis**	**FIFO analysis**	**Inventory analysis**	**Lean production waste**
Filtering	combine	reduce complexity	reduce complexity	reduce complexity	reduce complexity	reduce complexity	reduce complexity	reduce complexity	-
Clustering	-	-	-	identify clusters	identify clusters	-	-	-	-
Conformance checking	-	input feature	-	focus on process variants / value streams	-	-	-	-	-
Process discovery	-	-	-	-	extend by	extend by	-	-	Transportation, motion and over-processing
Lead times / frequencies	-	input feature	-	focus on process variants / value streams	-	focus on activities	focus on process variants	focus on value streams	-
Bottleneck analysis	-	-	-	-	-	-	-	-	Waiting
FIFO analysis	-	-	-	-	-	-	-	-	Waiting
Inventory analysis	-	-	-	-	-	-	-	-	Inventory

Figure 5.10: Reference model for the analysis (reading down a column reveals input sources, reading across a row indicates output sinks)

5.4.3 Practical guidelines for the analysis

This section describes the eight practical guidelines for the analysis. Each practical guideline provides an analysis objective, the link to lean production, the process mining technique(s), the analysis description, potential issues and lessons learned, and the relation to other practical guidelines (cf. Section 5.4.1).

5.4.3.1 Filtering

Objective. Including or excluding value streams based on the control-flow (e.g., activity), time (e.g., duration), and case perspective (e.g., attribute).

Lean production. Not related to lean production.

Process mining. Filtering (control-flow perspective, time perspective, case perspective) or process discovery (noise filter).

Description. Once an event log is created, it is typically filtered, which is an iterative process (VAN DER AALST 2016, p. 128). Filtering can be applied during preprocessing or ad hoc in the process mining software (VAN DER AALST 2016). Filtering can be applied multiple times and for each process mining perspective.

In the case perspective, enriched attributes in the event log are used to filter value streams: for internal logistics, different reference processes or clusters (e.g., KNOLL et al. 2019c; S.-k. LEE et al. 2013; Y. WANG et al. 2014a,b), storages (e.g., VAN CRUCHTEN & WEIGAND 2018; Y. WANG et al. 2018), and part-specific or supplier-specific attributes (e.g., ER et al. 2015a,b). Depending on the analysis questions, application-specific attributes can be extended in the internal logistics ontology, enriched into the event log, and then used for filtering.

In the control-flow perspective, either activity-independent filtering, i.e., to remove noise, or activity-based filtering, i.e., a process must contain a specific activity, can be applied (e.g., ER et al. 2015b; PASZKIEWICZ 2013). A refinement of the activity-based filtering is to remove incomplete cases that do not contain both start and end activity (e.g., LIIV & LEPIK 2014; Y. WANG et al. 2014a).

In the time perspective, cases are usually filtered using lead times and frequencies (e.g., ER et al. 2015a; KNOLL et al. 2019c). The statistics of the event log are used to separate main flows from infrequent variants or high lead times from low lead times. Additionally, the time frame of the event log (e.g., a certain period of the year) can be filtered (e.g., Y. WANG et al. 2014a).

Potential issues. Filtering is a simple technique to reduce the complexity of the analysis. However, a priori understanding of the value streams and related attributes is required. Furthermore, removing complete cases can hide specific problems.

Continue with. Any practical guideline.

5.4.3.2 Clustering

Objective. Find process variants of similar value streams (groups of instances) using clustering algorithms (based on VAN DER AALST 2016).

Lean production. Not related to lean production.

Process mining. Trace clustering and value stream clustering.

Description. Depending on the analysis question, either trace clustering or value stream clustering is suitable. Trace clustering uses cases without the context of the value stream to identify process-specific deviations that are independent of individual value streams. Frequent error patterns during the process execution can be identified independently of the value stream. In contrast, value stream clustering maintains the context of the value stream to identify value-stream specific deviations. For instance, value streams with unnecessary transports caused by quality defects can be clustered.

Both clustering types can be applied for the control-flow and the time perspective. In the control-flow perspective, the activities are used to discover different process variants (S.-k. LEE et al. 2013; Y. WANG et al. 2014a,b). In the time perspective, the frequency or cycle-time can be used (BECKER & INTOYOAD 2017). Typically, the time perspective extends the control-flow perspective. For value stream clustering, in particular, the frequencies of activity categories utilize domain-specific characteristics.

Potential issues. Clustering is an advanced technique that requires expert knowledge. Typically, several iterations can be required to determine the number of clusters and suitable perspectives, or input features. Statistical methods, the *gap statistic method*, for instance, can be used to derive the number of clusters (TIBSHIRANI et al. 2001).

Alternatively, work on trace clustering suggested maximizing the quality performance metrics to determine an optimal number of clusters (BOSE & VAN DER AALST 2009, 2010). Depending on the heterogeneity of the value streams, clustering should begin by focusing either on the control-flow or time perspective.

Continue with. Process discovery or lead times/frequencies (for each process variant).

5.4.3.3 Conformance checking (for each process variant)

Objective. Quantify and diagnose deviations by comparing the reality with the process model (e.g., reference process) (VAN DER AALST et al. 2012, p. 175).

Lean production. Not related to lean production.

Process mining. Conformance checking (trace fitness metric). In the case of multiple process variants, use the trace fitness metric for each value stream, grouped by the process variant in a box plot (e.g., in a box plot diagram).

Description. Conformance checking evaluates if reality, as recorded in the event log, conforms to the model, and vice versa (VAN DER AALST et al. 2012, p. 175). The alignment of the control-flow (e.g., skipped or additional activities) is measured as the trace fitness value using process models. Subsequently, this technique can be used to prioritize value streams but does not explain the root causes. If multiple process variants (e.g., reference processes) exist, the trace fitness is calculated for each value stream (cf. Section 5.3.2) and grouped by the process variant. Different process variants can be compared to systematically prioritize value streams when they are visualized in a box plot.

In general, a trace fitness of 1.0 represents a perfect alignment without any deviation. Therefore, a low trace fitness indicates a potential waste of unnecessary movement, transportation, and over-processing. If applied to multiple process variants, a low median value of a variant indicates process variability and instability. A short box plot indicates a systematic issue in the process, and a tall box plot indicates unstable processes (or part-specific issues of value streams). In contrast, a high median value (close to 1.0) indicates a high degree of standardization. (cf. KNOLL et al. 2019c)

Economic attributes (e.g., costs) of the process variants can be added to enhance the conformance checking. Consequently, individual value streams or process variants (e.g., reference processes) can be prioritized for a detailed analysis.

Potential issues. A process model is required (e.g., reference process) to apply conformance checking. In general, incomplete cases reduce trace fitness because activities are skipped. The trace fitness can only be used to compare value streams to each other relatively and not absolutely. Furthermore, in the case of a low number of cases in a value stream, the effect is strengthened. A threshold of a minimum of three cases for each value stream can be defined to overcome this potential issue. Another potential issue is concept drift, e.g., a manufacturing change that results in a change of the reference process within the time frame of the event log.

Continue with. Process discovery of value streams or process variants with a low (median) trace fitness. In the case of a tall box plot (high variance), trace clustering can be useful to identify different patterns.

5.4.3.4 Process discovery

Objective. Create a process model of the material and information flow of value stream(s) without a priori information (KNOLL et al. 2019c; VAN DER AALST 2016).

Lean production. Waste of unnecessary movement, transportation, and overprocessing. If combined with the time perspective: waste of waiting and (possibly) inventory.

Process mining. Process discovery, extended with the time perspective (frequencies, processing, and waiting times).

Description. A process discovery algorithm derives a process model based on the event log such that the model is "representative" for the behavior seen in the event log (VAN DER AALST 2016, p. 163). Process discovery can be used to identify and explain deviations and completes the conformance checking. In the case studies, the focus of process discovery is either set on the main flow and its efficiency or on infrequent and exceptional behavior. In both cases, the extension of the time perspective (e.g., frequencies or duration) is required.

The case studies reported three different patterns of unnecessary movement, transportation, and over-processing. Firstly, *multiple executions of the same activity* (non-value-added activities). Examples are a re-location in storage or sending material backward and forward between different storages (e.g., KNOLL et al. 2019c; S.-k. LEE et al. 2013; PASZKIEWICZ 2013; VAN CRUCHTEN & WEIGAND 2018; Y. WANG et al. 2014b). Secondly, the case studies highlight *additional, non-value-added activities*. Most often, additional quality activities were uncovered in the process discovery (e.g., ER et al. 2015a,b; KNOLL et al. 2019c; PASZKIEWICZ 2013). Also, rework, damaged pallets and unknown activities were identified (KNOLL et al. 2019c; PASZKIEWICZ 2013; VAN CRUCHTEN & WEIGAND 2018). Thirdly, *missing activities* at the beginning or end or skipped activities are reported: for instance, a scheduled quality check is missing (ER et al. 2015b; PASZKIEWICZ 2013) or skipped storage activities caused by urgent orders (KNOLL et al. 2019c).

Potential issues. If not combined with filtering, the product and process complexity can result in a complex process model that is difficult to analyze. The importance of infrequent process variants can be overestimated: use the time perspective to focus on the main paths (frequency) or costly paths. Process discovery algorithms remove noise (e.g., infrequent behavior) to create a representative process model. Iteration may be required (e.g., threshold parameters).

Continue with. Lead times/frequencies (for each process variant), bottleneck analysis, or verification (e.g., interview, shop floor).

5.4.3.5 Lead times and frequencies (for each process variant)

Objective. Identify and prioritize inefficient process variants or part-specific value streams with high and/or unexpected lead times.

Lean production. Not related to lean production.

Process mining. Activity mapping or performance analysis. In the case of multiple process variants: lead time for each value stream, grouped by the process variant or frequency (e.g., in a box plot diagram).

Description. The lead times and frequencies can be used to identify and prioritize inefficiencies, either in process variants or part-specific value streams. Therefore, actual lead times (e.g., mean) are compared to reference values, e.g., predefined standards (PASZKIEWICZ 2013). In total, three patterns of inefficiencies were identified.

Most frequently, process-specific deviations for process variants were identified (e.g., ER et al. 2015b; KNOLL et al. 2019c; VAN CRUCHTEN & WEIGAND 2018). In this case, waiting or processing times are independent of individual value streams. ER et al. (2015b), for example, compared the aggregated lead time (mean) of three different process variants. To address the product complexity, KNOLL et al. (2019c) developed an approach to compare different process variants using box plots. Based on the lead times of individual value streams, the distribution within a process variant can be used for the analysis. The bottleneck analysis can be used to identify and prioritize activities with unexpected waiting or processing times.

In contrast, PASZKIEWICZ (2013) identified part-specific root causes (e.g., high storage times caused by inventory). These inefficiencies are independent of the process variant. The category of the exceptional activity (e.g., storage) can be used to determine further analysis steps, such as an inventory analysis (NYHUIS et al. 2008).

Frequencies (demand), in combination with underlying process costs, can introduce inefficiencies and measurable deviations in lead times. For example, processing value streams with high demands using costly processes are different from processing value streams with low demands that use cost-efficient processes. The enriched cost information can be used for process leveling.

Potential issues. If not combined with frequencies, infrequent process variants without impact might be prioritized for further analysis steps (ER et al. 2015b). In particular, time-dependent characteristics (e.g., customer demand) can introduce concept drifts. Therefore, a normalization step can be useful when integrating frequencies (e.g., demand per day). Furthermore, leveling requires integrating the physical constraints of the logistics system, e.g., storage, packages, and part characteristics.

Continue with. Process discovery, bottleneck analysis, or inventory analysis.

5.4.3.6 Bottleneck analysis

Objective. Identify bottleneck activities or variance of processing or waiting times in the process.

Lean production. Waste of waiting (before an activity or during the execution).

Process mining. Process discovery (with the time perspective) or activity mapping.

Description. The bottleneck analysis can be used to detect and analyze processing times of activities or waiting times between activities (VAN DER AALST 2016, p. 292). Activities that represent a process bottleneck should be addressed first. If available, reference values (e.g., planned processing times) can be used for prioritization. For example, ER et al. (2015b) analyzed the processing times of blocked stock or quality activities. In contrast, ER et al. (2015a) analyzed the waiting time between the material request and the beginning of the picking activity.

The starting point of the bottleneck analysis is the mean duration. The variance of the waiting and processing times can also be analyzed. Therefore, activity mapping can be used to compare simple statistics (e.g., variance or maximum) of different activities. An advanced technique is the performance spectrum that covers time-dependent dynamics and non-static behavior (DENISOV et al. 2018). Notably, the activity mapping technique is independent of the process variant and can be used to address the process complexity.

Potential issues. If an activity only captures a start or complete event, the waiting time cannot be differentiated from the processing times. Another issue is neglecting the material flow activity: for instance, storage activities with high duration can be caused by individual value streams and are not necessarily bottlenecks of the process variant. Furthermore, depending on the process complexity, not every process variant or activity can be analyzed individually. Activity mapping can be used to prioritize activities with a high frequency (e.g., activities shared across multiple process variants).

Continue with. Verification (e.g., interview, shop floor).

5.4.3.7 FIFO analysis

Objective. Identify violations of the FIFO rule.

Lean production. Waste of waiting.

Process mining. Dotted chart visualization of the event log, including the start and end event of each case.

Description. The dotted chart provides a holistic view for each case of the process from the time perspective. Each event, or at least the start and end events, is visualized as a dot and aligned with the case (VAN DER AALST 2016, p. 278). Based on the dotted chart diagram, deviations of the FIFO rule can be identified. ER et al. (2015a) used the FIFO analysis to analyze batches in the storage that must be taken out first. In contrast, PASZKIEWICZ (2013) analyzed the shipping activities of finished products using the dotted chart.

Potential issues. The performance spectrum can be used in the case of a highly dynamic system with numerous cases (DENISOV et al. 2018).

Continue with. Verification (e.g., interview, shop floor).

5.4.3.8 Inventory analysis

Objective. Identify value streams with oversized inventories caused by cycle-stock or safety stock.

Lean production. Waste of inventory.

Process mining. Performance analysis and/or inventory profiling.

Description. The inventory analysis is a detailed analysis of a part-specific value stream. In general, the inventory analysis can be used to compare if the reality confirms the expected inventory or to question if the planned inventory is required or oversized. Depending on the application, the inventory can be measured in demand-independent metrics (e.g., 30 days of storage time) or relative metrics depending on the demand (e.g., three days of inventory range).

Filtering techniques must be applied in advance to reduce the complexity of value streams. Both cycle-stock and safety stock can be identified separately using the performance analysis inventory metrics. This step is essential as the cycle-stock and safety stock depend on a variety of inventory parameters and can occur independently.

To identify *waste of inventory caused by cycle-stock*, the average cycle-stock can be compared to a JIT concept, which has a lot size of one and, subsequently, no cycle-stock. The minimum order quantity can be decreased, and the delivery frequency can be increased to reduce the cycle-stock waste. The inventory on hand on the delivery day must be considered to identify *waste of inventory caused by safety stock*. Again, comparing the safety stock to a JIT concept, the optimum safety stock on the delivery day is zero. Then, related inventory control parameters (e.g., minimum stock) can be evaluated and reduced. Notably, in both cases, the economic effects of the inventory must be considered (KLUG 2010, p. 50). Potentially increasing order costs must be compared to the cost savings (e.g., inventory holding and inventory space), for example.

Potential issues. Both part-specific characteristics and internal and external constraints and risks must be considered when evaluating the inventory. According to BOYSEN et al. (2015, p. 110), "determining minimum and maximum stock levels, order sizes, and/or review periods in all its potential varieties is widely investigated in inventory theory." These variables can include demand, replenishment time, criticality, value, and package size (e.g., BABAI et al. 2015; HORENBEEK et al. 2013; KABIR & HASIN 2013). Furthermore, the variance (e.g., demand) or risks (e.g., forecasting errors, delays) can influence the actual inventory (e.g., BAKER 2007; KAPUSCINSKI et al. 2004; LUTZ et al. 2003).

Continue with. Verification (e.g., interview, shop floor).

6 Application and evaluation

This section focuses on the evaluation of the approach. The proposed approach has been applied in three case studies in an industrial environment. The findings and results of the application are outlined in Section 6.1. To complete the *Descriptive Study II* (cf. Section 1.4), a generally valid evaluation addresses (1) the fulfillment of the requirements (cf. Section 6.2.1), (2) a cost-benefit calculation (cf. Section 6.2.2), and (3) existing limitations (cf. Section 6.2.3).

6.1 Industrial application

6.1.1 Industrial environment

The concept was applied at a production plant of a German automotive manufacturer in 2017 and 2018. The three case studies focus on the internal logistics of a mixed-model assembly line, processing parts from the goods receiving to the line.

Characterizing the internal logistics system

The internal logistics system is characterized by a high product and process complexity. Due to the fact that multiple products are assembled on the line, more than 10,000 part numbers with individual value streams exist (KNOLL et al. 2019c). Furthermore, internal logistics provides a variety of different reference processes (e.g., JIT or warehousing). In total, more than 30 internal logistics reference processes exist (KNOLL et al. 2019c). To operate internal logistics, the information system of the company, an ERP system with a WMS module, takes on a key role. Transfer orders trigger material and information flow activities across a variety of resources (e.g., storage).

Within the last two decades, the management of the company put great effort into establishing a lean production and logistics system: e.g., standardizing processes, reducing inventories, and establishing continuous improvement principles. These initiatives resulted in a lean internal logistics system. According to the logistics experts, value stream mapping is limited due to the product and process complexity.

Setting up the case studies

An interdisciplinary project team consisting of experts from the logistics and information technology department was created to conduct the case studies. The team included management, process mining analysts, and logistics and information system experts. In general, the case studies were executed by the process mining analysts, and additional roles were integrated on demand. In total, 17,865,792 transfer orders were recorded by the information system within three months, spread across 13,083 part numbers[1]. For reasons of data privacy protection, there are three restrictions. Firstly, the total number of more than 30 logistics reference processes are sampled to 15 reference processes. Secondly, the part numbers are sampled to 5,000 parts. Thirdly, sensitive labels such as parts, storages, packages, and suppliers are anonymized. No comprehensive conclusion about the company can be made.

6.1.2 Implementing the concept

The concept must be implemented to enable the industrial application. The implementation requires the three steps of (1) planning and data extraction, (2) data preprocessing, and (3) mining (cf. Chapter 4). Afterward, three different case studies focusing on waste analysis and evaluation were conducted separately. Experience gained during the three case studies has been used to continuously improve the concept.

Step 1: Planning and data extraction

The first step of the concept aims to define objectives and analysis questions, to identify, extract and standardize data, and to validate data (cf. Section 4.4.1). The interdisciplinary project team conducted multiple workshops to define the objectives and analysis questions. Existing problems within operations and potential improvements were discussed. By iterating the analysis questions, three case studies were prioritized. A precise

[1] The reported results in this thesis are based on the sample of the internal logistics system. Decisions made during the case studies rely on the holistic picture, e.g., different time frames.

description of the case studies and the underlying analysis questions are provided for each case separately.[2]

- *Case Study I: Analyzing deviations of reference processes*. Identify and characterize systematic deviations of reference processes, e.g., quality issues.
- *Case Study II: Demand-based process leveling*. Identify inefficient processing of value streams based on the customer demand for product variants.
- *Case Study III: Analyzing the inventory*. Identify value streams with waste of inventory levels that can be reduced.

The internal logistics ontology was used as a fundamental source for identifying, extracting, and standardizing the data (cf. Section 5.1.1). The team identified the required classes and properties in the application-specific information systems. In total, the team identified four relevant information systems with multiple tables. The information technology department completed the extraction of the event data (transfer orders). Two application-specific attributes were required: activity categories and activity duration to provide the required input data for preprocessing. Occurring activities (events) were identified using activity mapping and prioritized by the event frequency to classify the activity category (cf. Section 5.3.3). The team classified activities with at least 100 events[3]. The remaining 526 activities, or 0.01% of all events, were classified as *unclassified*. Existing planning department reference data were used to complete the activity duration. Master data (e.g., packaging) were extracted using end-user reports, and the data were standardized using the taxonomy of the ontology. The practical guideline for event data validation was used to validate the data (cf. Section 5.1.2).

1. *Observe the process on the shop floor.* Based on multiple visits on the shop floor, existing material and information flow activities were uncovered, and the data creation was captured. Most of the time, mobile bar code scanners and terminals (e.g., tugger train) were identified as data creation points.
2. *Record your own data for each process.* Fifteen different storage locations were prioritized based on the case studies. The activities were observed and documented for each location (e.g., part, location, and time). At no time was

[2] The workshops and iterations were completed within 2017 and 2018.
[3] This includes transfer orders from April 1, 2018 to October 15, 2018.

any personalized information recorded. This step showed that the start and end timestamp of activities was not always documented with a separate bar code scan. However, the completion of a transfer order was always documented.

3. *Talk to people who execute the process every day.* In the third step, logistics operators were interviewed. The interviews confirmed the fact that only the completion of an activity is reliable. However, the logistics operators confirmed that all material flow activities are triggered by transfer orders, except the picking activities of parts in the supermarket (separate information system).

4. *Compare the findings with existing documentation.* Additional documentation was considered to extend the understanding gained on the shop floor. In particular, the documentation of reference processes, storage locations, and layouts of the production plant provided significant value. Furthermore, invisible activities within the storages (e.g., automated conveyor lines) were uncovered.

5. *Compare the findings with the event data.* The recorded data were compared to the event data extracted from the information systems, and the imperfection patterns were compared with the event data. In total, three imperfection patterns were identified: (1) scattered event (e.g., only one reliable timestamp), (2) scattered case (e.g., picking in the supermarket), and (3) collateral events (e.g., low-level activities of the automated conveyor lines).

Furthermore, the inventory of five value streams was validated by manually counting the packages. The product-related master data (e.g., product) were not further validated.

Step 2: Data preprocessing

The second step of the concept aims to preprocess the extracted data into enriched event logs suitable for multidimensional process mining. This requires (1) creating event logs, (2) enriching event logs, and (3) filtering event logs (cf. Section 4.4.2). The algorithms used to preprocess the extracted event data were implemented in Python[4]. Due to the standardized taxonomy of the extracted data, this step only required minor adjustments. As the transfer orders did not include the start timestamp, the event logs could only provide the completion event of the standard transactional life-cycle model.

[4] Python is an open source language suited for code that is often "fast enough to be immediately useful but also flexible enough to be sped up with additional extensions." (OLIPHANT 2007, p. 10)

The extracted data (e.g., product) were integrated into the event logs to enrich the event logs, and the event logs were filtered to the internal logistics of the assembly line. Due to privacy reasons, any personalized data had already been removed during the data extraction. The outcome of this step is enriched event logs stored for each value stream individually.

Step 3: Mining

The third step mines and clusters the value streams using process mining techniques (cf. Section 4.4.3). This process required an initial tailoring of the six process mining techniques to the requirements of the case studies, selecting metrics for the performance analysis. Here, standardized lean metrics were used (cf. Section 5.3.5). The five other process mining techniques required minor adjustments, e.g., to select the precision $\delta t = 1\ day$ for inventory profiling. A complete list of the parameters can be found in the Appendix A.3.1. The concept was implemented in Python and Java, which was required by the ProM framework[5] to reuse the process discovery and conformance checking algorithms. As an outcome, all results, i.e., process models, are created automatically for each value stream.

6.1.3 Case Study I: Analyzing deviations of reference processes

Case Study I aims to identify and characterize systematic deviations of reference processes, e.g., quality issues. The team set the objective to quantify deviations of the process and to understand the underlying root causes. Based on the assumption that reference processes are aligned with lean logistics theory, any deviation, such as additional activities, is wasteful. Subsequently, Case Study I refers to the waste of unnecessary transportation, over-processing, and motion. To support the objective, the team defined two analysis questions:

- Are the value streams processed according to the reference processes in reality, and if not, which reference processes show frequent deviations?
- What are the underlying root causes of frequent deviations?

[5] ProM is a framework for process mining in research that is sufficiently flexible and open to reuse code during the implementation of new process mining ideas (DONGEN et al. 2005, p. 444).

The two analysis questions were addressed in three consecutive stages. Four guidelines were applied: filtering, conformance checking, clustering, and process discovery. Notably, filtering was dynamically applied to each stage.

Stage 1: Conformance checking

The first stage aims to check the conformance of value streams with the planning department's reference processes to observe deviations. Therefore, the trace fitness was calculated for each value stream individually based on the event log. The trace fitness values of value streams are grouped by the reference process to identify systematic deviations of reference processes so that a comprehensive view of reference processes with all individual value streams can be made (cf. Figure 6.1).

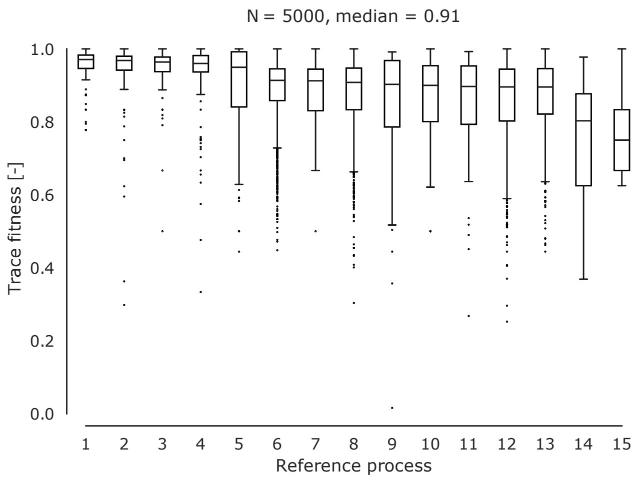


Figure 6.1: Conformance checking of value streams and 15 reference processes

The median trace fitness is 0.91 (Shapiro-Wilk test[6], p-value = 0.0 of the null hypothesis). This high value confirms the expectations of the management. The results demonstrate the achievement of focusing on a high level of standardization in logistics activities and processes within the last decade. Figure 6.1 shows three different groups of reference processes. The first group contains reference processes with a high trace fitness and a

6 The Shapiro–Wilk test is a statistical procedure for testing a complete sample for normality (SHAPIRO & WILK 1965, p. 591).

short box plot (cf. Reference process 1-4). The short box plot supports the conclusion that the individual value streams are executed similarly. Also, the second group can be characterized by a high trace fitness (cf. Reference process 5-13). In contrast to the first group, the box plot is comparatively tall. The distribution within the second group has a larger variance, indicating more process deviations. Consequently, the value streams within the first and second quartile must be analyzed in detail using process discovery. If product and process complexity do not allow this step, value stream clustering can be applied to separate and cluster value streams (cf. Section 5.4.3.2). The third group shows a low median value for trace fitness (cf. Reference process 14-15). An overall lower alignment with the reference processes can be identified by comparing the third group with the other two groups. These reference processes and the root causes for the systematic deviations must be investigated holistically. It can be concluded that trace fitness varies depending on the reference process model. In addition to these tendencies, individual value streams with a low trace fitness can be identified for further analysis across all reference processes. Nevertheless, the total number of value streams within a reference process has to be considered.

Stage 2: Value stream clustering

The second stage aims to understand the root causes of the deviations of reference processes. Reference process 13 has been selected for this thesis due to (1) the lowest median trace fitness in the second group and (2) the existing product complexity, including 238 value streams. Value stream clustering in the control-flow perspective proposes to separate the root causes based on the activity categories (e.g., quality or rework). For the application, the relative occurrence of cases of an activity category and the trace fitness values were selected as input for clustering. In addition to the maximum trace fitness (most likely reference process), the second and third highest trace fitness values were also used for clustering to separate systematic deviations from deviations introduced by concept drifts (cf. Section 5.3.6). The gap statistic method was used to determine the number of clusters. Then, K-means clustering was applied, and the results were visualized using t-SNE[7] (cf. Figure 6.2).

To understand the result, the six clusters are characterized in Table 6.1. The trace fitness (maximum) is aggregated to the median value of the cluster, and the duration is

[7] t-distributed Stochastic Neighbor Embedding is a nonlinear dimensional reduction technique for visualizing the resulting similarity data (MAATEN & HINTON 2008). Notably, the results are dimensionless.

normalized based on the reference process without any deviation[8].

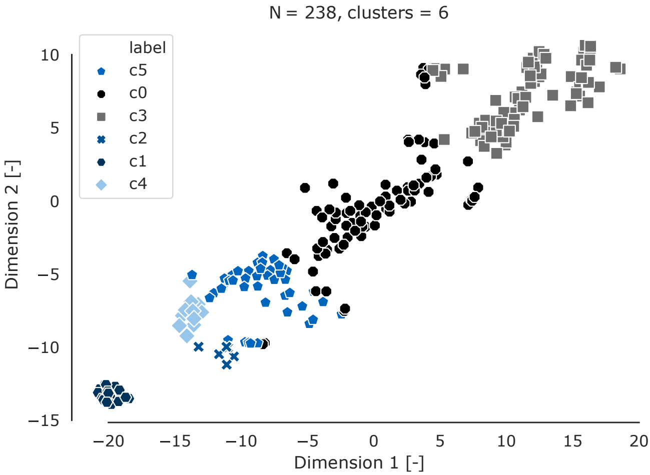


Figure 6.2: Value stream clustering for Reference process 13 (goods receiving, high rack to the assembly line)

Two groups of clusters exist. The first group (*c0*, *c1*, and *c4*) shows a high trace fitness (from 0.83 to 0.94). The largest cluster *c1* represents 135 value streams with a high trace fitness of 0.94 and very rare deviations (e.g., urgent order). Also, the second-largest cluster, *c4*, with 62 value streams, is characterized by a high trace fitness. However, more frequent deviations with slightly additional effort are introduced (e.g., damaged packaging). This information supports the conclusion that 201 (84.5%) value streams are well aligned. In contrast, the second group (*c2*, *c3* and *c5*) shows a significantly lower trace fitness. Three different root causes can be identified using value stream clustering. Firstly, replenishment orders introduce significantly higher effort (*c2*). Secondly, 13 value streams are affected by damaged packaging (*c3*). Thirdly, six value streams require unexpected quality checks (*c5*). The case perspective reveals that two value streams are related to the same supplier. Value stream clustering enhances the understanding of the conformance checking, and further steps can be derived systematically to reduce replenishment and quality activities.

[8] The duration reflects the effort to complete an activity according to the planning department. The normalization is required to due data privacy reasons of the company.

Table 6.1: Supporting metrics for value stream clustering of Reference process 13

				Activity category ratio [-]					
Cluster	Value streams [-]	Trace fitness [-]	Duration [-]	Damaged packages	Quality	Replenishment	Rework	Urgent order	Unknown
c0	4	0.90	2.92	0.01	0.00	0.00	0.00	0.00	0.01
c1	135	0.94	1.00	0.02	0.00	0.00	0.00	0.01	0.00
c2	18	0.60	3.33	0.04	0.00	0.89	0.00	0.00	0.01
c3	13	0.58	1.23	0.14	0.01	0.00	0.00	0.04	0.06
c4	62	0.83	1.09	0.06	0.02	0.00	0.00	0.02	0.02
c5	6	0.69	1.52	0.01	0.49	0.00	0.00	0.08	0.03

Stage 3: In-depth process discovery and evaluation

In the third stage, process discovery was applied to map the value stream and to identify potential for improvement. Figure 6.3 shows an example of a wasteful value stream (trace fitness = 0.72) from cluster *c5*. The event log contains 439 cases and 1,898 events. At first glance, process discovery shows one main material flow that is well-aligned with the reference process: the material flows from the goods receiving area to the line feeding using a tugger train. Notably, packages starting in the high rack are caused by inventory available before the event log is recorded. The process discovery uncovered three types of deviations. Firstly, 73 packages are processed to the quality area directly, and 36 packages are processed from the high rack to the quality area. If quality activities are required, the process shows a variety of outgoing material flows: to the high rack, to the damaged packaging area, or to the assembly line. The underlying quality checks must be standardized and reduced, e.g., by improving the part quality to reduce logistics effort. Secondly, 26 packages are processed from the goods receiving to the damaged packaging area. Then, line feeding is different to the reference process, and introduces non-standard activities. The logistics experts explained that these packages could not be stored in the automated high rack. Thirdly, the process discovery shows urgent orders are moved from the high rack to the assembly line with a forklift rather than the efficient tugger train. According to the lean philosophy, these movements are wasteful.

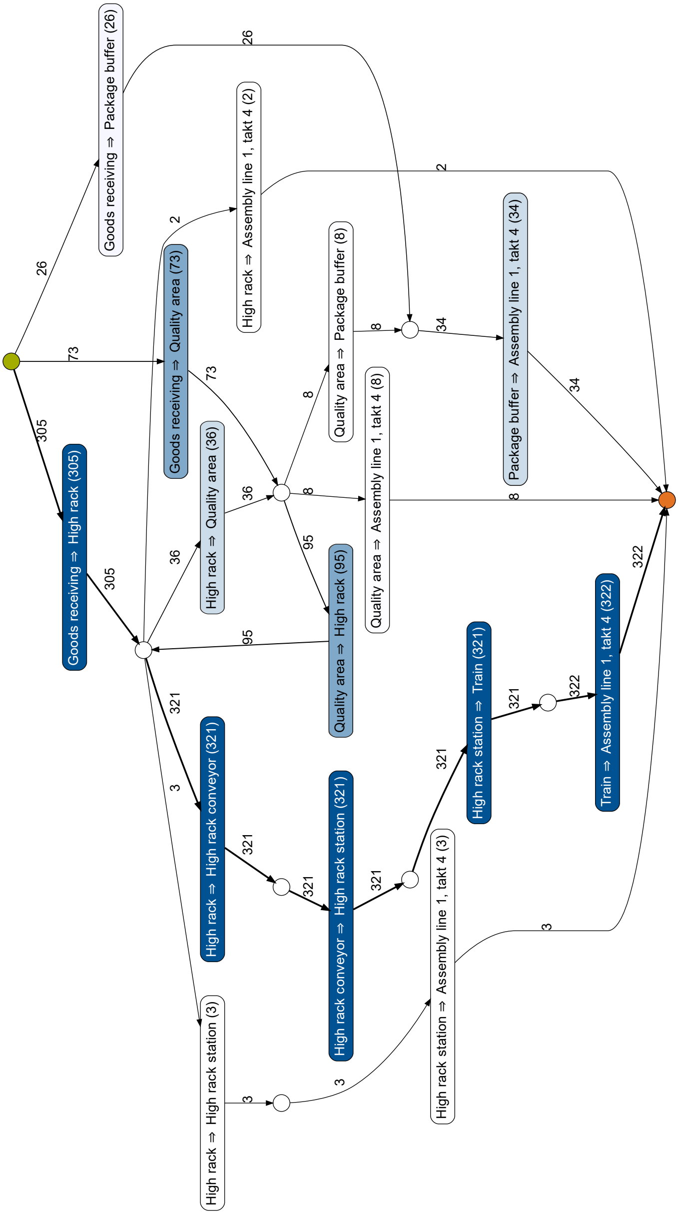


Figure 6.3: Process discovery for a wasteful value stream (trace fitness = 0.72)

6.1.4 Case Study II: Demand-based process leveling

Case Study II aims to identify inefficient processing of value streams based on the customer demand for product variants. The team set the objective to identify individual value streams that can be leveled between costly, e.g., requiring multiple handling activities, and cost-efficient, e.g., direct line feeding, processes. The value streams are planned based on the demand forecast. However, the logistics experts acknowledged that customer demand is dynamically changing over time. Not every individual value stream can be analyzed and evaluated continuously to identify the potential for improvement. Subsequently, Case Study II refers to waste of unnecessary transportation, over-processing, and motion. To support the objective, the team defined two analysis questions:

- Which value streams can be characterized by high demand in a costly process?
- Which value streams show a low or medium demand in a cost-efficient process?

The two analysis questions were addressed in two consecutive stages. Firstly, suitable reference processes and related value streams were selected for a detailed analysis. Secondly, value streams were analyzed using process discovery and case perspective. These steps were supported by three different guidelines: filtering, lead times and frequencies (for each process variant), and process discovery. Notably, the case perspective (e.g., packaging) is required for decision-making.

Stage 1: Filtering & lead times and frequencies (for each process variant)

In the first stage, suitable reference processes and value streams were selected. Comparing the approach with pen-and-paper-based value stream mapping, the logistics experts used (1) the additional attributes (e.g., packaging), (2) the actual reference process and the required effort, and (3) statistically representative metrics (e.g., average demand over three months) for the selection. The logistics experts suggested focusing on reference processes with small loading carriers (N = 4,417 value streams). To cover the product complexity, the demand is compared on the level of *packages per day* within a value stream. In contrast, comparing the quantity per day, which is available in the ERP system, would not reflect the logistics effort for each package. The demand of packages per day was calculated for each value stream and grouped by the reference processes. Within the case study, the box plot was selected because of its ability to compare multiple reference processes (cf. Figure 6.4).

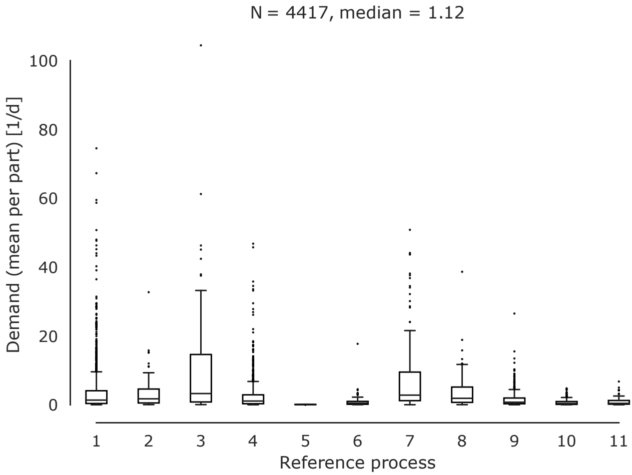


Figure 6.4: Demand (packages per day) for each reference process, filtered to small loading carriers and ordered by the effort (ascending)

Figure 6.4 shows two different groups of reference processes. The first group includes value streams with a line-side presentation (cf. Reference process 1-6). The second group includes value streams that are processed into kits in supermarkets (cf. Reference process 7-11). Hence, further effort is introduced by additional activities (e.g., picking) and shifting value streams between supermarkets would affect the part kit. The team selected value streams with a high demand, which mapped to Reference process 3, and value streams with a low demand, which mapped to Reference process 1. This allows a reduction of 27% effort for each package based on the planned processing times.

Stage 2: Process discovery & evaluation

In the second stage, 29 selected value streams were analyzed using process discovery and the case perspective. Again, process discovery provided a holistic view from goods receiving to the assembly line. In particular, the precise location and shelf at the assembly line can be determined. The case perspective provides packaging and supplier specifications and demand metrics (e.g., forecast) to enhance the process understanding. As a result of the analysis, the target policy was proposed (cf. Table 6.2). The results were discussed in seven weekly logistics experts' group meetings and evaluated by the responsible logistics experts afterward (cf. Appendix A.3.3).

Table 6.2: Identified value streams for demand-based process leveling

Target policy	Current state and improvements (n value streams)
Direct line feeding	High demand in costly process: • Remove additional storage and picking activities (12) • Free up the small parts storage (3)
Small parts storage	Low & medium demand in cost-efficient process: • Free up the automated high rack storage (14)

In total, three value streams were approved for direct improvement, and eight value streams were scheduled for adjustment during the upcoming production break. Two value streams were instantly shifted from the high rack storage to direct line feeding. Further improvements might require a modification of the line-side presentation. However, 18 value streams were declined due to a variety of physical logistics process restrictions. The three dominant restrictions relate to:

1. *Spatial restrictions*. The spatial restrictions at the assembly line prevented the shift of nine value streams. However, five value streams were scheduled for the production break as further modifications of the line feeding were required.

2. *Packaging restrictions*. The packaging characteristics prevented the shift of seven value streams to the automated small part storage. The limitations were caused by the conveyor line system that cannot process specific package types or packaging dimensions above a certain size.

3. *Other restrictions*. A variety of other restrictions impeded demand-based process leveling. For instance, similar parts cannot be stored next to each other due to an increased likelihood of picking failures.

6.1.5 Case Study III: Analyzing the inventory

Case Study III aims to identify value streams with waste of inventory, caused by cycle-stock or safety stock, which can be reduced. The team set the objective to create transparency about the actual inventory and to investigate whether reality confirms the expected inventory. This case study allows questioning if the planned inventory is required or oversized. In the application, the amount of inventory for each value stream is the result of a variety of control parameters (e.g., customer demand, order quantity, and frequency) that can be set in the ERP system. Aside from the product complexity, dynamics, i.e., multiple deliveries per week and fluctuation in demand, prevent value stream mapping without process mining. Subsequently, Case Study III provides support for continuous monitoring and reducing the amount of inventory. The team defined two analysis questions:

- Which value streams introduce waste of cycle-stock or safety stock?
- What are the root causes, and can the inventory be reduced?

The two analysis questions were addressed in two consecutive stages. Firstly, value streams with waste of inventory caused by cycle-stock or safety stock were identified. Secondly, inventory profiles of wasteful value streams were analyzed and enhanced by the case perspective to enable decision-making. These steps were supported by two guidelines: filtering and inventory analysis.

Stage 1: Filtering

In the first stage, filtering provides an approach for reducing complexity. The logistics experts specified that the analysis should focus on value streams with suppliers from Europe. Otherwise, the risk of supply shortages could offset the benefits. The value streams were filtered based on the case perspective. The cycle-stock and safety stock must be identified separately using performance analysis (cycle-stock and safety stock inventory metrics) to reduce waste of inventory. The cycle-stock refers to the inventory caused by orders (e.g., frequency), and the safety stock defines the minimum inventory and the risk of supply shortages on the delivery day (cf. Section 5.3.5).

To cover the product complexity, 100 value streams with small loading carriers and large loading carriers each were analyzed separately[9]. An extract of the sample is shown in Table 6.3, please refer to the Appendix (cf. Table A.4 and Table A.5) for statistics. The demand (mean) and the inventory (mean) were calculated on the case level (packages), and the mean lead time includes the storage time. The sample highlights the product complexity: the demand of packages per day, the inventory, and the lead time vary across the value streams. Uncovering the actual inventory characteristics using performance analysis provided a formerly unknown holistic picture of all value streams.

[9] For each loading carrier, half the value streams were selected based on the inventory metrics and the other half were sampled randomly. The results do not represent the population.

Table 6.3: Characterizing value streams with inventory waste metrics (extract of small loading carriers, ordered by inventory (mean))

				Cycle-stock		Safety stock	
Part number	Demand (mean)[1/d]	Inventory (mean)[-]	Lead time (mean)[d]	Waste[-]	Range (mean)[d]	Inventory (min)[-]	Range (mean)[d]
Z0ZJN3K	1.07	111.28	7.88	28.41	15.09	30.00	11.36
0LQ2A8M	3.41	88.34	21.03	16.90	9.12	23.00	17.88
SHKS04D	8.80	77.76	7.36	14.96	2.19	42.00	4.62
H2VUPC7	10.96	62.12	5.04	23.50	3.00	19.00	1.43
REB6T56	6.99	56.05	6.81	23.50	5.85	13.00	3.08
RJMAE8V	6.42	38.23	5.19	8.69	1.47	4.00	2.75
70YMS4F	3.78	33.64	7.26	12.96	5.00	7.00	3.62
QHNY6RM	1.33	33.59	14.74	23.50	23.67	6.00	4.00
ELJ4JAW	0.24	15.20	27.97	5.25	44.00	2.00	26.50

Either the cycle-stock or the safety stock can be reduced to address inventory levels. The company defines the safety stock for European suppliers between two and five days of inventory according to customer demand, mainly depending on the supplier reliability or the distance to the production plant. However, Table 6.3 shows value streams with up to 27 days of inventory. Notably, the demand-depending inventory range provided little value itself and must always be set in relation to the demand. The absolute number of packages (minimum) can be used to determine the risk of a supply shortage. For example, value stream 0LQ2A8M never falls below 23 packages. Lean production theory proposes the JIT concept with the lot size of one to reduce cycle-stock (cf. Section 5.4.3.8). In industry, the cycle-stock is always a trade-off between the amount of inventory and many external restrictions (e.g., order costs or transportation costs). Therefore, the cycle-stock waste metric can be used to compare and prioritize value streams for the inventory analysis rather than evaluating waste. In this stage, the logistics experts agreed on the usefulness of the statistical metrics but were required to analyze the inventory profile before acting. Thus, 35 value streams, including small and large loading carriers, were prioritized for the inventory analysis.

Stage 2: Inventory analysis & evaluation

In the second stage, two logistics experts from the production plant supported the inventory analysis for 35 value streams (cf. Appendix A.3.4). The inventory profiles with the case perspective were discussed for each value stream separately. During the workshops, a variety of questions arose from the logistics experts: e.g., “What is the logistics process, and how much space can we actually save if we reduce the order quantity?” The case perspective provided valuable information about the process, the supplier, and the packaging to answer these questions. In addition, the time frame of three months uncovered the actual inventory in reality, including unexpected effects of overlapping cycle-stock and safety stock. In contrast, the case perspective does not include historical values of control parameters. These variations made it difficult to explain the given behavior. The result of the inventory analysis is shown in Figure 6.5.

Figure 6.5: Result of the inventory analysis with logistics experts (N = 35 value streams)

In total, the logistics experts identified 22 of 35 (63%) value streams with the potential for improvement. The cycle-stock was dominant for small loading carriers. Here, the logistics experts suggested reducing the order quantity, e.g., by reducing the packages per pallet. This concept has already been adapted for many value streams. In contrast, the large loading carriers mostly provided the potential to increase the delivery frequency: a number of value streams receive a multiple of one pallet. When comparing the cycle-stock waste metric to the demand-depending range of the cycle-stock, different value streams were identified. In particular, value streams with minimal demand highlight the limitation of the inventory range metric when identifying value streams with little inventory on hand (e.g., one package). In conclusion, the cycle-stock waste metric identified value streams that can be reduced for both the small and large loading carriers.

For the safety stock, the seven value streams with large loading carriers offered potential for improvement. Primarily, value streams from local suppliers in Germany were identified as having more than three days of inventory. The absolute number of packages (minimum) clearly showed the actual potential for improvement, while the demand-depending range of safety stock provided an approximation for the actual risk of shortage. It must be mentioned that the absolute numbers of the minimum safety stock can be significantly lower than the mean inventory within a daily period (e.g., high demand). An example of the inventory analysis of a value stream with cycle-stock and safety stock waste is shown in Figure 6.6. Dimensionless metrics, i.e., the demand or inventory level, refer to packages (case level).

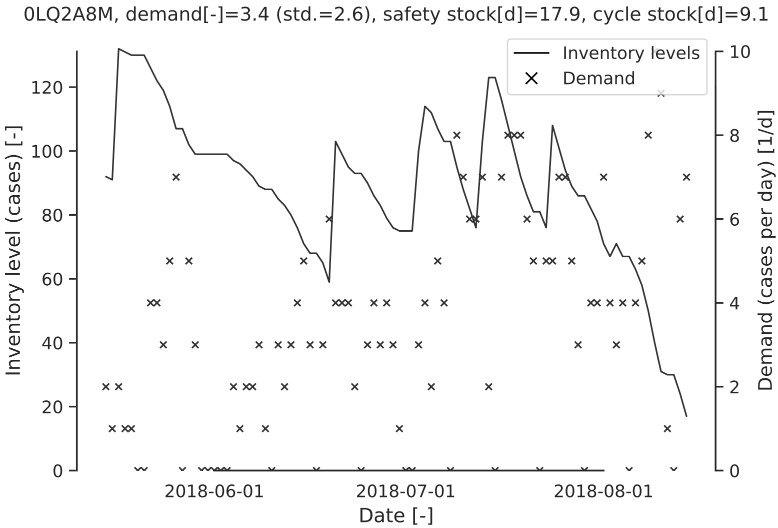


Figure 6.6: Inventory profile of a wasteful value stream (cycle-stock and safety stock)

The remaining 13 value streams that did not show potential for improvement were declined due to different causes: for example, (1) supplier restrictions, (2) parts at the end of the life-cycle, or (3) peak effects within a historical time frame. In conclusion, the inventory analysis provided value to uncover the actual behavior and to analyze the inventory. The logistics experts characterized this as a suitable tool that can enable a continuous monitoring and improvement process.

6.2 Evaluation of the approach

This section aims to identify whether the approach provides the expected impact. Therefore, the approach is evaluated with respect to the fulfillment of the eight requirements specified in the conceptual design (cf. Section 4.1). Because of its central role for an industrial application, the requirement to *reduce manual effort (cf. R4)* is assessed within a cost-benefit calculation (cf. Section 6.2.2). Both theoretical and practical existing limitations are critically discussed (cf. Section 6.2.3).

6.2.1 Fulfillment of requirements

Value stream mapping

R1. *Creating a holistic view of the value stream using process mining*. A holistic view of the value stream includes the process, data boxes, inventory, and associated specifications (ROTHER & SHOOK 1999). Hence, the approach supports creating a holistic view in these dimensions. The value stream, including the material and information flow of internal logistics, can be observed from the goods receiving up to the assembly line using process discovery. In addition, extensible data boxes are provided using performance analysis and process discovery in the time perspective. Similarly, the algorithm developed to mine for the actual inventory profile fulfills the inventory dimension. Associated specifications about the supplier, the product, and the customer (assembly line) are provided to complete the holistic view. The steps to create a holistic view and to identify waste are provided in an applicable methodology (cf. *R5*-*R8*).

R2. *Scaling to cover product and process complexity*. The application must be able to address the product and process complexity in terms of both technical feasibility and usability. Firstly, multidimensional process mining is tailored to internal logistics. The value stream-specific event logs (e.g., definition of cases) and algorithms create a holistic view for each value stream. Secondly, the concept allows horizontal scalability independent of the number of products and processes. Thirdly, the algorithms can be applied for complex processes with thousands of events, shifting the complexity to the analysis itself. Here, eight practical guidelines provide support for the analysis and to identify waste (cf. *R8*).

R3. *Capturing dynamics*. The static pen-and-paper-based value stream mapping tool does not capture dynamics; only a limited snapshot is recorded on the shop floor. In contrast, the proposed approach takes advantage of the ground truth of occurring events, as shown in the event logs. Hence, the proposed approach provides a reliable view of dynamic reality, covering fluctuation in demand and inventory and unobservable activities that do not create value. In addition to the ground truth itself, the flexibility of the proposed approach (e.g., filtering) supports reconstructing any time and perspective, if required.

Process mining

R5. *Supporting the planning stage according to lean production theory*. Process mining theory identified that defining concrete objectives and analysis questions is important for a successful process mining project (ECK et al. 2015). The concept includes a generic process mining methodology, and the planning stage is tailored to internal logistics. This tailoring includes (1) an interdisciplinary project team with lean experts and the management and (2) the alignment of objectives and analysis questions with lean production theory. The established types of waste can be used to identify suitable guidelines for the analysis and overcome the challenges of application-specific objectives.

R6. *Providing a domain ontology for internal logistics*. An internal logistics ontology was developed using the methodology of NOY & MCGUINNESS (2001) to support data identification, extraction, and standardization. A literature review of 42 relevant publications presenting ontologies in the manufacturing and logistics domain was used to enumerate important terms and to define the objects and (data) properties and hierarchy. In particular, this step was aligned with the main purpose of process mining: focusing on the material and information flow of internal logistics. Further extensions, including relations, were iteratively documented.

R7. *Providing algorithms for creating and enriching event logs for internal logistics*. Standardized event logs are required to apply process mining techniques. Firstly, the approach includes an algorithm to create event logs for internal logistics, including the characteristics of domain-specific activities (e.g., de-palletizing unit loads). Secondly, the concept specifies domain-specific attributes to enrich the event log. Standardized data can be provided using the internal logistics ontology for this. The algorithms are organized to process each value stream individually and scale to cover the product and process complexity (cf. *R2*).

R8. *Supporting the analysis according to lean production theory*. The eight practical guidelines enable an iterative analysis according to lean production theory. As each practical guideline integrates lean production with process mining techniques, a goal-oriented answer for each analysis question can be supported. Furthermore, the extendable guidelines with standardized properties provide lessons learned from other case studies to handle product and process complexity, to provide potential outcomes, and to avoid common pitfalls. Nevertheless, the analysis remains challenging and requires the interdisciplinary project team.

6.2.2 Cost-benefit calculation

The evidence for lean production and the benefits of value stream mapping have been successfully demonstrated across the manufacturing and logistics industry (cf. Chapter 1). In addition, an industrial application with three case studies and the fulfillment of requirements highlights the effectiveness of the process mining-based approach to address existing shortcomings (cf. Section 6.2.1).

A cost-benefit calculation will be discussed in detail (cf. *R4: Reducing manual effort*). The three case studies in the industrial application confirmed the benefits in terms of reduced transportation and inventory. However, the three case studies do not allow a generally valid statement about resulting benefits. The cost-benefit calculation focuses on the break-even analysis of pen-and-paper-based and process mining-based value stream mapping in the industrial application.

Cost structure

The cost structure of pen-and-paper-based and process mining-based value stream mapping is required for a break-even analysis. The cost structure covers the initial effort and continuous efforts and includes the working days of the interdisciplinary team (cf. Table 6.4). The experiences gained and discussed with practitioners in the industrial application, student assistants, and estimations of the author were used to quantify the effort of the two approaches.

Table 6.4: Effort in working days of pen-and-paper-based and process mining-based value stream mapping

Item	Description	Value stream mapping: Pen and paper	Value stream mapping: Process mining
Initial effort (working days)			
1	Planning and data extraction	0	30
2	Data preprocessing	0	20
3	Mining	0	25
4	Overhead	0	9
Continuous effort (working days per value stream)			
5	Create the current state map	2	0
6	Analyze the value stream	1	0.5
7	Improve the future state	-	-
8	Monitoring of the future state	2	0.5
Continuous effort (fixed working days per year)			
9	Software maintenance	0	15
10	Overhead	0	5

The *initial effort* to set up the two approaches shows contradictory features. Pen-and-paper-based value stream mapping can be used without any initial effort. In contrast, the process mining-based approach requires an initial effort to deploy the concept. Planning and data extraction require effort to identify, extract and standardize, and validate the data (cf. *Item 1*), requiring all roles of the interdisciplinary project team. Technical tasks, such as reviewing the database model, and logistics tasks, such as five days of validation on the shop floor, were considered. Notably, the logistics experts suggested that the definition of objectives and analysis questions is comparable for both approaches; therefore, that effort is not considered. It is assumed that a process mining software is available, e.g., the open source software ProM framework. The proposed algorithms for data preprocessing and mining are implemented on site (cf. *Item 2-3*). For example, this includes company-specific tailoring of performance metrics. Additional overhead is required to cover additional effort, such as training the process analysts on the software (cf. *Item 4*).

The *continuous effort* is split up into a variable amount for each value stream, such as creating the current state map, and fixed costs per year, such as operating the software, independently of value stream mapping itself. A visit on the shop floor is required to map each value stream (with pen and paper) to record the material and information flow from the goods receiving up to the assembly line and to document the results, including calculating metrics (cf. *Item 5*). In contrast, this task does not have any effort in the proposed approach. Later, the analysis (cf. *Item 6*) is simplified as the algorithms and metrics highlight deviations and enhance the understanding with additional perspectives (e.g., supplier or packaging). The improvement of the future state requires the same effort for both approaches (cf. *Item 7*). Additional effort is introduced for pen-and-paper-based value stream mapping to monitor the effects of improvements (cf. *Item 8*). The proposed approach introduces a fixed effort per year, e.g., for software maintenance (cf. *Item 9-10*). More details about the cost structure can be found in Appendix A.3.5.

Break-even analysis

The break-even analysis compares the total effort for both approaches depending on the number of value streams. This assumption is beneficial as the number of value streams was identified as the main cost driver for pen-and-paper-based value stream mapping (cf. Section 1.1). Figure 6.7 shows a break-even of 36 value streams, including a fixed amount of continuous effort for three years. The proposed approach is beneficial if value stream mapping is done monthly (12 value streams per year).

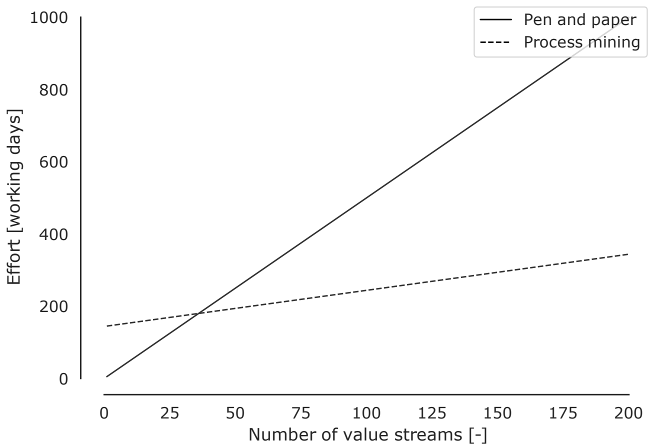


Figure 6.7: Break-even analysis of pen-and-paper-based and process mining-based value stream mapping (including a continuous effort of three years)

6.2.3 Limitations

The underlying assumptions of the approach were defined in the conceptual design (cf. Section 4.2) to specify the validity range. Possible limitations occur if the assumptions cannot be validated or if simplifications are required. In the following section, possible limitations are theoretically discussed against the assumptions. In addition, the general limitations of the evaluation approach are critically reflected.

L1. *Lean production and lean logistics*. The approach is only valid if the system is designed and operated according to lean philosophy. A common understanding of objectives (e.g., short lead times), principles (e.g., continuous improvement), and the reduction of waste (e.g., inventories) is necessary. Otherwise, the lean philosophy must be established first. Standardized material and information flow activities are essential; otherwise, no improvements for the future state can be derived using the recorded value stream. However, this limitation also exists for static pen-and-paper-based value stream mapping.

L2. *Product and process complexity and dynamics*. The approach is an extension of pen-and-paper-based value stream mapping and only suitable if existing challenges of value stream mapping are significant. The case studies demonstrated the capability to create transparency about a logistics system with product and process complexity and dynamics. However, the challenges of value stream mapping are shifted from the mapping to the analysis of the value stream. Even though the approach includes eight practical guidelines to support the analysis, this step remains challenging. While the approach demonstrates its value, further effort is introduced, and a cost-benefit calculation between the approach and the pen-and-paper-based value stream mapping is necessary. Without any product and process complexity or dynamics, the effort exceeds the benefits.

L3. *Data availability*. The approach utilizes event data created within the material and information flow, based on the assumption that event data is created and recorded. If the logistics processes are not operated by information systems or do not create event data, the approach cannot be applied. However, if the logistics system can be operated without information systems, existing product and process complexity is comparatively low, and pen-and-paper-based value stream mapping might be suitable (cf. *L2*).

L4. *Data reliability*. The approach assumes that the data is reliable. The event data represent the actual behavior in reality by recording events frequently and storing events without exceptions. Although the imperfection patterns, such as different information systems, can be identified during the data validation step, further effort might be required to fix the issues and to ensure data reliability.

L5. *Interdisciplinary project team*. The approach requires an interdisciplinary project team, including logistics experts and process analysts. In contrast to pen-and-paper-based value stream mapping, additional IT competencies are required. This affects the logistics experts, who understand where data is created, and process analysts familiar with the process mining software who must be trained.

The nature of the evaluation approach, an *application evaluation*, introduces additional limitations to the identified limitations of the proposed concept. An application evaluation aims to identify whether support can be provided for the task for which it is intended (BLESSING & CHAKRABARTI 2009, p. 37). The application evaluation focuses on the identified shortcomings of pen-and-paper-based value stream mapping. While the three case studies confirm the benefits in terms of effectiveness and efficiency, the outcomes do not allow a generally valid statement that equal benefits for each value stream, case study, or manufacturing company can be achieved.

The cost-benefit calculation focuses on the break-even analysis to overcome these limitations. Nevertheless, the underlying cost structure of the two approaches is based on the author's estimations. The estimated effort depends on the available skills and roles, resources, and information systems in the industrial application. This limitation is lessened in this case because the three case studies were carried out within one production plant of one manufacturing company. Thus, individual experiences and decisions of the interdisciplinary project team also affected the estimation.

7 Conclusion

7.1 Summary

Pen-and-paper-based value stream mapping is the established tool for recording processes, identifying waste, and deriving recommendations for action. Today, however, its application in the manufacturing and logistics industry requires a high level of effort and is challenging due to product and process complexity and issues involving dynamics.

Process mining is a relatively young research discipline that helps to utilize event data to discover, analyze, and improve processes. Process mining connects business process modeling and analysis with data mining. Today, the day-to-day business of internal logistics is based on information systems that create a vast amount of event data.

Therefore, the overarching objective of the thesis is to enable an effective and efficient application of value stream mapping in internal logistics using process mining. The thesis contributes (cf. *Research Contributions (RCs)*) to the synthesis of the research streams of value stream mapping and process mining (cf. *Research Questions (RQs)*).

RQ1. *Which data is required, and how must that data be prepared for value stream mapping for internal logistics using process mining?*

- RC1. Process mining theory proposes ontology-based data extraction and preprocessing. Therefore, an internal logistics ontology for process mining has been developed using a systematic review approach. The ontology includes the main classes, object properties, and data properties of internal logistics.

- RC2. Many data quality issues have been reported in the field of process mining. A practical guideline to validate the data has been developed to close the gap between event data, processes, and activities on the shop floor.

RC3. Process mining requires event logs as input. Algorithms that create, enrich, and filter event logs for each value stream have been developed to prepare the event data of internal logistics for value stream mapping.

RQ2. *Which process mining methods, concepts, and algorithms are capable of extracting and characterizing process models while capturing product and process complexity?*

RC4. Many algorithms, techniques, and concepts exist in process mining theory. Existing literature on process mining, with applications in manufacturing and logistics, has been reviewed systematically and evaluated in terms of support for the thesis.

RC5. The process discovery and conformance checking techniques have been tailored to provide a holistic view of each value stream. As process mining does not cover the inventory perspective of value stream mapping, an algorithm for inventory profiling using event logs has been developed.

RC6. Performance analysis, activity mapping, and clustering have been tailored to provide a comprehensive picture of all value streams so that a systematic analysis in the context of product and process complexity can be made possible.

RQ3. *Which steps are required to enable a systematic analysis according to lean production theory?*

RC7. Eight practical guidelines that enable a systematic and iterative analysis have been developed and organized using an Activity-based DSM. These guidelines integrate lean production theory (e.g., types of waste) and process mining (e.g., techniques and perspectives). Existing findings of process mining applications in manufacturing and logistics have been integrated using a review-based approach.

RC8. A methodology for practitioners has been developed to apply the developed concepts for value stream mapping using process mining. The methodology focuses on the practical outcomes according to lean production theory.

The concept has been implemented in industry, and three case studies have been conducted to evaluate the practical benefit. The findings have been used to evaluate the strengths and limitations of the approach.

7.2 Future research

This thesis concludes with an outline of three potential directions for future research: (1) extending the approach, (2) evaluating the concept in other applications and domains, and (3) linking the concepts to other research streams.

Extending the approach

Planning and data extraction. The research stream of value stream mapping can provide further support for defining objectives and analysis questions. For example, by reviewing case studies or carrying out a survey with manufacturing companies, frequently used objectives and analysis questions can be extracted, linked to process mining, and integrated as a set of best practices. Data extraction and validation can be further supported by integrating algorithms to check data failure patterns (VAN CRUCHTEN & WEIGAND 2018, p. 3). Further research can also improve the data availability itself by specifying how and which data must be created and recorded on the shop floor. For instance, when integrating mobile devices or replacing forklifts with autonomous transport robots, process mining requirements can be included.

Data preprocessing. The proposed approach focuses on event data (transfer orders) created by the WMS. Today, promising concepts have been developed that use the RFID data available in internal logistics (e.g., GERKE et al. 2009; ZHONG et al. 2016). This direction can be used to improve the precision of value stream mapping.

Mining. The developed approach covers time-dependent dynamics using the event logs and allows a manual analysis of different time frames. However, process mining theory proposes concepts to detect concept drifts automatically. Then, time-dependent patterns across multiple value streams (e.g., increasing inventory) can be identified. During mining, further support can be provided by integrating additional domain-specific characteristics, e.g., waste types, into process discovery algorithms (cf. YAHYA et al. 2016). Another promising research direction is the prediction of future states. Bayesian networks, for example, could be used to predict the lateness of line feeding activities to avoid production shutdowns (cf. SUTRISNOWATI et al. 2015).

Analysis and evaluation. The proposed approach includes eight practical guidelines to support the analysis with the main objective of eliminating waste. Here, future research activities can focus on further principles of lean production theory: e.g., synchronizing the takt time, or developing continuous flow or supermarket pull systems. Also, the analysis could be enhanced using advanced visualization techniques. For example, process analysts can be guided during the analysis by highlighting critical wastes in the process model. Recent literature on process mining proposes other data mining approaches to correlate various features, such as attributes. For example, clustering can be combined with decision trees or frequent itemset mining to identify the most dominant attributes for each cluster (e.g., LEONI et al. 2016; SYAMSIYAH et al. 2017).

Evaluating the approach in other applications and domains

For now, the approach has been implemented in an industrial application, and three case studies have been conducted. However, further evaluation in internal logistics with different objectives and analysis questions, teams, or information systems must be completed. The approach, for example, can be applied in different companies or in a long-term study. Then, a cross-case analysis can provide further insights about strengths and limitations.

Aside from internal logistics, the approach must be tailored to manufacturing processes, (1) providing a manufacturing ontology for process mining, (2) extracting and preprocessing data from manufacturing processes (e.g., MES or MRP), (3) and tailoring the concept of value stream mapping and the analysis for manufacturing-specific requirements.

Adapting the techniques to other research streams

The concepts of the thesis can support related research streams, such as performance measurement, simulation, or operations research. These research streams require accurate and valid input data. Here, the manual effort can be reduced, and the quality can be improved if event logs and process mining techniques are applied.

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Appendix

A.1 Fundamentals

A.1.1 Analysis of eight Warehouse Management Systems (WMS)

The event data in internal logistics are essential for the proposed approach. Fundamentals of logistics refer to WMS that operate internal logistics (cf. Section 2.1.3). While business processes are controlled by workflow systems, internal logistics does not record high-quality event logs explicitly. Instead, every physical material movement within the material flow is controlled by a transfer order. (KNOLL et al. 2019b, p. 133) To ensure the theoretical findings, an analysis of eight WMS, both commercial and open source systems, was completed. Available data models were searched on the internet and were requested on February 8, 2019. The analysis focused on the underlying data models and is summarized in Table A.1.

Table A.1: Analysis of eight Warehouse Management Systems (WMS) in terms of transfer orders and the underlying data models

-	Category	Product	Transfer orders	Tables (columns)
1	Commercial	SAP R3 ERP WM	Yes	8 (39)
2	Commercial	Microsoft Dynamics	Yes	3 (37)
3	Commercial	Oracle SCM	Yes	1 (13)
4	Commercial	Fishbowl Inventory	Yes	3 (17)
5	Open source	Odoo Inventory	Yes	4 (40)
6	Open source	Apache OFBiz	Yes	5 (43)
7	Open source	openWMS	Yes	5 (22)
8	Open source	myWMS	Yes	5 (26)

A.2 Detailed design of the approach

A.2.1 Planning and data extraction

A.2.1.1 Literature-based development of the internal logistics ontology

This section provides further details about the literature-based development of the internal logistics ontology. The *Ontology Development Guide* by NOY & MCGUINNESS (2001) has been used in this thesis. The *Ontology Development Guide* consists of seven steps and is often used for developing ontologies.

Step 1: Determining the domain and scope

In the first step, the domain and scope of the ontology are defined. The ontology must support the ontology-based data extraction and preprocessing in the field of process mining (cf. Section 2.3.3). The ontology must create a shared understanding of the process perspective of internal logistics and required concepts (e.g., case identifier) that must be annotated. In addition, related attributes to enrich the event logs (e.g., costs) must be defined.

Step 2: Considering reusing existing ontologies (a systematic review)

In the second step, reusing existing ontologies is considered, as the work of NEGRI et al. (2017) provides evidence that relevant ontologies exist. NEGRI et al. (2017) recently carried out a literature review of ontologies related to internal logistics. The purpose of the review of NEGRI et al. (2017) is to develop an internal logistics ontology focusing on the resource perspective. The systematic review builds on the findings of NEGRI et al. (2017) and provides an overview of work that focuses on the process perspective of internal logistics. Similar to Chapter 3, the literature review approach consists of three stages and eight steps. Based on the objectives of the thesis, the literature review provides support for RQ1 (cf. Section 1.3). The unit of the analysis is specified as ontologies in the area of internal logistics. The articles are classified and evaluated in terms of the coverage of the main concepts of internal logistics.

The work of NEGRI et al. (2017) is extended to collect the articles by a keyword search for *ontology AND ("internal logistics" OR "production logistics")*, which found 45 articles published before April 10, 2018. Further literature was identified by selectively going forward and backward in the articles (e.g., three upper ontologies or articles available in German). Articles that did not provide support for the process perspective of internal logistics or enriching event logs were excluded to limit the number of publications. For example, 24 articles focus on the inter-organizational perspective of logistics. After excluding these articles and removing duplicates, 42 relevant articles were reviewed in detail. Fourteen articles were compared and (partially) reused for merging or extending existing concepts in support of the development of the internal logistics ontology. (cf. KNOLL et al. 2019a)

Step 3: Enumerating important terms

In the third step, important terms are enumerated based on the frequency of their occurrence in the literature.

Step 4-6: Define the classes, properties, and facets

The ontology is modeled in the fourth, fifth, and sixth steps (cf. Section 5.1.1.2). If possible, concepts of existing domain ontologies and upper ontologies, i.e., *PSL*, were integrated.

The *PROMPT* methodology has been selected to merge ontologies, based on the review of KALFOGLOU & SCHORLEMMER (2003). *PROMPT* is designed to integrate formalized ontologies (NOY & MUSEN 2003) and maintain classes, object, and data properties. Annotations for process mining were extended to complete the modeling.

Step 7: Create instances

In this context, the last step of creating instances is skipped as instances are stored in information systems (JAREEVONGPIBOON & JANECEK 2013).

A.2.2 Data preprocessing

A.2.2.1 Further specification of the enriched event log

The algorithms to create, enrich and filter event logs were developed in Section 5.2). An extract of the enriched event log L_e (XES Standard Definition 2.0) is shown in Table 5.10. Table A.2 completes the extract of the enriched event log L_e with additional attributes.

Table A.2: Additional attributes to be enriched into event log L_e (Extensible Event Stream (XES) Standard Definition 2.0)

Extension	Level	Key	Type	Description
resource	event	location_id_source	integer	The ID of the start location.
resource	event	location_id_destination	integer	The ID of the destination location.
resource	event	location_name_source	string	The name of the start location.
resource	event	location_name_destination	string	The name of the destination location.
resource	event	location_section_source	string	The section of the start location.
resource	event	location_section_destination	string	The section of the destination location.
packaging	trace	id	integer	ID of the packaging.
packaging	trace	size	float	Size of the packaging.
supplier	trace	id	integer	ID of the supplier.
supplier	trace	address	string	Address of the supplier.
supplier	trace	zip	integer	Zip code of the supplier.
supplier	trace	city	string	City of the supplier.
part	trace	quantity	integer	Quantity of the part.
part	trace	part_family	string	The part family.
part	trace	reference_process	string	The (assigned) reference process.

A.2.3 Mining

A.2.3.1 Conformance checking

Various approaches and algorithms for conformance checking exist in process mining theory. According to VAN DER AALST (2016, p. 256), the token-based replay is easy to understand and implement but has some limitations (cf. VAN DER AALST 2016, p. 256). Therefore, *alignments* are introduced. Using alignments, *log moves* and *model moves* are compared to the *optimal alignment*. For this thesis, the implementation in *ProM* refers to the plugin *PetrinetReplayerWithoutILP*, which is an implementation of the *Escaping Edges Precision* algorithm. Please refer to BUIJS et al. (2012), TAX et al. (2018), & VAN DER AALST et al. (2012) for further discussion.

The basic approach of token-based replay is presented in the following equation. The trace fitness of a case with the trace σ on a process model M is defined as follows (VAN DER AALST 2016, p. 250):

$$fitness(\sigma, M) = \frac{1}{2}\left(1 - \frac{m}{c}\right) + \frac{1}{2}\left(1 - \frac{r}{p}\right) \tag{A.1}$$

where:

p = produced tokens
c = consumed tokens
m = missing tokens (consumed in the event log)
r = remaining tokens (produced in the model)

The precision of an event log L on a process model M is defined as (VAN DER AALST et al. 2012, p. 193):

$$precision(L, M) = \frac{1}{|E|} \sum_{e}^{E} \frac{en_L(e)}{en_M(e)} \tag{A.2}$$

where:

E = events in the event log L
$en_L(e)$ = behavior in the event log L
$en_M(e)$ = behavior in the process model M

The generalization of an event log L on a process model M is defined as (VAN DER AALST et al. 2012, p. 193):

$$generalization(L,M) = 1 - \frac{1}{|E|}\sum_{e}^{E} pnew(|diff(e)|, |sim(e)|) \tag{A.3}$$

where:

E	= events in the event log L
$pnew(w,n)$	= estimated probability that a next visit
	= to state $s = state_M(e)$ will reveal a new path not seen before
$w = \lvert diff(e)\rvert$	= number of unique activities observed leaving state s
$n = \lvert sim(e)\rvert$	= number of times s was visited by the event log L

A.2.3.2 Inventory profiling: demand and delivery algorithms

This section specifies the algorithms of the demand (cf. Algorithm 7) and delivery profile (cf. Algorithm 8), which are additions to inventory profiling.

Algorithm 7 Demand profile

Input: $\langle L_{e,1},\ldots,L_{e,N}\rangle$... Enriched event logs
Input: k... Time-intervals
Output: $\langle DP_1,\ldots,DP_N\rangle$... Demand profiles

```
procedure CREATEDEMANDYPROFILE
    for all L_e in ⟨L_{e,1}, ..., L_{e,N}⟩ do
        DP ← range_zeros(k)
        for all E in filter(L_e, category = outgoing_goods) do
            E ← remove_duplicates(E)        ▷ remove duplicate events
            DP(E(date), quantity) = DP(E(date), quantity) + E(date, quantity)
        end for
    end for
    return ⟨DP_1, ..., DP_N⟩
end procedure
```

Algorithm 8 Goods receiving profile

Input: $\langle L_{e,1}, ..., L_{e,N} \rangle$... Enriched event logs
Input: k... Time-intervals
Output: $\langle RP_1, ..., RP_N \rangle$... Goods receiving profiles

procedure CREATERECEIVINGPROFILE
  for all L_e in $\langle L_{e,1}, ..., L_{e,N} \rangle$ **do**
    $RP \leftarrow range\_zeros(k)$
    for all E in filter(L_e, category = goods_receiving) **do**
      $E \leftarrow remove\_duplicates(E)$ ▷ remove duplicate events
      $RP(E(date), quantity) = RP(E(date), quantity) + E(date, quantity)$
    end for
  end for
  return $\langle RP_1, ..., RP_N \rangle$
end procedure

A.2.4 Analysis and evaluation

A.2.4.1 Literature-based development of the analysis

This section provides supporting material that was used for the literature-based development of the analysis (cf. Section 5.4.1).

Because many articles apply the same process mining perspectives (e.g., control-flow) and techniques (e.g., process discovery), the *added value* of integrating all articles is limited. Consequently, the articles were prioritized by their value in terms of the practical benefit (e.g., reduce unnecessary transports) or the theoretical contribution (e.g., novelty of the technique).

The mapping of the resulting 12 articles is shown in Figure A.1 and Figure A.2.

Perspective		Internal logistics: Knoll et al. (2019b)	Er et al. (2015a)	Er et al. (2015b)	VanCruchten & Weigand (2018)	Wang et al. (2018)	Lee et al. (2013)
	Filtering	storage/producation areas, trace fitness	Lead times and frequencies	Quality-related activities in case. Lead times and frequencies	Quality-related inspection activity in case. Storage locations	Storage locations	clusters
	Clustering	-	-	-	-	-	Trace clustering (activities)
Control-flow perspective	Conformance checking for process variants	Automated, multiple processes and variants	Manual, one process (no variants)	Manual, one process (3 sub-variants)	-	-	-
Control-flow perspective	Process discovery	Automated, multiple processes and variants	One process (3 variants)	One process (3 variants)	One process (quality activities)	-	One process (4 variants using clustering)
Control-flow perspective	Multiple executions, non-value added activities	Sending from/to goods receiving	-	-	Sending from/to quality (repeatition)	-	Yes, frequent transportation loops
Control-flow perspective	Additional, non-value added activities	Quality, buffer area	Quality and picking		Unknown locations / flows (e.g. sending backward)	Sending from production backwards (and different storages)	-
Control-flow perspective	Missing activities (begin, end or skipped)	Urgent process (e.g. tugger train, goods receiving)	Create transfer order for storage (or picking)	Quality check is required	-	-	-
Time perspective	Lead times / frequencies (for each process variant)	Lead times (process variant or demand)	-	Lead times and frequencies (systematic, process variant)	Correlation of lead time with a systematic process variant	-	-
Time perspective	Bottleneck analysis	Processing time	Waiting time (request to start picking)	Waiting time for blocked stock and quality (maximum)	-	-	Processing and waiting times for each process variant
Time perspective	First in first out (FIFO) analysis	-	Dotted chart	-	-	-	-
Time perspective	Inventory analysis	-	-	-	-	-	-

Figure A.1: Mapping of practical guidelines for the analysis (1 of 2)

		Internal logistics			Infrastructure logistics		
		Becker & Intayod (2017a)	Paszkiewicz (2013)	Liiv & Lepik (2014)	Wang et al. (2014a)	Wang et al. (2014b)	Denisov et al. (2018)
	Filtering	-	Quality-related (not accepted) activities in the case	Incomplete cases, noise (invalid start event)	Selecting: logistics attributes (e.g. cargo type), time span, complete cases	Cargo type, trade type, ship arrival month, …	-
	Clustering	Frequency and cycle-time	-	-	In process clustering (group of activities)	Trace clustering (activities)	-
Control-flow perspective	Conformance checking for process variants	-	Manual and automated, one process (no variants)	-	Manual and automated, one process (no variants)	-	-
	Process discovery	-	One process (10 variants)	One process (most frequent of 8 variants)	One process (1 variant in detail)	One process (3 variants using clustering)	-
	Multiple executions, non-value added activities	-	On fork to rest, shipped to on fork	-	-	Truck weighting, new certificate	-
	Additional, non-value added activities	-	Quality (not accepted / deleted) and pallet damage handling	Sending out to storage activity	-	-	-
	Missing activities (begin, end or skipped)	-	Quality check is required, On fork after	Sending out a pallet	Signing contract (start), forecast & documentation (skipped)	Multiple activities (e.g. charging the certificate)	-
Time perspective	Lead times / frequencies (for each process variant)	-	Lead times and frequencies (part-specific value streams)	Lead times and frequencies (high frequency)	Lead times and frequencies (cargo type variant, time frames)	Frequencies	Lead times (variability over time)
	Bottleneck analysis	-	-	Processing times	Waiting times	-	Processing times (variability over time)
	First in first out (FIFO) analysis	-	Dotted chart (two products)	-	-	-	Performance spectrum
	Inventory analysis	-	Storage time, but no inventory profile	-	Active events over time?	-	-

Figure A.2: Mapping of practical guidelines for the analysis (2 of 2)

A.3 Application and evaluation

A.3.1 Industrial environment

Table A.3 summarizes the parameters of the approach used for the industrial application. These parameters were set during the implementation and used for each case study. Other parameters of the clustering algorithm refer to the default values of the Python library *Scikit Learn 0.23* and *ProM 6*.

Table A.3: Parameters of the approach used for the industrial application

Category	Property	Value
Event log	Time frame	3 months
Process discovery	Algorithm	Alpha Miner, Inductive Miner
Process discovery	Threshold	0.1 - 0.2 (Inductive Miner)
Conformance checking	Algorithm	Escaping Edges Precision
Inventory profiling	δt	1 day
Clustering	Algorithm	K-means, full
Clustering	Number of clusters	Individual (gap statistics)
Clustering	Iterations (max.)	300

A.3.2 Case Study I: Analyzing deviations of reference processes

Case Study I describes an extract of a quality initiative at a German car manufacturer between 2017 and 2018. *Stage 1: Conformance checking* was used to identify deviations of reference processes. *Stage 3: In-depth process discovery and evaluation* uncovered waste of unnecessary transportation and motion related to quality activities. The objectives of the project were set in alignment with the organizational and financial aspects of the company. Within this project, interviews were conducted with experts from logistics and the procurement department in 2018. The results presented in the thesis present an update of the results published in KNOLL et al. (2019b). In addition, value stream clustering was developed at MIT in 2019.

A.3.3 Case Study II: Demand-based process leveling

This section provides a summary of the seven 15-minute group workshops conducted during a weekly meeting of the logistics experts. The notes were captured and anonymized during the workshops and were supported by the student thesis of Raffaela Rill.

Workshop 1 (December 11, 2018)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- Focus on two different reference processes within the same assembly line hall. The majority of parts are handled and stored within these storage areas, which is why they are under inspection within the logistics planning department.
- High demand is defined as more than 20-25 packages per day (two shifts). A medium demand is defined as 10-15 packages per day (two shifts). A low demand is defined as less than two packages per day (two shifts). However, no clear distinction is made, and this definition is only used for an initial classification.
- The demand forecast of the value streams should be included due to the dynamics.
- Critical parts refer to a low demand and a high inventory.

Workshop 2 (January 15, 2019)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- The automated small part storage is restricted to a maximum of two packages per part and hour. Value streams with high demand cannot be processed in this storage/reference process.
- Direct line feeding should be the target for value streams with high demand. Complementary value streams should be evaluated for a medium demand.

- In the case of a direct line feeding policy, the analysis should focus on value streams with one distinct line delivery location. Parts with multiple locations are out of scope.

Workshop 3 (January 22, 2019)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- Confirmation of one value stream that was proposed as direct line feeding.
- Re-scheduling of one value stream for the production break.
- One value stream was not considered for improvement because the employee responsible for that stream had special workspace requirements and modifications because of a disability.

Workshop 4 (February 05, 2019)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- Confirmation of one value stream that was proposed as direct line feeding.
- Two value streams were impeded due to packaging restrictions. According to the experts, a change of packaging bins is not practical. Two other value streams were declined because of spatial restrictions and another because of risks related to picking failures.

Workshop 5 (February 19, 2019)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- Two value streams were declined because of spatial restrictions (too many racks). Another value stream was declined because of packaging restrictions.

Workshop 6 (March 3, 2019)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- Four value streams were declined because of risks related to picking failures.
- Four other value streams were declined because the packaging bins were either too high or are not compliant with the company's standard.

Workshop 7 (March 13, 2019)

Roles: Logistics experts (e.g., process improvements and quality) and data analysts.

Participants: Group of three to five logistics experts and two data analysts.

Findings: Discussion of the proposed value streams:

- One value stream was approved for direct line feeding.
- Another value stream was shifted to the automatic storage system.

A.3.4 Case Study III: Analyzing the inventory

This section provides a summary of six 30–90-minute workshops. The notes were captured and anonymized during the workshops and were supported by the student thesis of Quirin Bachmeier.

Workshop 1 (September 27, 2018)

Roles: Logistics experts (procurement/inbound) and data analysts.

Participants: Group of two logistics experts and one data analyst.

Findings:

Table A.4: Statistical description of the analyzed value streams (small loading carriers)

Metric	Demand (mean)[1/d]	Inventory (mean)[-]	Lead time (mean) [d]	Cycle-stock Waste [-]	Cycle-stock Range (mean)[d]	Safety stock Inventory (min)[-]	Safety stock Range (mean)[d]
count	100.00	100.00	100.00	100.00	100.00	100.00	100.00
mean	2.35	23.00	7.83	8.14	7.88	4.27	4.07
std	2.99	29.00	4.60	9.18	7.68	10.47	5.83
min	0.00	0.30	0.01	-0.09	0.00	-47.00	0.00
25%	0.35	4.15	4.92	1.50	2.40	0.00	0.97
50%	1.10	12.35	7.30	5.06	5.70	2.00	2.26
75%	3.42	31.20	9.23	11.50	10.33	5.25	4.30
max	14.03	190.25	27.97	47.50	44.00	56.00	39.00

- High inventory ranges (in days) are mainly caused by low customer demand profiles. For value streams with very low demand, typically, the transportation costs are optimized because of very low effects on inventory (e.g., low absolute number of packages). Another aspect of high inventories was related to part numbers at the end of a life-cycle. If a new version is introduced, the supplier's remaining inventory will be shipped to the manufacturer. In both cases, the effect is a high inventory range.

- The logistics experts also mentioned the risk of supply shortages and that parts with suppliers outside Europe require a higher inventory (safety stock). For example, imported goods must be cleared through customs. The inventory analysis should focus on European suppliers.

Workshop 2 (October 1, 2018)

Roles: Logistics experts (procurement/inbound) and data analysts.

Participants: Group of two logistics experts and two data analysts.

Findings:

Table A.5: Statistical description of the analyzed value streams (large loading carriers)

				Cycle-stock		Safety stock	
Metric	Demand (mean)[1/d]	Inventory (mean)[-]	Lead time (mean) [d]	Waste [-]	Range (mean)[d]	Inventory (min)[-]	Range (mean)[d]
count	100.00	100.00	100.00	100.00	100.00	100.00	100.00
mean	1.19	8.15	4.60	1.22	2.75	2.42	2.87
std	2.20	13.49	3.04	2.37	3.87	7.14	3.58
min	0.03	0.08	0.09	-0.06	0.10	-4.33	0.00
25%	0.20	1.18	2.62	0.03	1.12	0.00	0.39
50%	0.43	3.03	3.71	0.34	1.88	0.00	1.46
75%	1.24	7.99	5.58	1.06	2.59	2.00	3.97
max	17.15	73.05	19.50	14.91	33.00	57.00	19.60

- The logistics experts highlighted that the main objective is to achieve a service level of 100%.
- The logistics experts discussed the aspects that the cycle-stock is independent of the safety stock and that the two important control parameters are: (1) order quantity and (2) delivery frequency. However, the safety stock is controlled by demand and not in absolute numbers of inventory. Consequently, the actual safety stock varies over time.

Workshop 3 (October 11, 2018)

Roles: Logistics experts (procurement/inbound) and data analysts.

Participants: Group of two logistics experts and two data analysts.

Findings:

- If the quantity of inventory does not match the ordered quantity, urgent orders are triggered to cover missing quantities.
- The order quantity can be adjusted in the ERP system.

Workshop 4 (October 16, 2018)

Roles: Logistics experts (procurement/inbound) and data analysts.

Participants: Group of two logistics experts and one data analyst.

Findings:

- Fluctuation in demand is common due to different production schedules or seasonal effects. However, the production schedule is frozen within a reasonable time frame that is longer than the replenishment time. The demand can be assumed as deterministic.
- The target value of the safety stock inventory in days depends on the supplier. Variables include the distance between the supplier and the production plant. The logistics experts stated that the goods are not instantly transferred into and stored in the warehouse, and additional buffers of inventory may be required, depending on the logistics reference process. Furthermore, quality issues require a sufficient time span to check and subsequently block incoming goods or to react to defective products. The procurement/inbound experts do not consider the value of the goods.
- Regular orders are scheduled for a specific date but do not include a specific time on that date. Therefore, the delivery time is unknown and can vary. Furthermore, critical dates exist that can require additional orders or quantities (e.g., public holidays).
- For the assessment of waste of inventory, the absolute number of loading carriers must be considered.

Workshop 5 (October 19, 2018)

Roles: Logistics experts (procurement / inbound) and data analysts.

Participants: Group of two logistics experts and data analyst.

Findings:

- The most common inventory control parameters are the inventory range of the safety stock, the order quantity, and the delivery frequency. The absolute safety stock is rarely used.

- The order quantity can be set to a multiple of the small loading carriers on the pallet. However, this provides only value if the packages are stored separately, rather than on the pallet.

Workshop 6 (October 23, 2018)

Roles: Logistics experts (procurement / inbound) and data analysts.

Participants: Group of two logistics experts and two data analysts.

Findings:

- Waste of safety stock can be immediately reduced without restrictions. In contrast, the cycle-stock typically requires evaluating further aspects, for example, the number of deliveries per day and time.

A.3.5 Underlying assumptions of the cost-benefit calculation

The proposed cost structure of the cost-benefit calculation includes a variety of assumptions about the industrial application. The assumptions about the initial effort and continuous effort are outlined in this section.

Initial effort

The set-up requires the deployment of the developed approach.

- *Planning and data extraction.* The logistics experts stated that the definition of objectives and analysis questions is comparable for both approaches. Subsequently, the effort is not considered. For the data extraction, it is assumed that the ERP is available and can be accessed by the team. The effort for identifying, extracting, and standardizing the data equals 20 working days. Existing ERP reports are used. This assumption is based on the personal estimation of the author and the reported effort in the literature (cf. Chapter 3). It is assumed that five working days of validation, for example, conducting interviews on the shop floor, are required to validate the data. Further on, five working days are required to evaluate the data consistency (e.g., outlier detection). Therefore, the effort to validate the data equals ten working days.

- *Data preprocessing.* This step requires the implementation of the algorithms by the software engineer. The team discusses critical attributes to specify the attributes for filtering. The effort to set-up data preprocessing equals 20 working days.

- *Mining.* This step requires the implementation of the algorithms by the software engineer. It is assumed that a process mining software, such as the open source framework *ProM*, is available. Existing software implementations can be used (e.g., the inductive miner for process discovery). The team implements suitable metrics based on the requirements of the company. The effort to set-up mining equals 25 working days.

- *Overhead.* Unpredictable tasks can be required depending on the company-specific environment (e.g., existing skills of the people). Nine working days are included to cover any additional effort.

Continuous effort

The continuous effort depends on the variable amount (per value stream):

- *Create the current state map.* A visit to the shop floor is required to map each value stream with pen and paper. This step records the material and information flow from the goods receiving up to the assembly line, visiting at least two different locations at the production plant. All activities of the value stream are observed once. The performance metrics must be calculated, and the recorded value stream map must be drawn, to validate the results. The effort equals two working days for each value stream.

- *Analyze the value stream.* Both approaches require effort for the analysis. However, the process and product complexity and dynamics can be covered using process mining. Enriched attributes (e.g., supplier specification) are included. In contrast, the analysis step of pen-and-paper-based value stream mapping requires further interviews or data collection on the shop floor. The additional effort in comparison to process mining equals 0.5 working days for each value stream.

- *Monitoring of the future state.* Monitoring the future state requires creating or updating the current state map and comparing the different states over time. Notably, comparing the different states is required for both approaches. The additional effort in comparison to process mining equals 1.5 working days for each value stream.

In contrast to pen-and-paper-based value stream mapping, the proposed approach introduces fixed costs per year:

- *Software maintenance.* The software maintenance covers any effort required during operations, such as implementing additional performance metrics or refreshing the data. The effort for software maintenance equals 15 working days.
- *Overhead.* Any additional effort is covered by five working days.

A.4 Software used

- *Camuda BPMN.io*. BPMN process modeling tool, including a visualization of the business process. Available at: https://bpmn.io/
- *Fluxicon Disco*. Process mining software for professionals and academia. Available at: https://fluxicon.com/disco/
- *Java stack*. The software development sack for Java includes many open source and commercial libraries. In this thesis, the primary libraries applied are the *ProM 6* stack and the *Spring* framework.
- *LaTeX stack*. The documentation of the thesis is written in LaTeX. The open source tool *Sublime Text 3* was used as an editor. The tool is available at https://www.sublimetext.com
- *Microsoft Office*®. A commercial set of office tools that support various applications. Work on this thesis used MS Excel®and MS PowerPoint®most often.
- *ProM 6*. Process mining software for academia. Available at: http://www.promtools.org
- *Python stack*. The software development stack for Python includes numerous open source libraries. The libraries used the most often are Docker, Pandas, PySpark, Numpy, Multithreading, Pyodbc and Jupyter.

A.5 Theses supervised

Between 2015 and 2019, the author extensively supervised and guided 19 students at the Institute for Machine Tools and Industrial Management (*iwb*). The students completed their master's theses, bachelor's theses, or semester projects in the fields of process mining, value stream mapping, logistics, logistics planning, packaging planning, and change management in a strong collaboration with the author. In particular, the author supervised the research clarification, objectives, research questions, approach, activities, and content. Discussions with the students and selected parts of the results contributed to this work (cf. Table A.6). The author expresses his great thanks to all students for their great support.

A.6 Publication list

Preliminary results related to this thesis have been presented at conferences and published in conference proceedings or journal publications. These publications are listed in the following.

KNOLL et al. 2016
Knoll, D.; Prüglmeier, M.; Reinhart, G.: Predicting Future Inbound Logistics Processes using Machine Learning. *Procedia CIRP* 52 (2016), pp. 145–150.

KNOLL et al. 2017
Knoll, D.; Prüglmeier, M.; Reinhart, G.: Materialflussanalyse mit ERP-Transportaufträgen. *wt Werkstattstechnik online* 3 (2017), pp. 129–133.

KNOLL et al. 2019a
Knoll, D.; Neumeier, D.; Prüglmeier, M.; Reinhart, G.: An automated packaging planning approach using machine learning. *Procedia CIRP* 81 (2019), pp. 576–581.

KNOLL et al. 2019b
Knoll, D.; Waldmann, J.; Reinhart, G.: Developing an internal logistics ontology for process mining. *Procedia CIRP* 79 (2019), pp. 427–432.

KNOLL et al. 2019c

Knoll, D.; Reinhart, G.; Prüglmeier, M.: Enabling value stream mapping for internal logistics using multidimensional process mining. *Expert Systems with Applications* 124 (2019), pp. 130–142.

REINHART et al. 2017

Reinhart, G.; Knoll, D.; Teschemacher, U.; Lux, G.; Schnell, J.; Endres, F.; Distel, F.; Seidel, C.; Berger, C.; Klöber-Koch, J.; Pielmeier, J.; Braunreuther, S.: Anwendungsfeld Automobilindustrie. In: *Handbuch Industrie 4.0*. Ed. by G. Reinhart. München: Carl Hanser. 2017.

SCHUH et al. 2019

Schuh, G.; Reinhart, G.; Prote, J. P.; Sauermann, F.; Horsthofer, J.; Oppolzer, F.; Knoll, D.: Data mining definitions and applications for the management of production complexity. *Procedia CIRP* 81 (2019), pp. 874–879.

Table A.6: List of theses supervised (chronologically sorted)

Name	Title	Year	Related to chapter
Kral, Marian	Identification of potentials for the provision of information within logistics planning departments of the BMW Group	2016	-
Poss, Christian	Creating a reference model of inbound logistics in a multi-variant assembly production	2016	5.1.1
Stapff, Susanna	Development of a model-based approach for the quantification of structure complexity in assembly logistics using the example of BMW Group	2016	-
Quitterer, Niklas	Verification and validation of a multi-crtierial optimization model for the configuarion of production networks	2016	-
Ballauf, Maximilian	Concept for an automated reconstruction of process chains using the Digital Shadow in the area of production logistics	2016	2.2
Neumeier, Daniel	Development of a machine learning based prediction model for selecting packaging for products in high model-mix assembly line production	2017	-
Haid, Charlotte	A method for the automated derivation of process indicators using movement data from the high model-mix production logistics	2017	5.3.5
Lie, Stephan	Analyzing inbound logistics planning processes in the highmodel-mix assembly line production focusing knowledge transfer	2017	-
Waldmann, Julian	Development of an Ontology for production logistics in the automotive sector	2017	5.1.1
Hoffmann, Philipp	Development of a Methodology to quantify and identify Waste due to oversized Stock Levels in the Production Logistics	2017	2.2.2
Blessing, Robert	Designing and Implementing a Process Mining Methodology for an automated Analysis of Logistics Processes	2017	2.3, 5.3.1, 5.3.2
Roltsch, Floris	A Data-Driven Approach for Predicting the Impact of Engineering Changes on Logistics Processes	2018	-
Schlesinger, Lorena	Designing and Implementing a Data-driven Methodology Towards an Automated Waste Analysis of Processes within Production Logistics	2018	5.3.3, 5.4
Bachmeier, Quirin	A data driven approach for identifying and prioritizing oversized inventory levels based on part-specific properties and inventory movements	2018	6.1.5
Walther, Paul	Improvement of the automated data-driven change impact prediction in logistics to reduce economic risk	2018	-
Straßl, Florian	Causes of fluctuations in material requirements - Analysis and description of the effects from programme and demand calculations applied to the example of the automotive industry	2019	-
Greschl, Simon	Development of a method for a quantitative evaluation of value streams and a framework for potential for action	2019	1
Rill, Raffaela	Designing and Implementing a Process Mining supported Methodology for Evaluating Value Streams within Internal Logistics	2019	6.1.3, 6.1.4
Linnenweber, Tim	Development of a Systematic Approach to Improve and Maintain a Productive Machine Learning Model for Change Impact Prediction in Logistics	2019	-

List of Figures

List of Tables

List of Abbreviations

ABC	Activity-based Costing
BFS	Breadth-First Search
BPMN	Business Process Modeling Notation
DFD	Data Flow Diagram
DRM	Design Research Methodology
DSM	Design Structure Matrix
ERP	Enterprise Resource Planning
FIFO	First In - First Out
JIT	just-in-time
JIS	just-in-sequence
MIT	Massachusetts Institute of Technology
MES	Manufacturing Execution System
MRP	Material Resource Planning
ONTO-PDM	Product-driven ONTOlogy for Product Data Management
RFID	Radio frequency identification
RC	Research Contribution
RQ	Research Question
PM^2	Process Mining Project Methodology
PSL	Process Specification Language
SCM	Supply Chain Management
TPS	Toyota Production System
TUM	Technical University of Munich
WMS	Warehouse Management System
XES	Extensible Event Stream

List of Symbols

Global symbols

n	Index variable of a set
N	Number of value streams

Process mining fundamentals

e	Event
E	Event universe, i.e., the set of all possible event identifiers
AN	Attribute name
c	Case
C	Case universe, i.e., the set of all possible case identifiers
σ	Trace
L	Event log
L_e	Enriched event log
M	Process model

Data preprocessing

λ_{TO}	Flattened transfer orders
u, v	Vertexes in a graph
$edge(u, v)$	A directed edge from u to v
λ_A	Flattened process activities
λ_{ST}	Flattened storage resources
λ_{PG}	Flattened packaging resources
λ_{SU}	Flattened suppliers
λ_{PT}	Flattened parts
$\delta_{k,v}$	Key-value pair for filtering

Mining

IP	Inventory profile
DP	Demand profile
GP	Goods receiving profile
δt	Time-interval
k	Number of time-intervals δt
f	Feature