Technische Universität München
TUM School of Engineering and Design

A Data-Driven Approach for Predictive Maintenance Integrated Production Scheduling

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Vollständiger Abdruck der von der TUM School of Engineering and Design der Technischen Universität München zur Erlangung eines

Doktors der Ingenieurwissenschaften (Dr.-Ing.)

genehmigten Dissertation.

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Die Dissertation wurde am 20.04.2023 bei der Technischen Universität München eingereicht und durch die TUM School of Engineering and Design am 21.08.2023 angenommen.

Editor’s Preface

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

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

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

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

Rüdiger Daub Gunther Reinhart Michael Zäh

Acknowledgment

This dissertation was elaborated during my engagement as a research associate at the Institute for Machine Tools and Industrial Management (*iwb*) at the Technical University of Munich (TUM).

First and foremost, I would like to express my heartfelt gratitude to my supervisor, Prof. Gunther Reinhart, and fellow *iwb*-Professor Michael Zäh for their guidance, trust and support throughout my dissertation journey. Having faith in me in even the toughest times was crucial to the success of this project. The journey we have taken throughout Europe for our research project, the challenges we faced and the experience we made as a team enabled me to grow not only intellectually, but also personally.

My gratitude further extends to all colleagues and staff at *iwb* for their continuous support and fruitful discussions. In particular, I would like to thank Sarah Wagner and Maximilian Benker for their critical review of this dissertation and their valuable feedback. In addition, I would like to thank the colleagues of my research field *Data Analytics in Production Management* as well as the research groups *Production Management and Logistics* and *Machine Tools* at *iwb* for their friendship and support throughout the years.

I am also grateful and proud of the many students whom I had the honor to supervise and who supported me and my research. It was one of the greatest pleasures during my time as a research associate. Special thanks go out to Alex, Benedikt, Meltem and Max for all the discussions and working sessions.

Finally, I would like to extend my sincerest thanks to my parents, Yan and Yuyou, and sister Linda, without whom all of this would not be possible.

Munich, December 2023 *Simon Zhai*

Abstract

Predictive Maintenance (PdM) is one of the core innovations of *Industrie 4.0* that captures the interest of research and industry alike. While prediction models and related artificial intelligence technology have become more potent due to ongoing research, most models are not designed considering actual industrial practice and are not validated with industrial data. In addition, the predictive information about the remaining lifetime and the health condition of machines is rarely used to integrate production and maintenance scheduling which is crucial for creating actual value-added.

To overcome these limitations, this dissertation proposes a holistic approach that directly integrates PdM models with production and maintenance scheduling: the *Predictive Maintenance Integrated Production Scheduling* (PdM-IPS) *approach*. Since the manufacturing of different product variants causes different levels of degradation to the machine, an operation-specific health prognostics model is developed. Thus, to enable PdM-IPS, a generative deep learning model based on the conditional variational autoencoder that is able to derive an operation-specific health indicator from large-scale industrial condition monitoring data is proposed. This model outputs the estimated change in a machine's health condition after producing a specific production sequence. Operation-specific degradation information is subsequently used for integrated production and maintenance scheduling. Specifically, a flexible job shop problem with maintenance constraints is formulated and solved by a two-stage genetic algorithm.

Results indicate that the PdM-IPS approach is able to find feasible high-quality PdM integrated production schedules using both simulated and real industrial data. Finally, the PdM-IPS approach was prototypically implemented in a real production line in the automotive industry. Expert interviews indicate that the PdM-IPS approach returns promising results and shows a reasonable amortization period.

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List of Abbreviations

Abbreviation	**Description**
AI	Artificial Intelligence
CbM	Condition-based Maintenance
CGAN	Conditional Generative Adversarial Network
CM	Condition Monitoring
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation
CNC	Computerized Numerical Control
CRISP-DM	Cross-Industry Standard Process for Data Mining
CVAE	Conditional Variational Autoencoder
DRM	Design Research Methodology
DS	Data Simulator
FJSSP	Flexible Job Shop Scheduling Problem
GA	Genetic Algorithm
GAN	Generative Adversarial Network
HA	Health Assessor
HI	Health Indicator
IPSMP	Integrated Production Scheduling and Maintenance Planning
JSSP	Job Shop Scheduling Problem
MP	Maintenance Plan
OpRegSeq	Sequence of Operating Regimes
OR	Operating Regime
ORI	Operating Regime Identification
ORSS	Operating Regime-specific Standardization
OSSE	Operation-specific Stress Equivalent
PdM	Predictive Maintenance
PdM-IPS	Predictive Maintenance Integrated Production Scheduling
PHM	Prognostics and Health Management
PM	Preventive Maintenance
PS	Production Schedule
R	Requirement

R/E	Researchers and Engineers
RML	Remaining Maintenance Life
RUL	Remaining Useful Life
S/I	Student Researchers and Interns
TSGA	Two-stage Genetic Algorithm
VAE	Variational Autoencoder
VDMA	Verein Deutscher Maschinen- und Anlagenbauer (German Mechanical Engineering Industry Association)

List of Symbols

Vectors are printed in bold (such as $\boldsymbol{u}$), and matrices are capitalized and printed in bold (such as $\boldsymbol{U}$). To increase the readability, the list includes only important symbols and is sorted in the chronological appearance of the symbol in this thesis.

Symbol	Description
$\boldsymbol{u}$	Operational condition
O_p	Operating Regime p
op	Operational parameter
O_i	Operation i
δ_{ik}	Operation-specific stress equivalent/degradation of O_i on machine k
p_i	Processing time of O_i
RUL_{ik}	Remaining Useful Life of machine k processing only O_i
Δ_k	Cumulative degradation of machine k
λ	Failure rate
$R(t)$	Reliability function
η	Remaining operational lifetime
β	Shape parameter of the Weibull distribution
C_{max}	Makespan
C_{max}^R	Reliability Weighted Makespan
C_i	Completion time of O_i
$\boldsymbol{x}$	Sensor data (e.g., condition monitoring data)
$\boldsymbol{c}$	Conditioning vector, e.g., used to condition $\boldsymbol{x}$ to operations/products
$\boldsymbol{z}$	Latent representation of sensor data $\boldsymbol{x}$
$\hat{\boldsymbol{x}}$	Reconstruction of $\boldsymbol{x}$
T_{total}	Total tardiness
f	Fitness function
$\Delta'_{critical}$	Scaled critical, i.e., maximum degradation of a single machine
Δ'_{total}	Scaled total degradation of all machines
$t_{k,fail}$	Failure time of machine k

1 Introduction

Manufacturing companies today face various challenges: increased competition due to globalization, shorter product life cycles, as well as product diversification and individualization (ELMARAGHY 2012, ABELE & REINHART 2011, WARNECKE ET AL. 2003). The resulting competitive pressure forces the manufacturing industry to innovate and create new means to stay competitive. Recent advancements in information and communications technology, together with developments in Artificial Intelligence (AI), enable the so-called fourth industrial revolution, *Industrie 4.0*, which in turn empowers industrial companies to increase productivity and efficiency (REINHART 2017) significantly. *Predictive Maintenance* (PdM) is one core innovation made possible by the fourth industrial revolution and is able to increase productivity and efficiency by reducing machine downtimes, hence gaining vast attention from academia and industry alike (ZHAI & REINHART 2018).

1.1 Motivation

Many manufacturing companies, however, apply so-called predetermined preventive maintenance (PM), in which maintenance actions are carried out based on production cycles or simply time – regardless of the actual health condition of the machine (MÄRZ 2017, p. 691). Using recent advances in the research of AI and condition monitoring (CM) measurements from sophisticated sensors, the health condition and remaining useful life (RUL) of the machine and its components can be estimated (LEI ET AL. 2018). These advances enable the new maintenance strategy PdM. Knowing the health condition of machinery allows the operator to conduct maintenance just in time, thus not wasting RUL by maintaining prematurely, as is often time the case when preventive maintenance strategies are utilized (ZHAI & REINHART 2018). Costs, therefore, can be reduced by preventing unexpected machine breakdowns and unnecessary maintenance actions (BEN ALI ET AL. 2011, DENKENA ET AL. 2012, CHEN ET AL. 2014). PdM approaches rely on physical, knowledge-based and data-driven modeling for RUL predictions (BEKTAS ET AL. 2019b, p. 4). Data-driven modeling has been the focal point of recent research activities due to the developments in AI research. Higher effectiveness and broader applicability, particularly for more complex machining systems (BEKTAS ET AL. 2019b, p. 5), such as machine tools, resulted from such research undertakings. A study conducted by the German Mechanical Engineering Industry Association (VDMA) states that more than 80 % of companies consider applying PdM (FELDMANN ET AL. 2017).

Recent studies also confirm the high potential of PdM, particularly in increasing machine availability and preventing unexpected failures (DUSCHEK ET AL. 2021, ZHAI ET AL. 2020, FELDMANN

ET AL. 2017, STAUFEN AG 2018). However, these studies also indicate that the manufacturing industry requires models tailored to its constraints, such as limited data quantity and quality. While nearly three-quarters of respondents expect that PdM will have high relevance for maintaining their machinery in the near future, only 7 % are satisfied with current PdM solutions. Figure 1-1 displays the discrepancy of PdM's expected importance for manufacturing companies in the following years compared to the capabilities of current PdM solutions (STAUFEN AG 2018). The vast majority state that improvements in terms of PdM's scope and functionality are necessary. Holistic approaches, as well as the inclusion of industrial constraints, are requested. These approaches shall improve the whole production line and should not focus only on maintenance.

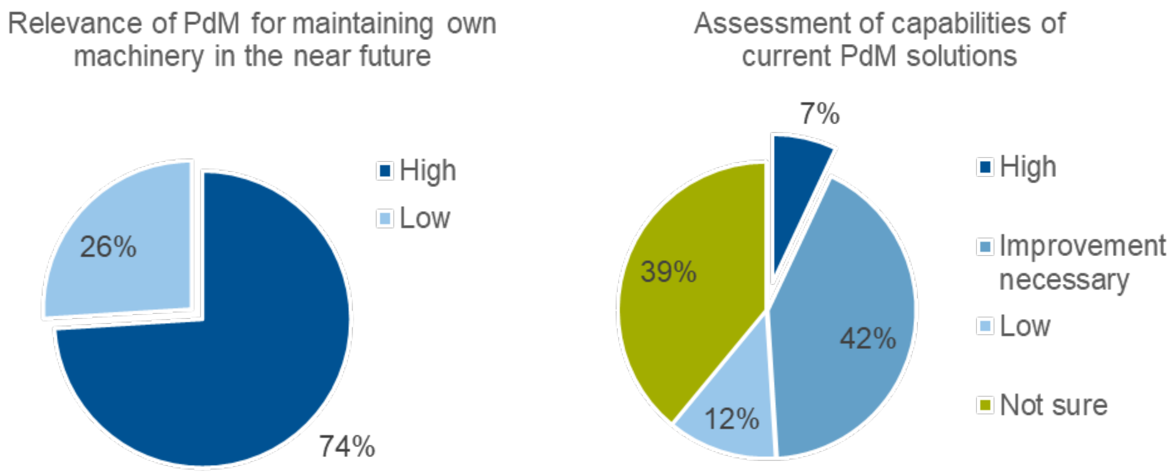

Figure 1-1: Relevance of PdM in the near future and current capabilities of PdM solutions (STAUFEN AG 2018, n=450).

Such holistic approaches include integrated production scheduling and maintenance planning (IPSMP). IPSMP describes the general problem of finding an optimal production and maintenance schedule subject to both production and maintenance constraints (ZANDIEH ET AL. 2017), which in theory enables the transfer of PdM information to the place where the actual value is created: the shop floor (LADJ ET AL. 2019, ZHAI ET AL. 2019, PAN ET AL. 2012). However, most existing IPSMP approaches only focus on integrating preventive maintenance actions and production scheduling. The challenge of integrating PdM into IPSMP lies in the operation-specific modeling of degradation (BOUGACHA ET AL. 2019, ZHAI ET AL. 2021). Different machining operations on multifunctional machine tools lead to different degradation levels, i.e., the degradation of the machine is dependent on the operation running on the machine (C. FITOURI ET AL. 2016). This implies that PdM solutions must be modeled operation-specifically to be industrially viable.

Product variants are manufactured using different machining operations and thus, different production schedules impose different levels of degradation on the machine. Existing IPSMP approaches assume the operation-specific degradation to be linear to the processing time of the operation (LADJ ET AL. 2019, C. FITOURI ET AL. 2016). This does not necessarily hold in industrial use cases. For example, operations involving the processing of harder materials usually lead to higher degradation than softer materials, even if the softer material is processed longer. Hence, operation-specific modeling of degradation and predicting the future health condition, therefore enabling *PdM Integrated Production Scheduling* (PdM-IPS). The development of an approach for PdM-IPS is the objective of this dissertation and includes the application of PdM information in IPSMP problems by operation-specifically estimating degradation and optimizing the production and maintenance schedule accordingly.

1.2 Problem Statement and Objective

Two key challenges can be identified that prevent the holistic application of PdM-IPS in the industry:

1. **Need for operation-specific modeling of degradation and health condition prediction**

   As the degradation of machine tools and their components is non-linear, models estimating and predicting the health condition must consider non-linear operation-specific degradation. Hence, more elaborate and complex modeling is required. In addition, the output of these models has to be designed to be used for the subsequent IPSMP.

2. **Low industrial data quality and availability**

   Industrial data differs heavily from benchmark data used in academia for modeling, e.g., the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset by SAXENA & GOEBEL 2008 in terms of both quality and availability (YAN ET AL. 2017):

   a. Data quality

   Noisy and, in some cases, even missing or redundant data is common in the industry. Industrial data typically is unstructured, multi-dimensional, heterogenic and sometimes even not available in digital form. Furthermore, industrial data has to be acquired from multiple sources. As such, extensive data preprocessing is necessary to derive meaningful data that can be used to model machines' health conditions.

   b. Data availability

   Modeling the health condition requires data where the machine was both in healthy and faulty states. Preventive maintenance actions lead to rare failures of the machine in practice. This limits the applicability of PdM models since most of them rely on failure labels.

Data is abundant when the machine is in a healthy state, while data corresponding to failures is sparse.

The overall objective of this dissertation is thus the development of a novel data-driven Predictive Maintenance Integrated Production Scheduling (PdM-IPS) approach. It aims to specifically design and apply health condition models and IPSMP algorithms with regard to each other and focus on their seamless interaction. The approach shall cater to the industrial reality regarding data that manufacturing companies face today, realize operation-specific health prediction and its application in IPSMP. The PdM-IPS approach ensures that recent PdM achievements are used for planning purposes, hence harmonizing production scheduling and maintenance planning. Specifically, the PdM-IPS approach aims at:

- Modeling and applying operation-specific health condition information of a machine for scheduling purposes,
- Preventing machine breakdowns, thus increasing machine availability,
- Reducing the number of unnecessary maintenance actions,

hence, overall,

- Generating a feasible integrated production schedule and maintenance plan.

The scientific work required to design and realize the PdM-IPS approach can be split into four sub-objectives:

1. Identification of requirements and success factors for PdM-IPS.
2. Operation-specific modeling of degradation for subsequent PdM-IPS.
3. Development of a suitable IPSMP algorithm and integration of operation-specific degradation information.
4. The validation of PdM-IPS in an industrial setting.

1.3 Requirements

To reflect specific requirements (R) of the PdM-IPS approach, they are divided into general requirements, PdM requirements, and IPSMP requirements. All presented requirements were derived from analysis of the state of the art and expert studies. This represents the first stage of the applied research methodology of this dissertation, which will be introduced in the next section.

General requirements refer to requirements that apply to the general application of the approach. PdM requirements describe specific requirements that concern the modeling of the health condition of the machine. Lastly, IPSMP requirements refer to the requirements concerning the design of the scheduling algorithm. Both PdM and IPSMP requirements are derived from the general requirements and industrial constraints.

1.3.1 General Requirements

R1 General applicability

The approach shall be generally applicable and valid. The models developed within the approach must have the ability to be applied in different production scenarios, i.e., different shop floor layouts and machinery. This entails that the application of the approach must be independent of the type of machine on the shop floor.

R2 Industrial applicability

The approach shall be applied in an industrial setting and should generate value-added for the applying company. Hence, industrial constraints must be addressed accordingly.

R3 Modularity

The models developed within the approach shall be modular to account for the dynamic and disruptive manufacturing companies face nowadays. This necessitates that the models shall be easily exchanged or modified to account for changing circumstances.

R4 Economic viability

The approach shall be economical, i.e., the application of the approach shall be financially amortized in a reasonable time. Improved collaboration of production and maintenance should facilitate improved planning, resulting in less machine downtime and higher machine utilization. The resulting profits shall be higher than the additional costs, e.g., for implementing and maintaining the approach.

1.3.2 Predictive Maintenance Related Requirements

R5 Robustness

To account for R1 and R2, the modeling of the health condition of the machine shall be robust to noise, missing data, mixed data outliers and different operational and fault conditions, see LEI ET AL. (2018).

R6 Ability to handle high-dimensional data

Since industrial CM data is usually high dimensional (see R1 & R2), the models shall operate efficiently with high dimensional data and extract meaningful health indicators (HIs), see MICHAU ET AL. (2018).

R7 Ability to handle a low amount of labeled failure data

In order to be industrially viable (see R2), the health condition model within the approach shall be able to generate health assessments and predictions in a setting where failure data corresponding to the CM data is rarely available. Due to the low number of labeled failure data, a (semi-)unsupervised learning model shall be preferred over a supervised learning model, see GUGULOTHU ET AL. (2018).

R8 Operation-specific health assessment and prediction

As motivated in section 1.2, operation-specific modeling of the health condition is critical for subsequent application in planning algorithms. Hence, the model shall assess the current and predict future health conditions operation-specifically, see ZHAI ET AL. (2021).

1.3.3 Integrated Production Scheduling and Maintenance Planning Related Requirements

R9 Flexibility regarding shop floor layout

R1 and R2 lead to the requirement of a planning model capable of being widely applicable. The planning model within the PdM-IPS approach shall be based on a flexible job shop layout, where job operations can be scheduled on multifunctional machines capable of executing multiple operations. Flexible job shops are thus representative of many industrial shop floors (ROSHANAEI ET AL. 2013).

R10 Time-efficiency

The planning and scheduling algorithm and its interaction with the health condition model shall use reasonable computing power and time to compute its results to be viable for industrial application (see R2). Reasonable computing power refers to systems that are typically available for decision-makers, e.g., desktop computers. Reasonable computing times depend on the planning horizon and frequency of planning and thereupon have to be evaluated use case dependently.

R11 Multi-objective optimization ability

As the term entails, IPSMP has two objectives: optimizing both production scheduling and maintenance planning. The planning algorithm shall consequently handle multiple objectives simultaneously and compute feasible solutions in reasonable time. Objectives can be competing, so trade-offs might be necessary.

R12 Consideration of the decision maker's preferences

The approach shall allow user inputs regarding objective functions and other parameters to reflect the preferences of the decision-maker, e.g., the production and maintenance planner. Objectives may conflict with each other and on that account, the decision-maker has to carefully assess the priorities according to entrepreneurial needs (STRUNZ 2012, p. 23). This includes weighing objectives of production schedules and maintenance plans against each other and setting thresholds for critical machine degradation, maximum calculation time, and other parameters.

1.4 Research Methodology and Structure of This Dissertation

This dissertation utilizes the Design Research Methodology (DRM) by BLESSING & CHAKRABARTI (2009) as the underlying methodology to scientifically develop, implement and evaluate the approach. The DRM was created to facilitate design research through the establishment of a cohesive, interdisciplinary framework that aims at enhancing the integration and assessment of various design support tools and methods and to develop a standard experimental and validation methodology (BLESSING & CHAKRABARTI 2009). Herein, the "primary focus lies on supporting engineering and industrial design research" (BLESSING & CHAKRABARTI 2009, p. 2). The authors define the term *design* as "activities that actually generate and develop a product […] or technology […] needed to realize the product and to fulfill the needs of the user and other stakeholders" (BLESSING & CHAKRABARTI 2009, p. 1). The term *product* is referred to as a broader concept comprising both physical (e.g., a machine tool) and virtual solutions (e.g., software or process), or a combination of both. *Needs* can be social and also "economic (e.g., manufacturing systems for mass production)" (BLESSING & CHAKRABARTI 2009, p. 1).

Since the objective of this dissertation is to design and realize an industrial viable PdM-IPS approach (see Chapter 1.3), the DRM is well-suited in supporting the research process as well as ensuring that the above-mentioned economical needs are fulfilled. Thus, the DRM is chosen as the underlying research methodology of this dissertation.

The DRM consists of four stages: Research Clarification, Descriptive Study I, Prescriptive Study, and Descriptive Study II.

Research Clarification states the focus, as well as the success criteria and requirements of the research project. The *Descriptive Study I* provides a basis for subsequent development of support, as well as to identify factors that facilitate or hinder success. The *Prescriptive Study* builds upon these findings, develops support and enables its evaluation, with the latter being the focus of the *Descriptive Study II*. BLESSING & CHAKRABARTI (2009) note that the DRM stages do not have to be traversed sequentially, nor does every stage have to be examined with the same level of detail. Iterations have to take place and variations of the DRM are necessary to cater to the individual needs of each research project.

As presented in Figure 1-2, this thesis uses the introduced stages of the DRM as the framework for the scientific work. Each stage is utilized to fulfill one sub-objective introduced at the end of section 1.2. It should be noted that the transition between stages is seamless and thus, the allocation of stages to chapters is not to be understood strictly. The chosen traversing of the stages in the presented manner supports the deductive research in order to design the PdM-IPS approach: By analyzing technical fundamentals and the state of the art the research is clarified and the research deficit and the research objectives are derived. The Descriptive Study I is applied in order to derive crucial success factors, which subsequently are taken into account in the Prescriptive Study. The Descriptive Study II is finally utilized to validate the developed PdM-IPS approach.

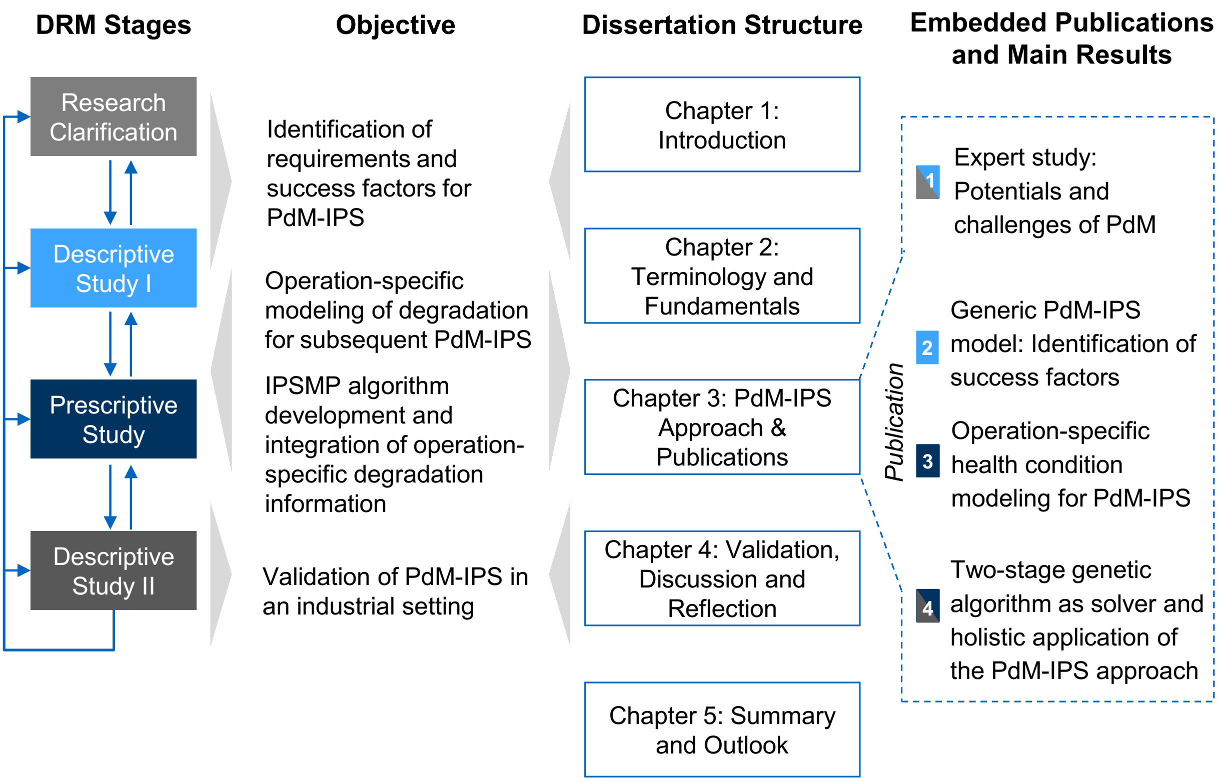

Figure 1-2: Relation between the DRM, the objective of each stage, the structure of this dissertation and the embedded publications.

<u>Research Clarification</u>

This stage was applied to clarify the research deficits, identify the research goal and its related requirements. Chapters 1 and 2 motivate the research and introduce corresponding terminology, methods and fundamentals. The status quo is presented by reviewing recent studies. The introduction of PdM-IPS-related terms and the following analysis of scientific literature on current approaches for the problem at hand serve as the basis for developing the support in the prescriptive study. By doing so, these chapters clarify the research objectives as well as the requirements to achieve these objectives.

The third chapter represents the central chapter of this thesis, comprises a short introduction to the PdM-IPS approach and presents the associated embedded publications. These four publications mainly focus on the *Descriptive Study I* and the *Prescriptive Study* and focus on systematically developing the means needed for support and fulfilling the sub-objectives introduced in section 1.2.

Descriptive Study I

The objective of the first Descriptive Study is to identify crucial success factors. Two publications are at the core of this study in order to identify these factors. These analyze the current challenges of industrial PdM application and develop a first generic model for PdM-IPS, thus focusing on sub-objective 1 (see section 1.2.). This model is tested in a simulative environment to identify and describe crucial success factors needed for the industrial application of PdM-IPS, namely an operation-specific health modeling and an efficient integrated solving algorithm.

Prescriptive Study

The Prescriptive Study is utilized in order to develop the support for success: The two publications of the *Prescriptive Study* build upon the findings of the previous stage and develop the PdM-IPS approach. The first publication develops an operation-specific health model capable of predicting the future health condition of a machine conditioned to a given production sequence and covers sub-objective 2. The second publication uses this health model in an IPSMP setting to develop a time-efficient two-stage genetic algorithm as the solver, hence realizing sub-objective 3. The PdM-IPS approach is verified with simulative data and validated using industrial data in a realistic application scenario in both publications.

Descriptive Study II

The second Descriptive Study aims to validate, evaluate and discuss the designed approach. Thus, this study was applied in order to achieve sub-objective 4. The *Descriptive Study II* comprises a critical discussion and reflection and an economic evaluation of the approach and is presented in chapter 4. The approach is discussed according to the requirements introduced in section 1.3 and its potential is evaluated using expert interviews. Different scenarios of a prototypical application of the approach are examined in the economic evaluation. Finally, a summary and outlook on possible further research directions conclude the dissertation.

2 Terminology, Fundamentals and State of the Art

This chapter introduces the key terminology, fundamentals and the state of the art of this dissertation to ensure a common understanding. As such, it is part of the *Research Clarification* stage of the DRM. In particular, the introduced terms are used in the publications presented in chapter 3. Emphasis is put on the state of the art of IPSMP and recent developments in health condition modeling at the end of each subchapter.

2.1 Maintenance Terminology

According to DIN EN 13306, **maintenance** is defined as the

"combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function."

Hence, the primary maintenance objectives for manufacturing companies are to ensure machine availability, prolong useful life, and prevent machine failures (STRUNZ 2012, p. 2). It should be noted that a *failure* refers to a point in time after which the machine cannot fulfill its intended function, such as manufacturing products within the required tolerances. In the context of this dissertation, a maintenance action refers to repair actions that restore the state of an item, thus ensuring availability. An *item* in the definition above refers to a part, component or (sub-)system that can be described individually. *Items* include objects that are subject to degradation and therefore may require maintenance, e.g., machines or machine components. Machines, in turn, are represented by a single or a set of predetermined critical components.

The health condition of machinery can be represented by a health indicator (HI) (LEI ET AL. 2018) that decreases with degradation. HIs are frequently bounded and range from 0 to 1 for better comparison, with 1 being the "perfect healthy state", while 0 denotes an "absolutely degraded" or failing state. Figure 2-1 depicts an exemplary HI of an item. The useful life describes the timespan of one run to failure, i.e. $t_{failure} - t_0$. The HI drops due to degradation between t_0 and an arbitrary time point t_1. The remaining useful life (RUL) denotes the timespan from time point t_1 and $t_{failure}$. It should be noted that after failure, a maintenance action resets the HI to 1.

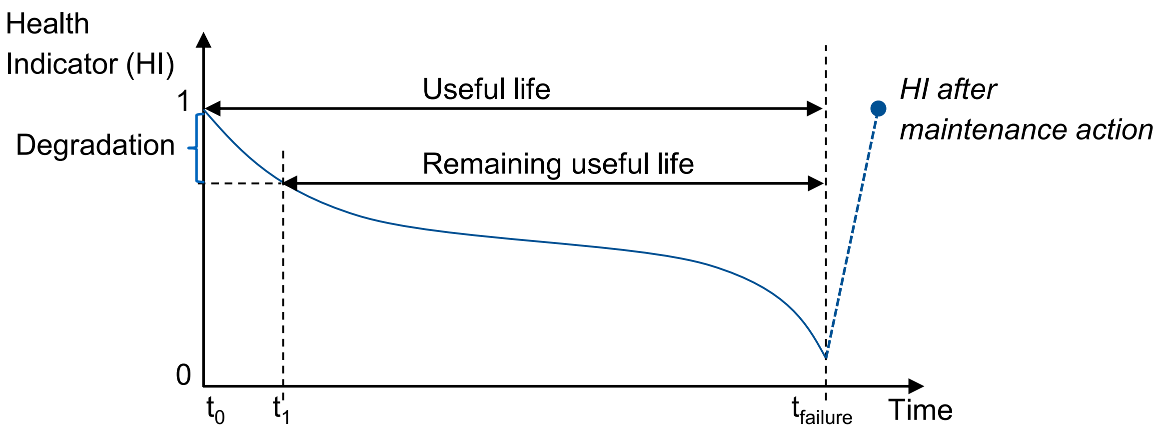

Figure 2-1: Schematic visualization of HI, degradation, (remaining) useful life and corresponding points in time.

Using a preventive maintenance strategy (see next section), maintenance is planned and scheduled according to predetermined time intervals. The item's condition is determined by condition monitoring or by predicting the degradation evolution before all useful life is depleted. Corrective maintenance is not scheduled since it is conducted after the failure of an item. It is thus a reactive strategy. Table 1 presents key terms related to maintenance used in this dissertation.

Maintenance Strategies

Maintenance strategies are used to achieve maintenance objectives, i.e., by repairing and as such, restoring the functionality of items. These strategies can be generally divided into the categories of *preventive* and *corrective* according to DIN EN 13306 (2018, p. 58). Corrective maintenance is carried out after the item in question has failed to restore its function (DIN EN 13306 (2018, p. 38). Preventive maintenance is carried out to "asses and/or to mitigate degradation" (DIN EN 13306 (2018, p. 24) and can be further divided into *predetermined* and *condition-based* maintenance (CbM). Figure 2-2 presents the categorization of maintenance strategies according to DIN EN 13306.

Table 1: Maintenance-related terms of this dissertation.

Term	**Definition**	**Source**
Maintenance schedule	“Plan produced in advance detailing when a specific maintenance task should be carried out.”	DIN EN 13306 (2018, p. 46)
Maintenance plan	“Structured and documented set of tasks that include the activities, procedures, resources and the time scale required to carry out maintenance.” In the context of this thesis, a maintenance plan refers to a plan produced in advance detailing the point in time and duration of a maintenance task.	DIN EN 13306 (2018, p. 10)
Availability	“Ability of an item to be in a state to perform as and when required, under given conditions, assuming that the necessary external resources are provided.”	DIN EN 13306 (2018, p. 17)
Useful life	“Time interval from first use until the instant when a limiting state is reached.”	DIN EN 13306 (2018, p. 22)
Failure	“Loss of the ability of an item to perform a required function.”	DIN EN 13306 (2018, p. 26)
Degradation	“Detrimental change in physical condition, with time, use or due to external cause.” Subsequently may lead to failure.	DIN EN 13306 (2018, p. 28)
Condition Monitoring (CM)	“Activity, performed either manually or automatically, intended to measure at predetermined intervals the characteristics and parameters of the physical actual state of an item.”	DIN EN 13306 (2018, p. 41)
Repair	“Physical action taken to restore the required function of a faulty item.”	DIN EN 13306 (2018, p. 44)
Health Indicator (HI)	“HIs are constructed using signal processing techniques, artificial intelligence (AI) techniques, etc., to represent the health condition of machinery.”	LEI ET AL. (2018, p. 800)
Remaining Useful Life (RUL)	“The remaining useful life (RUL) of an asset or system is defined as the length from the current time to the end of the useful life.”	SI ET AL. (2011, p. 1)

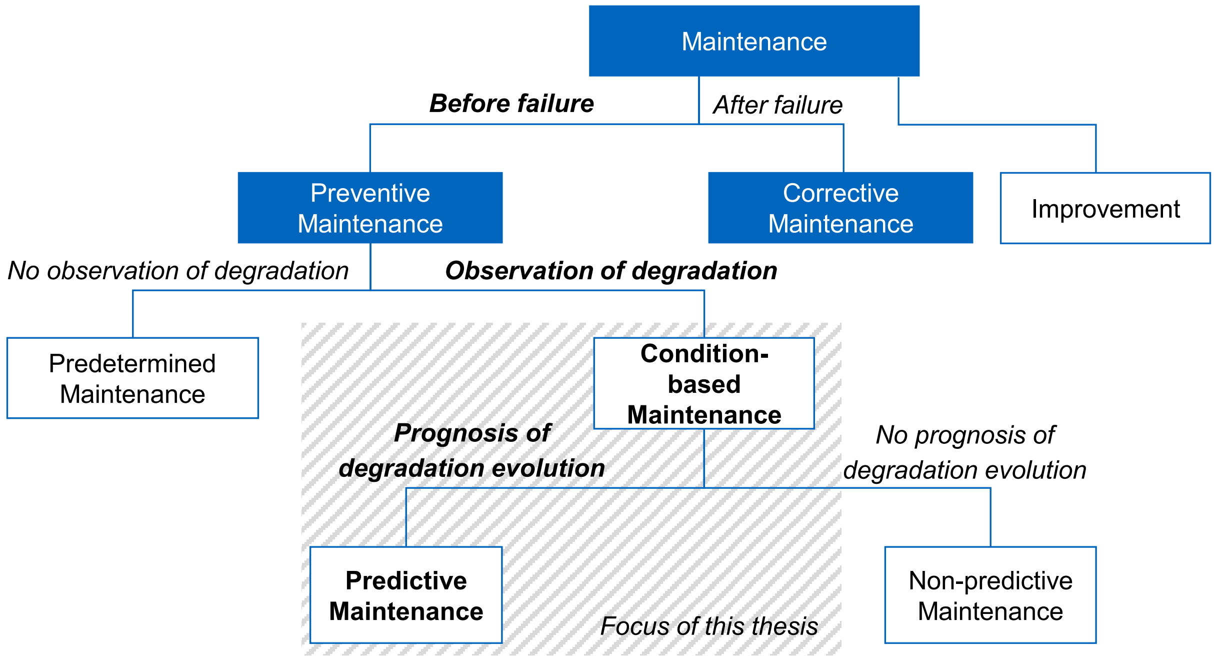

Figure 2-2: Classification of maintenance strategies according to DIN EN 13306 (2018, p. 58).

Predetermined maintenance actions are executed in regular time intervals or after a certain number of production cycles in use without assessing the actual condition of the item in question. The term preventive maintenance is often used to refer to *predetermined* maintenance in the industry (ZHAI & REINHART 2018). Hence, for the remainder of this thesis, preventive maintenance will be used to refer to predetermined preventive maintenance. Condition-based maintenance (CbM) assesses the physical condition of an item before deciding on whether or not to maintain it. CbM is funded on CM by using sophisticated sensors that measure physical parameters like vibration, which represent the condition of a component (LEI ET AL. 2018). Figure 2-3 schematically visualizes the typical point in time of maintenance actions for the presented strategies. While corrective maintenance actions occur after failure, PM and CbM conduct the maintenance action while the machine is still in a healthy state. CbM actions tend to be closer to failure than predetermined PM actions and thus utilize more useful life. This is enabled by monitoring the actual condition of the machine instead of following predetermined maintenance intervals.

CbM can be conducted with or without the prognosis of degradation evolution. *CbM without degradation prognosis* is referred to as *non-predictive* maintenance or frequently referred to as *CbM* in industry, i.e., when maintenance actions are conducted based on exceeding predetermined thresholds of CM data and not prognosis (ZHAI ET AL. 2020). Hence, for the remainder of this thesis, non-predictive condition-based maintenance is referred to as CbM.

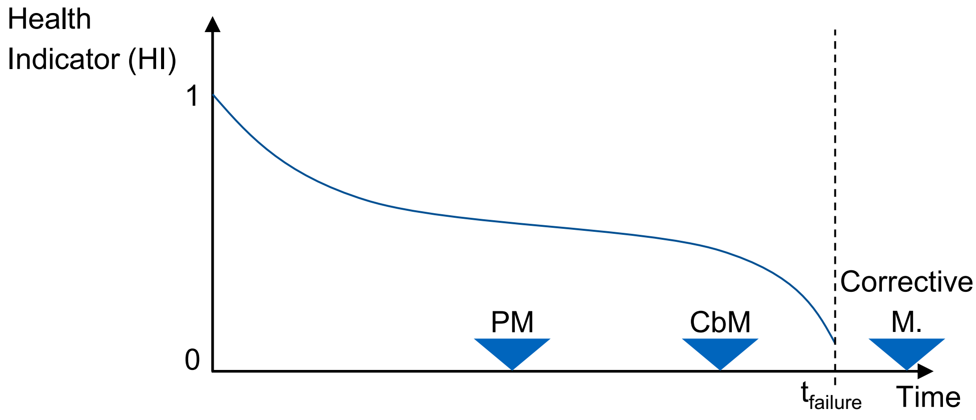

Figure 2-3: Schematic visualization of typical maintenance point in time for different maintenance strategies.

On the other hand, *predictive* maintenance uses CM data to predict the health condition of an item. The maintenance action is then carried out “following a forecast […] of the significant parameters of the degradation of the item” (DIN EN 13306 (2018, p. 24). PdM can be seen as the latest development in the realm of maintenance strategies in the era of Industrie 4.0, emerging from the traditional maintenance paradigms of preventive and CbM (ZHAI & REINHART 2018). PdM uses the same CM data foundation as CbM, but unlike CbM, PdM predicts the future health condition and plans maintenance accordingly, instead of simply reacting to surpassing a threshold. The need for this new paradigm is caused by recent trends and change drivers of maintenance (STRUNZ 2012, pp. 9-11):

- the increased complexity, degree of automation and interlinking of production machinery, where the failure of one machine leads to a standstill in production,
- the over-proportional price increase for replacement parts and machines, therefore stressing the demand to utilize components and avoid premature maintenance entirely,
- the increase in processing speeds in manufacturing leads to components and tools becoming more susceptible to failure due to higher processing forces.

These change drivers caused maintenance strategies to evolve, as Figure 2-4 depicts. Corrective maintenance was viable when no flow production was established and singular failures did not cause production stops. This changed with the introduction of flow shops and predetermined preventive maintenance was applied. With the introduction of automated solutions and computational power to production, CM enabled CbM to warn operators of imminent failures and possibly dangerous situations. Building upon CM data and using AI to predict future health conditions, PdM now enables the efficient use of RUL information.

Furthermore, the degradation behavior and maintenance point in time can be influenced (ZHAI & REINHART 2018). As depicted in Figure 2-2, beneficially applying PdM will be the focus of this dissertation.

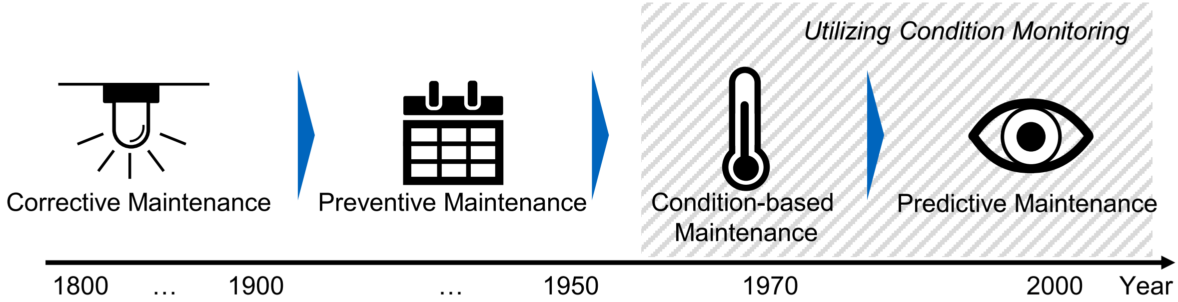

Figure 2-4: Evolution of maintenance based on ZHAI & REINHART (2018).

2.2 Integrated Production Scheduling and Maintenance Planning

Research on integrated production scheduling and maintenance planning (IPSMP) has gained attention in recent years and deals with optimally planning production subject to maintenance actions (DA ET AL. 2016, p. 951). Most approaches have treated maintenance planning and production scheduling independently in the past, leading to "suboptimal solutions, due to the fact that they are interrelated" (HADIDI ET AL. 2012, p. 21). IPSMP is also referred to as "machine scheduling with availability constraints", with the availability constraints being attributed to maintenance actions, machine breakdowns or tool replacements during the scheduling period (HARRATH ET AL. 2012, p. 13).

IPSMP can be categorized as models with *time-based* and *condition-based* maintenance actions (GHALEB ET AL. 2020). Time-based approaches schedule maintenance actions according to predetermined time intervals, i.e., following the PM paradigm. In contrast, condition-based approaches plan maintenance actions based on either an item's assessed or predicted health condition.

In the following, state-of-the-art time and condition-based IPSMP approaches will be presented. The focus will be on condition-based approaches since the IPSMP approach of this dissertation also follows the condition-based paradigm. For the sake of brevity, only the most relevant literature will be presented. Since IPSMP is the focus of publication no. 4, the reader shall be referred to Appendix 7.1 for a more detailed literature review. Table 2 summarizes key terminology concerning IPSMP used in the following sections as well as throughout this dissertation.

Table 2: IPSMP-related terminology.

Term	Definition	Source
(Production) Scheduling	"[Scheduling] deals with the allocation of resources to tasks over given time periods and its goal is to optimize one or more objectives". In the context of production, resources are oftentimes machines and/or operators and objectives can be the minimization of makespan.	PINEDO (2016, p. 1)
Maintenance Planning	Closely related to production scheduling, it focuses on allocating resources for the maintenance of machines such that it is ensured that a production system is "the most available (or the least unavailable) possible […] to execute the production jobs as soon as possible". See also the definition of "maintenance plan" in Table 1.	BERRICHI ET AL. (2010, p. 1584)
Single machine	Describes a production system layout, where a set of jobs have to visit only one machine.	PINEDO (2016, p. 33)
Flow Shop	Production system layout where jobs have to undergo a series of operations following the same route. "The machines are then assumed to be set up in series and the environment is referred to as a flow shop."	PINEDO (2016, p. 151)
(Flexible) Job Shop	Production system layout where "the routes are fixed, but not necessarily the same for each job", i.e., jobs have to visit machines in a special order with precedence constraints. In flexible job shops, one job can be manufactured on multiple machines.	PINEDO (2016, p. 183), KACEM ET AL. (2002, p. 1)

2.3 Time-Based Integrated Production Scheduling and Maintenance Planning Approaches

CASSADY & KUTANOGLU (2003) and CASSADY & KUTANOGLU (2005) were some of the first researchers to formulate the IPSMP problem. The authors examined production scheduling on a single machine with preventive maintenance actions, with the objective to minimize the expected total weighted tardiness. Their proposed integrated model yielded improved results than scheduling production and planning maintenance independently.

BENBOUZID-SITAYEB ET AL. (2011) formulated a flow shop problem subject to preventive maintenance actions. These actions were associated with time intervals $[T_{min}, T_{max}]$, in which they have to be started and completely executed. T_{min} referred to the point in time after the predefined minimum time between two maintenance actions has passed, whereas T_{max} described the maximum time between two maintenance actions. Early and delayed PMs were penalized using a cost function. Two metaheuristics were proposed to solve cost the subsequent minimization problem. The results indicated that "the simultaneous optimization of both production and maintenance criterion gives better results" (BENBOUZID-SITAYEB ET AL. 2011, p. 45f.) than sequentially optimizing the problem.

A flexible job shop problem with integrated preventive maintenance actions was studied by YE & MA (2015). The authors established a multi-objective optimization model to minimize the makespan and maintenance costs for the integrated production and maintenance schedule. The decision to plan maintenance was made before assigning each job operation to the machine. To simultaneously optimize both production and maintenance objectives, the weighted sum method was applied. A genetic algorithm was implemented to solve the formulated problem. Compared to an independent planning approach with fixed preventive maintenance periods in simulative studies, the proposed approach resulted in better outcomes regarding both makespan and maintenance costs.

SCHREIBER (2022) developed a system for integrated production and maintenance planning, which consists of a technical subsystem aiming at describing and optimizing the planning problem and the social subsystem, which describes the methodology for integrated production and maintenance planning. The whole system aims at holistically optimizing production and maintenance planning with respect to the objectives costs, time, quality and flexibility of the manufacturing system. Predetermined maintenance actions were planned according to the number of manufactured products and linear accumulation of degradation was thus assumed. The multicriterial optimization problem was solved using the Goal programming method[1].

[1] The Goal programming method describes a multiobjective optimization approach that seeks to find a solution that satisfies all objectives as much as possible while considering the priorities and trade-offs between them (SCHNIEDERJANS 1995).

2.4 Condition-Based Integrated Production Scheduling and Maintenance Planning Approaches

Condition-based IPSMP approaches, as opposed to the approaches presented in the previous section, apply health assessment to determine the health condition of machines and use this information to plan maintenance actions accordingly. As mentioned, the condition can be either *assessed* using CM to plan the immediately following action or *predicted* to enable a longer planning horizon. As with the time-based approaches, different concepts for single machine, flow and job shop layout exist.

IPSMP using *assessed* degradation information

While not directly taking operation-specific degradation into account for future prognosis of health conditions, PAN ET AL. (2012) utilized CM continuously assess a machine's health condition. In a single-machine layout, the health condition was evaluated while processing a specific job sequence. Maintenance actions were scheduled based on the health assessment at the same time as production jobs. A health indicator quantified the assessed health condition of a machine. Predefined thresholds indicate the failing state HI_{fail} and HI_{safe}, which described the state where manufacturing was deemed safe. In order to determine the optimal time for maintenance, the authors extended the RUL concept to include the remaining maintenance life (RML), which refers to the remaining time until maintenance needed. RUL spans until HI_{fail}, while RML marks the time until HI_{safe} is reached, see Figure 2-5. RML thus acts as a buffer and allows for uncertainties in RUL prediction.

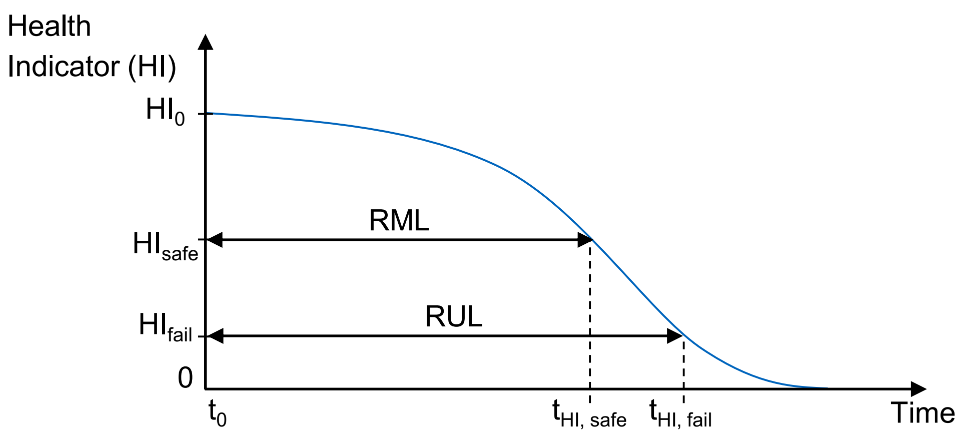

Figure 2-5: Concept of Remaining Maintenance Life based on PAN ET AL. (2012, p. 1052).

GLAWAR ET AL. (2018) developed an IPSMP concept using CbM consisting of a CM system, communication and production sequence optimization layer. The CM system returns so-called *health points,* indicating the current health condition of the machinery. The authors explicitly acknowledged the need for product-specific degradation modeling for subsequent scheduling. Depending on its health point value, production shall continue or a maintenance action shall be executed. The presented approach did not go beyond the conceptual phase and the authors state that further research is needed.

KARNER ET AL. (2018) applied this concept to a use case in the metal forming industry. Due to the product's different thickness and material, the degradation was modeled linearly, but nevertheless product-specifically. By incorporating the current health condition and linearly extrapolating the health condition after the execution of the following product, the decision-maker can decide whether to conduct maintenance. Hence, only very short-term decision support was realized.

IPSMP using predicted operation-specific degradation

C. FITOURI ET AL. (2016) established an IPSMP model based on the JSSP and presented a heuristic for solving the problem. Their modeling of operation-specific degradation is one of the most common approaches found in literature: The authors assumed that an arbitrary prognostics module supplies the information on the RUL of each machine. The degradation Δ_i dependent on job or operation i is calculated as the proportion of its processing time p_i and the RUL of the machine,

$$\Delta_i = \frac{p_i}{RUL} \tag{2-1}$$

The resulting total degradation of a machine imposed by a specific sequence of jobs, i.e., production schedule, is based on the linear accumulation of operation-specific degradations of the assigned operations, $\Delta_{total} = \sum_i \Delta_i$. A minimum and a maximum threshold of accepted degradation were assigned to each machine to plan maintenance actions. The proposed heuristic aims to find the starting times for the maintenance actions and the production jobs by minimizing makespan and total costs.

The linear operation-specific degradation modeling presented in equation (2-1) serves as the basis for various other approaches: LADJ ET AL. (2016) and LADJ ET AL. (2017b) solved a single-machine ISPMP instance using genetic algorithms. LADJ ET AL. (2017a) and LADJ ET AL. (2019) extended the degradation modeling by introducing fuzzy logic to capture the uncertainty of degradation. A flow shop IPSMP instance is modeled and solved using variable neighbor search (LADJ ET AL. 2017a) and genetic algorithm (LADJ ET AL. 2019), respectively.

BENAGGOUNE ET AL. (2020) also studied a single machine instance with linear degradation behavior of operations as outlined in equation (2-1) and the impact of RUL uncertainty on IPSMP. An unspecified prognostics module supplied the RUL information. Job operations subject to linear operation-specific degradation δ are scheduled with respect to a predefined degradation threshold Δ, which must not be exceeded. The objective of the model is the minimization of total maintenance cost C_B:

$$C_B = C_0 + C_m(\delta_i(t)), \tag{2-2}$$

where C_0 represents the fixed cost per maintenance action and C_m the cost of advance, i.e., costs of premature maintenance:

$$C_m(\delta_i(t)) = \begin{cases} \alpha(\Delta - \delta_i(t)) & if\ \delta_i(t) < \Delta \\ 0 & if\ \delta_i(t) = \Delta \end{cases}, \tag{2-3}$$

α hereby represents the cost of advance per unit of time.

As such, the model penalizes premature maintenance actions that do not make use of the RUL. Particle swarm optimization[2] is used to solve the resulting problem optimally.

In order to optimize production planning, DENKENA ET AL. (2020) apply a statistical method to estimate the failure durations of machine tools. Data was acquired from practical experiments to model failure durations and their approach showcases high accuracy. These estimations can in turn be used for production scheduling. It should be noted that operation-specific prediction of RUL and subsequent scheduling was not within the scope of their work. Nevertheless, the prognosis of failure duration does possess the potential to improve IPSMP holistically.

In summary, IPSMP approaches using both current and predicted health conditions exist. Still, the lack of industrial applicability due to simplified linear assumptions of degradation evolution hinders the actual application in industry. In particular, holistic approaches which include the interaction of actual operation-specific PdM applications, i.e., applications capable of predicting RUL using industrial data and respective IPSMP algorithms, are missing.

[2] Particle swarm Optimization describes a population-based heuristic optimization algorithm that utilizes a swarm of particles that iteratively explore the search space to converge towards the global optimum (KENNEDY & EBERHART 1995).

2.5 Prognostics and Health Management (PHM)

As presented in the previous section, at the core of most IPSMP approaches is a prognostics module, also referred to as the PHM module, that returns the health condition or RUL of a machine. Hence, the field of PHM deals with health assessment and its prediction based on real-time information (KIM ET AL. 2017, p. 1). The main tasks of PHM can be summed up as follows (KIM ET AL. 2017, p. 3, LEI ET AL. 2018, ASSAF 2018, p. 18):

1. **Data Acquisition**

   Data Acquisition deals with collecting meaningful "measurement data from sensors and process them to extract useful features for diagnosis" (KIM ET AL. 2017, p. 3).

2. **Diagnostics**

   Diagnostics detect the cause and severity of a failure. By comparing the measured data with its defined thresholds, failures are detected. The failure is then isolated and its severity is assessed.

3. **Prognostics**

   Prognostics aim at predicting the RUL of a component or machine. The health state is estimated using the acquired data and subsequently, the RUL is predicted.

   a. State estimation and HI construction

      The acquired raw data is further processed by applying AI or signal processing techniques to derive HIs. These extract relevant health condition information while filtering out measurement noise. HIs represent the health condition of the monitored machine.

   b. State prediction

      The degradation trend is predicted with regard to historical data and the future state, i.e., the future HI is predicted. It should be noted that HIs trend downwards with increasing degradation, while a degradation indicator trends upwards with increasing degradation. Further, it should be noted that HIs range from 0 to 1 (see Table 1) and only represent how "healthy" a machine is for a given point in time.

   c. RUL prediction

      As mentioned, RUL is defined as the time left before the HI reaches a defined failing threshold. Based on the estimated current HI and future HI, RUL can therefore be predicted and calculated. Approaches for predicting RUL vary from statistical, physics, AI or hybrid approaches.

4. **Health management**

   Health management deals with optimally managing the logistics, organization and planning of maintenance. Apart from scheduling maintenance, health management aspects will not be the focus of this thesis.

Prognostics is regarded as the “key enabler that permits the reliability of a system to be evaluated” (KIM ET AL. 2017, p. 3). In this thesis, prognostics is the main focus of the PHM application. Thus, the term “PHM module” refers to models that use the underlying techniques of prognostics. As described in section 1.2, operation-specific predictions are needed for PdM-IPS. In the following, the origin and the definition of the term *operation-specific* and state-of-the-art approaches for data-driven prognostics will be presented.

2.5.1 Operational Conditions and Operating Regimes: The Significance of Time-Varying Operational Conditions for HI Modeling

Operation-specific predictions refer to predictions that were made concerning the machine’s actual operational condition, i.e., the “physical loads and environmental conditions experienced by the item during a given period” DIN EN 13306 (2018, p. 24). A detailed examination of PHM literature reveals that depending on the field of application, the term “operating” or “operational condition” has been defined slightly differently, as shown in Table 3.

While WANG (2010) and SAXENA ET AL. (2008) described operational conditions from an abstract, general perspective, PEYSSON ET AL. (2019) focused on traditional machine tools in a manufacturing environment. Operational conditions further can be clustered to operating regimes[3]. All definitions share a certain causality: system inputs, such as a specific setting for a machining process, cause certain behavior of the item. Thus, the definition of healthy behavior depends on these system inputs.

[3] An operating regime refers to a defined subspace of an operational condition that can be induced by machining operation. The definition of operating regime and examples are given on p. 24.

Following literature findings, this dissertation defines operational conditions regarding manufacturing and machine tools as follows:

> An operator of a manufacturing company chooses the corresponding machine program according to the production demand. This machine program (e.g., CNC-program) defines a set of machining parameters, also referred to as operating parameters, which in turn define the machine's operational or operating condition. Subsequently, the active operational condition causes the system behavior. Sensors can both measure, the operational condition as well as the system behavior. Measurements are saved as multivariate sensor time series data over the item's lifetime. Only the operational condition can be influenced directly, e.g., in the case of machine tools, the measurable feed rate can be set and controlled (i.e., operational condition).

Table 3: Definitions of the term "operational condition" in PHM literature.

Definition	**Reference**
"Operational conditions are a set of variables that decide the settings of the system's operation. They can be considered as 'inputs' to the system in general […]. For instance, the speed and feed rate for a machining process are operational conditions while the power consumption of the spindle is not […]."	WANG (2010, p. 58)
"Let $c_m^l(i)$ be an operational condition at time index i, where $m = 1, 2, \dots, M$ is the condition number, and $l = 1, 2, \dots, L$ is the UUT (Unit Under Test) index. The operational conditions describe how the system is being operated and are sometimes referred to as the load on the system."	SAXENA ET AL. (2008, p. 3)
"A machine tool […] aims at performing successive operations to raw material to produce a finished workpiece. Each operation may involve the use of a specific tool and axis movements with optimized machining parameters, such as spindle speed […]. The structuration of machine operating conditions […] [contains] the following layers: production, cycle, step, tool change (TC) and move (M). […] The different operating conditions can be collected directly from the machine's numerical command. If it is not the case, they should be inferred from the raw sensor measurements such as axis positions."	PEYSSON ET AL. (2019, 139 f.)

At the same time, the system reacts with measurable vibrations that cannot be directly controlled (i.e., system behavior or system condition). Intuitively, products or parts of the same product family seen from a manufacturing perspective can form an operational condition since they require similar operational parameters. This is caused by similar characteristics such as product geometry or material, requiring similar manufacturing processes. The operational condition thus has a significant effect on the system behaviors, with different operational conditions causing large variances in the measurement of the system behavior.

Figure 2-6 schematically presents and summarizes the definition of the operational condition of this dissertation and its relationships.

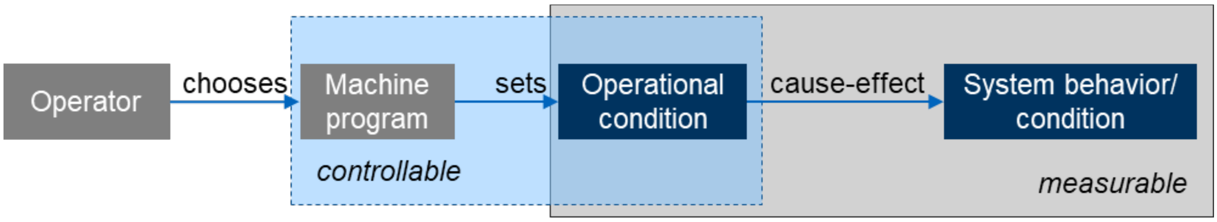

Figure 2-6: Relation between operational conditions and system behavior.

Often, an operational condition is synonymously referred to as an *operating regime* (OR) in the scientific literature (BEKTAS ET AL. 2017, MALHOTRA ET AL. 2016, JOHANSEN 1994). This dissertation follows the distinction between these terms as outlined by WANG (2010) and ZHAI ET AL. (2021). An *operating or operational condition* $\boldsymbol{u}$ refers to a vector of operational parameters op, e.g., machining settings. These operational conditions $\boldsymbol{u}$ belong to an operational space $\boldsymbol{U}$, i.e. $\boldsymbol{u} \in \boldsymbol{U}$.

An OR O_p is defined as a meaningful subspace or cluster in the operational space $\boldsymbol{U}$ (WANG 2010, p. 61, JOHANSEN 1994, p. 7). The operational conditions $\boldsymbol{u} \in \boldsymbol{U}$ can be clustered into a finite number P of operating regimes $\Omega = \{O_1, O_2, \dots, O_P\}$ by an arbitrary clustering or space partitioning algorithm $f_c(\boldsymbol{u})$. A membership vector $\boldsymbol{xOp}$ is introduced to assign an operational condition $\boldsymbol{u}$ to an operating regime O_P which can represent a fuzzy assignment (e.g., $\boldsymbol{xOp} = [0.1, 0.9, 0]^T$) or a discrete membership assignment (e.g., $\boldsymbol{xOp} = [0,1,0]^T$) for each timestep. Thereby, the dimensionality of $\boldsymbol{xOp}$ equals the number of operating regimes.

Figure 2-7 shows an example of an arbitrary sensor measurement of operational parameters over a given time period. op_1, op_2, op_3 represent operational parameters, e.g., machine settings for feed rate, cutting speed and cutting depth. The operational condition $\boldsymbol{u} \in \boldsymbol{U}$ represent a combination of these parameters. In this example, $\boldsymbol{u_1}$ features the operational parameters $op_1 = op_2 = 1, op_3 = 0$. A clustering algorithm $f_c(\boldsymbol{u})$ determines the membership to the operating regime. In this discrete case, $\boldsymbol{u_1}$ belongs to the bright green cluster O_5.

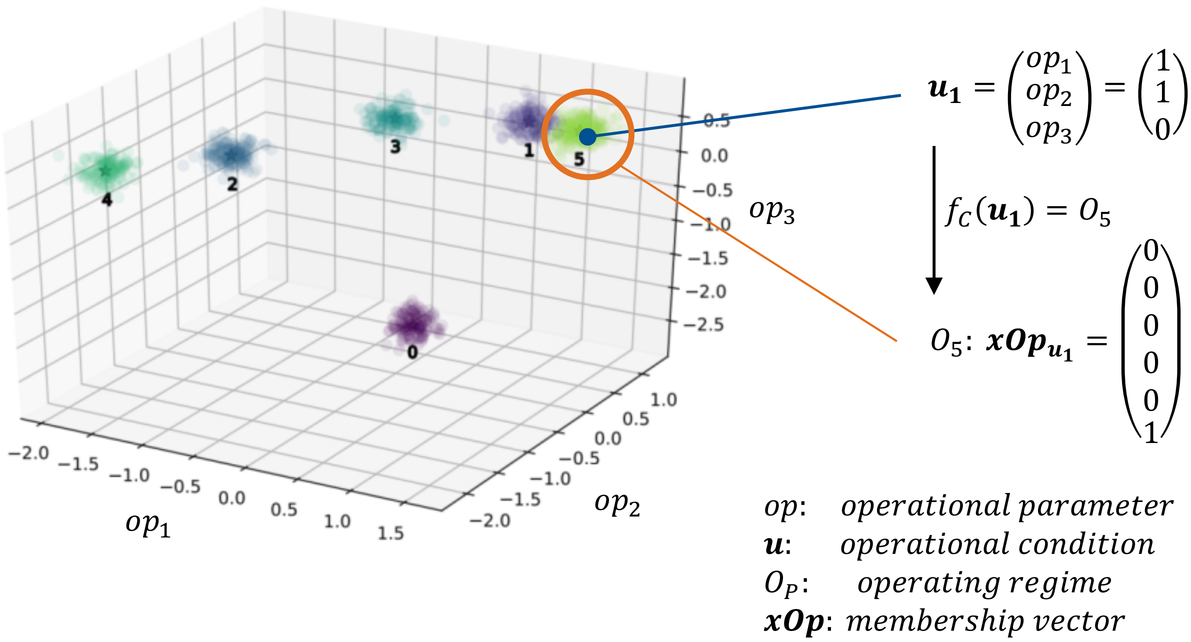

Figure 2-7: Operational conditions and operating regimes.

A set or sequence of operating regimes *OpRegSeq* can represent required machining operations to manufacture different product variants. For example, the manufacturing of product A requires the *OpRegSeq* of ORs O_1, O_2, O_4, O_5, while product B only utilizes operating regimes O_1, O_2, O_3. By introducing operating regimes, new product variants can be represented by the recombination of existing operating regimes or the addition of new operating regimes. This approach ensures that historical CM data can still be used even if new product variants are introduced to the production program.

LANZA ET AL. (2009), BIAN ET AL. (2015) and LI ET AL. (2019) emphasized the significance of modeling the health condition of machinery subject to time-varying operational conditions since these lead to different loads and result in different degradation rates. Furthermore, the definition of a healthy system condition is also dependent on the active operational condition.

LUO ET AL. (2019) collected the vibration signal of a cylinder machining process that consists of four operations: surfacing, milling, drilling and boring. As Figure 2-8 illustrates, the raw vibration signals and corresponding spectra differ significantly and indicate different degradation on the machine. Therefore, time-varying operational conditions have to be taken into account for health modeling.

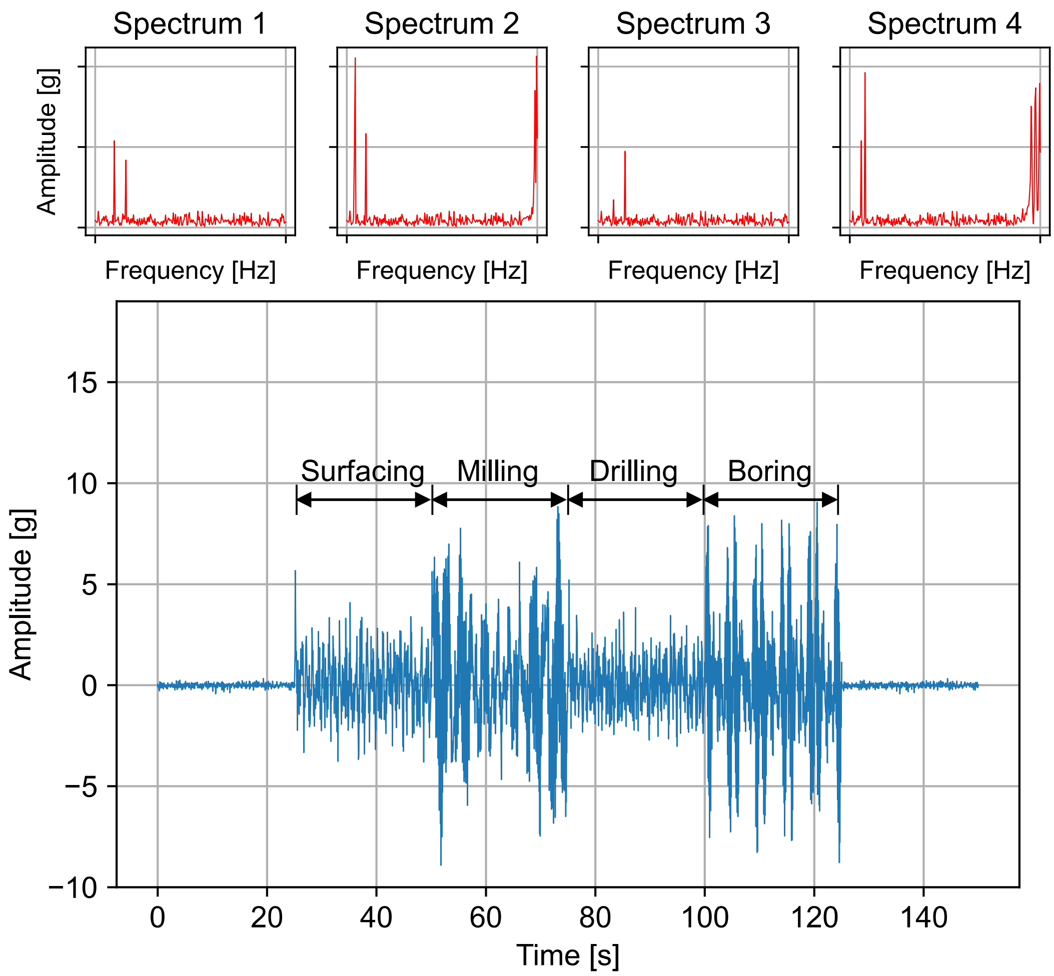

Figure 2-8: Four different machining operations and their corresponding vibration data, own schematic representation based on LUO ET AL. *(2019, p. 510).*

LI ET AL. (2019) presented an artificial scenario for an operation-unspecific prognostics approach, see Figure 2-9. An exemplary machine has two operational conditions, 0 and 1. The actual condition (in Figure 2-9: "system state") of the machine degrades until it fails, indicated by the final value of 1.0. As opposed to health indicators, which denote 0 as depleted and 1 as a fully healthy state, the system state described by the degradation signal uses 1 as fully depleted and 0 as a fully healthy state. It should be noted that the actual health condition or system state usually cannot be directly observed. The corresponding "degradation signal", e.g., vibration or other sensor signals, is significantly higher when in operational condition 1 and thus could lead to a false alarm, even if the actual system state is not critical.

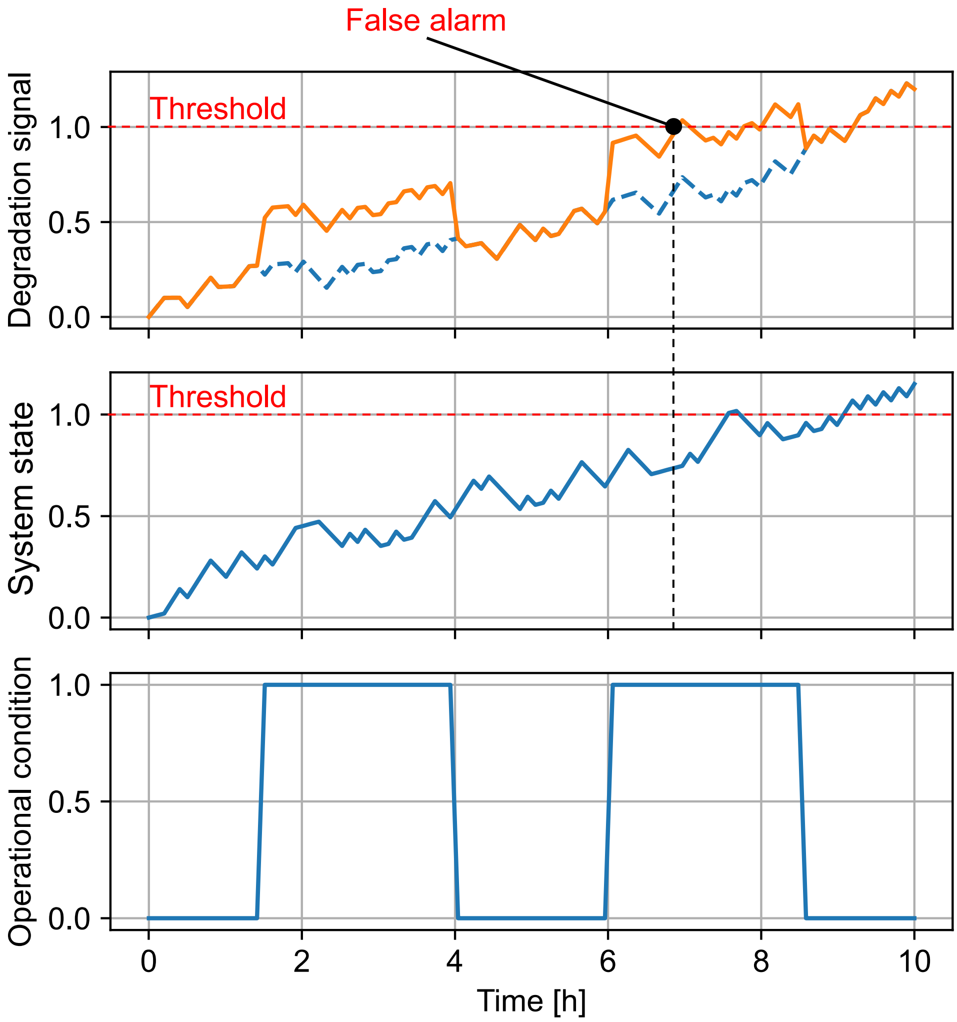

Figure 2-9: Effect of operational condition on degradation signal, own schematic representation based on LI ET AL. (2019, p. 90).

BIAN ET AL. (2015) described two major challenges of dynamic operational conditions on the CM signals: First, different operational conditions cause changing degradation rates. Second, changes in operational conditions may cause sudden jumps at changepoints in the CM signals. Consequentially, the degradation patterns in the sensor signals are overlaid with large variances and complicate the interpretation of these signals. Naïve health indicators, e.g., a single trending signal, tend to trigger many false alarms when the signal exceeds the prespecified failure threshold due to operational condition changes (LI ET AL. 2019). In reality, the system might still have wear reserves for additional operation cycles, as can also be seen in Figure 2-9.

Reliable prognostic models need to differentiate whether a signal change is caused by a change in the operational condition or by increasing degradation. In addition to the effects of operational conditions on CM data, the task of prognostics itself for longer time horizons is getting more demanding since future operational conditions cannot be reliably predicted (SANKARARAMAN & GOEBEL 2014). To account for condition-induced variance and to enable prognostics in a setting of time-varying operational conditions, researchers have proposed different preprocessing techniques such as operation-specific standardization, i.e., standardizing the range of the data according to the operation regime (WANG ET AL. 2008, WANG 2010, BABU ET AL. 2016, LIAO ET AL. 2018).

2.5.2 Modeling Operation-Specific Health Indicators

As presented in the section above, different operational conditions of a system yield different loads and cause different degradation rates. For modern data-based prognostics, it is essential to consider varying operational conditions, as they strongly impact condition monitoring data. An overview of different operation-specific HI modeling techniques is presented in the following. Given that operation-specific HIs are the focus of publication no. 3, the reader shall be referred to Appendix 7.1 for a more detailed literature study.

Among the first works that explicitly consider time-varying operational conditions for degradation modeling are WANG ET AL. (2008) and WANG (2010). Their approach comprises two core procedures: HI construction and RUL prediction. The preprocessing step of the operating regime partitioning is required to consider multiple operational conditions. This partitioning requires clustering operational parameters into ORs and subsequently min-max normalizing the data with respect to the data collected under the same OR. The task of health indicator learning was formulated as a supervised learning problem. By applying linear regression models on a set of normalized sensor data with a consistent trend over time, the HI is predicted. The HI can be used for the ensuing RUL prediction by comparing the HI trajectory of a system instance to a database of HI curves of run-to-failure instances using a curve-matching algorithm. Based on the training instances' HI trajectories and RULs, the final RUL was computed by comparing the most similar trajectories (WANG 2010). The approach was validated using NASA's simulated C-MAPSS dataset developed by SAXENA & GOEBEL (2008), which is regarded as one of the most prominent benchmark datasets in PHM research.

LANZA ET AL. (2009) formulate a statical method based on the Weibull Distribution in order to model variable operational conditions. The shape parameter of the Weibull Distribution is considered to be the load-dependent parameter and is obtained by applying the Maximum Likelihood Estimation on collected failure data. Using the derived Weibull Distribution, the timing of preventive maintenance actions and spare part provision is optimized thereafter.

LI ET AL. (2019) proposed a state-space model in which the challenges of changing degradation rates and jumps at change points in CM data are modeled as separate influences. Using a state transition function based on a Wiener process, the dynamic and operation-specific degradation rate was modeled. Measurement functions were used to account for the mentioned sudden jumps in the degradation signal due to change points. These functions smoothen the jumps in the signal whenever the operational condition changes. This was done by mapping each operational condition to a condition-specific reference baseline. False alarms could be reduced and RUL predictions were retrieved. Further, the results obtained by applying this approach to a simulated bearing data set indicate a high performance and outperforming previous models, e.g., developed by BIAN ET AL. (2015).

MICHAU & FINK (2019) developed an unsupervised learning approach utilizing a variational autoencoder (VAE) for system monitoring of a fleet of similar systems. Due to the similarity of these systems, the training data for one specific system instance can be and thereafter is enhanced by CM data from other instances of the fleet. The health prediction was based on a one-class classification using a variational autoencoder that aims at predicting whether the CM data is faulty or healthy. A real data set of a fleet of 112 power plants running under different operating and environmental conditions was used to evaluate and validate the developed approach.

KARNER ET AL. (2019) compared different machine learning algorithms to predict changes in health conditions in order to enable the subsequent IPSMP approach proposed by GLAWAR ET AL. (2018) introduced in section 2.4. While acknowledging the need for product-specific modeling, the proposed orthogonal matching pursuit approach for estimating the health condition of tools in the steel industry did not explicitly display how product-specific health conditions are estimated. Nevertheless, the approach achieved high metrics in terms of R^2 and RMSE values.

Using a neural network-based model, BEKTAS ET AL. (2019a) constructed a HI and predicted RUL for the simulated dataset C-MAPSS. Emphasis was being put on transforming raw and noisy sensor data under varying operational conditions and modeling a HI. By comparing different HI trajectories, a similarity-based RUL prediction model was inferred. The approach performed well in terms of error metrics compared to other state-of-the-art approaches on the same dataset.

In summary, approaches to model operation-specific health conditions do exist. However, these advanced models cannot be directly combined with the existing IPSMP approaches and thus, the potential of these prediction models is not realized. Value-added from sophisticated operation-specific health models can only be realized if they are applied in a manufacturing environment that plans its production according to the predicted health states of its production machines.

2.6 Facit: Research Deficits

After examining the state of the art of both IPSMP and operation-specific HI modeling literature, it becomes clear that significant advancements in both fields have been made in recent years. Figure 2-10 schematically presents the current state of IPSMP, its relationship with production scheduling and maintenance planning, as well as the research gap that PdM-IPS aims to fill.

On the one hand, researchers developing algorithms for production and maintenance planning have realized that joint planning of both production and maintenance results in significant improvements in terms of machine availability and makespan. PdM enables the development of more sophisticated IPSMP models that can schedule maintenance actions based on the actual condition of the machine. Existing IPSMP models usually apply a simplified linear degradation model to estimate the wear on machines. Also, these IPSMP models postulate the existence of arbitrary PHM models capable of operation-specifically modeling the machine's condition and outputting the required information for planning purposes.

On the other hand, recent PHM research developed sophisticated models capable of operation-specifically modeling the health condition, i.e., taking time-varying conditions into account. However, these models were not designed for subsequent scheduling purposes in industrial manufacturing settings. Existing PHM approaches are not validated with industrial data in many cases, so the viability for actual application remains unclear. The disaggregation of products into their respective operating regimes is needed to ensure operation-specific health condition modeling. Furthermore, the recombination of sequences of operating regimes back to products is required for scheduling purposes. Hence, the identification of operating regimes of different product variants in CM data, the health indicator modeling and subsequent product and production plan specific health prediction have to be improved.

The research deficits can be summed up as follows:

1. Operation-specific health modeling using industrial data.
2. Enablement of operation-specific health model for scheduling purposes.
3. IPSMP algorithm that is capable of using operation-specific health information and returns feasible solutions in reasonable time.

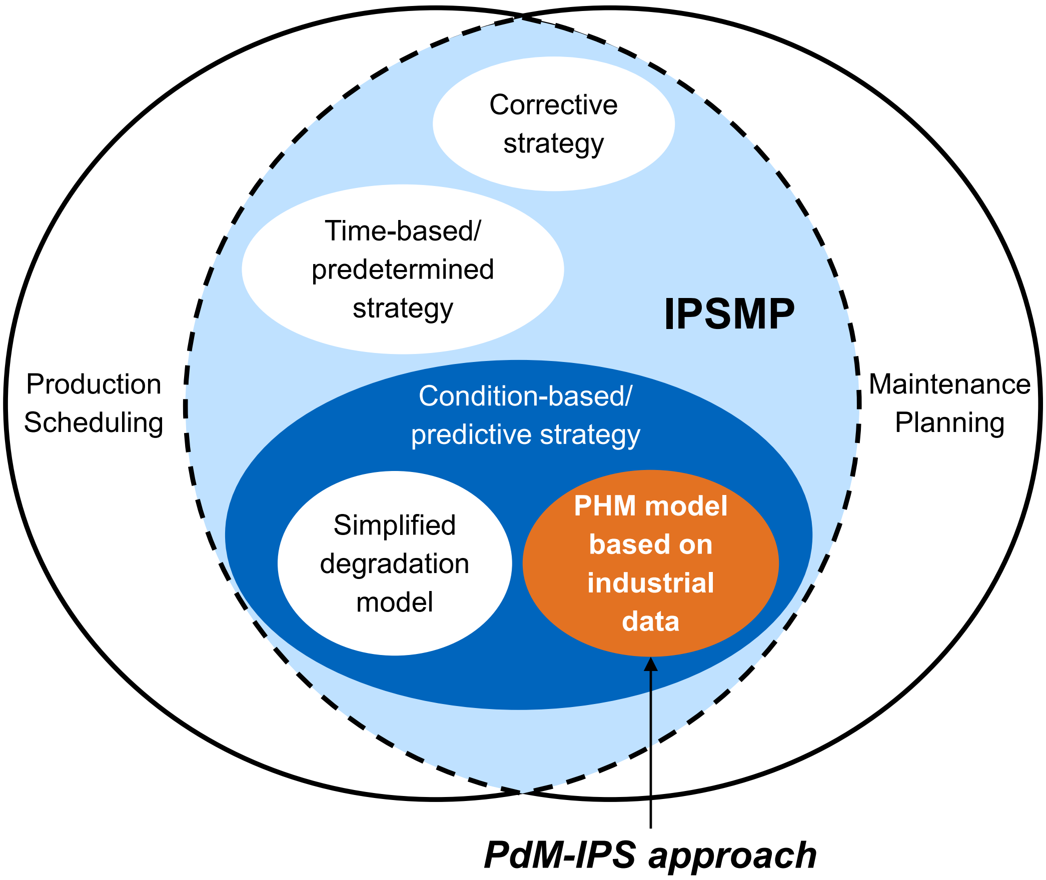

Figure 2-10: Identified research gap for the PdM-IPS approach.

In conclusion, a holistic approach for the industrial application of the PdM-enabled IPSMP, i.e., a PdM-IPS approach, is needed. The PdM-IPS approach shall include HI modeling and scheduling approaches that work together in a synchronized way to optimally plan production and maintenance such that the RUL of machines is optimally consumed.

3 Predictive Maintenance Integrated Production Scheduling

The overarching objective of this dissertation is the development and implementation of the PdM-IPS approach in the manufacturing industry. As such, this chapter concisely presents the PdM-IPS approach and summaries of the embedded publications that lead to its development. As outlined in the previous chapter, the PdM-IPS approach aims to build upon existing IPSMP approaches and fill the identified research deficits. In addition, the formulated approach shall fulfill the requirements defined and presented in section 1.3.

Three modules are at the center of the PdM-IPS approach: the *Planning Module*, the *Interface Module*, and the *PHM Module*. Each module has been developed to fulfill the requirements defined in section 1.3 and the identified research deficits in the previous chapter. Thereby, each module addresses the different identified needs of PdM-IPS.

The *PHM Module* enables operation-specific HI estimations based on CM data of industrial production machinery and supplies the *Planning Module* with the required information to schedule maintenance actions. This module, therefore, addresses research deficits one and two. Unlike existing approaches, the *PHM Module* returns the estimated change in the health condition of production machinery caused by the processing of distinct product sequences and production schedules, thus enabling the *Planning Module* to schedule production and maintenance optimally.

The *Interface Module* acts as a bridge of communication between the *PHM* and the *Planning Module*, it converts the production schedules generated by the *Planning Module* into operational data that the *PHM Module* can utilize. Additionally, it also sends back the expected degradation information of the same production schedule to the *Planning Module.* The *Interface Module* resolves research deficit two.

The *Planning Module* focuses on the optimal planning of production and PdM jobs and falls within the category of IPSMP approaches. In contrast to existing approaches, the *Planning Module* is explicitly designed to operate with health indicator estimations from prediction modules, particularly from the PdM-IPS approach's own *PHM Module* with the support of the *Interface Module.* Hence, the *Planning Module* addresses research deficit three.

3.1 Concept Overview

Figure 3-1 provides a conceptual overview, including all the modules of the PdM-IPS approach. The *Planning Module* is founded upon a genetic algorithm to conduct IPSMP optimally. It receives production orders and production and maintenance performance measures (e.g., makespan) to base the optimization on and outputs an integrated production and PdM schedule. Corresponding priorities of these production and maintenance objectives are also obtained in the form of weights from the decision-maker (usually a production planner or scheduler) to formulate the cost function, i.e., the objective function.

The parameters of the objective function, i.e., the costs, are derived from both production and maintenance metrics and the health condition of the machines required to execute and manufacture the developed schedule. The module calculates the cost-optimal integrated production and PdM schedule based on the cost function.

The *Interface Module* receives the generated PdM integrated production schedule from the *Planning Module*, transforms this schedule to respective *OpRegSeqs* and transmits this information to the *PHM Module.* The predicted degradation imposed by the schedule that the *PHM Module* computes is then received and sent back to the *Planning Module*.

The *PHM Module* is based on a special neural network architecture: the conditional variational autoencoder (CVAE). CVAEs apply *representation learning* which enables them to learn the feature pattern. The *PHM Module* takes CM data and production order data as input and estimates the health condition based on this data. In particular, the CVAE is trained with historical CM and production order data and is able to both assess and predict the degradation imposed by a specific production schedule that it receives from the *Planning Module* via the *Interface Module*. By estimating the change in the health condition of production machinery after processing specific schedules, the *Planning Module* can now determine whether to proceed with production or plan a maintenance action instead.

As depicted in Figure 3-1, the presented modules interact with each other to generate an optimal integrated production and PdM schedule by incorporating information from the scheduler, respective production orders and the CM of production machines from the shop floor. The resulting schedule includes timeslots for set-up and production as well as for PdM actions, i.e., timeslots for maintenance actions.

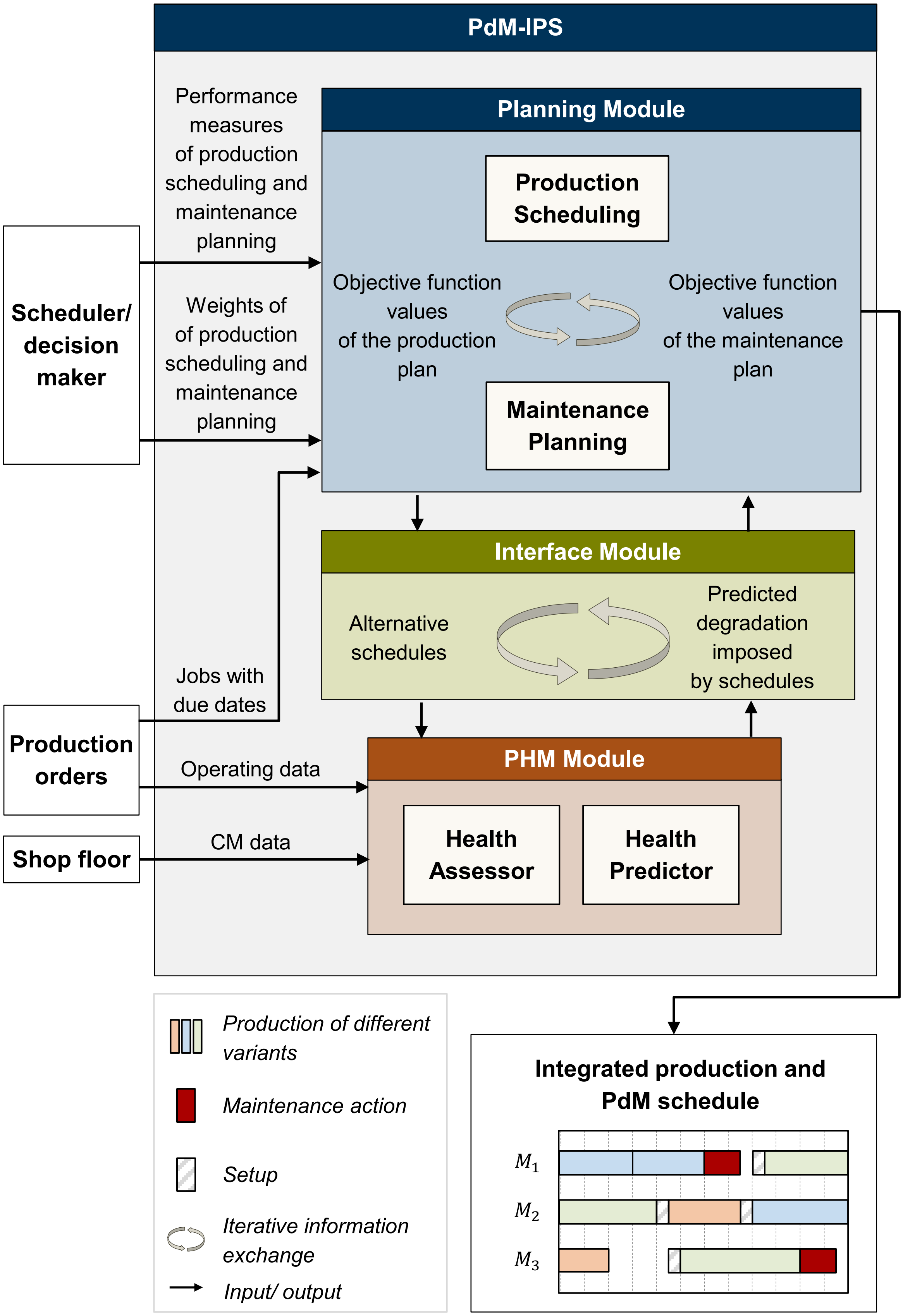

Figure 3-1: Overview of the PdM-IPS approach.

3.2 Embedded Publications

Four publications are at the center of the development and implementation of the PdM-IPS approach and will be presented in the following subsections. Titles and authors of these publications can be retrieved from Table 4, as well as the primary focus area of each publication with regard to the overall PdM-IPS approach (see Figure 3-2). These embedded publications can be found in Appendix 7.1.

The number of four publications was chosen in order to cover all four stages of the DRM as well as achieve the outlined objectives in section 1.2. While publications 1 and 2 mainly focus on DRM's *Research Clarification and Descriptive Study I*, the latter two publications deal with the *Prescriptive Study and Descriptive Study II.* The first two publications examine the status quo of PdM in industry and postulate a theoretical PdM-IPS model, thus creating the basis for the development of support. Crucial factors that determine the success of PdM are identified. The latter two publications build upon these findings and create the actual support for the PdM-IPS approach by developing and implementing the *Planning, PHM* and *Interface Module.*

Table 4: Overview of publications.

No.	Title	Year of publication	Authors	Focus area
1	An empirical expert study on the status quo and potential of predictive maintenance in Industry	2020	Zhai, S.; Achatz, S.; Groher, M.; Permadi, J.; Reinhart, G.	Industrial requirements for successful PdM application
2	Formulation and solution for the predictive maintenance Integrated job shop scheduling problem	2019	Zhai, S.; Riess, A.; Reinhart, G.	Planning Module
3	Enabling predictive maintenance integrated production scheduling by operation-specific health prognostics with generative deep learning	2021	Zhai, S.; Gehring, B.; Reinhart, G.	PHM Module
4	Predictive maintenance integrated production scheduling by applying deep generative prognostics models: approach, formulation and solution	2022	Zhai, S.; Kandemir, M. G.; Reinhart, G.	Planning Module, Interface Module

Publication 1 sheds light on the perceived potentials as well as challenges of PdM application by the manufacturing industry. Expert studies indicated that holistic approaches for applying PdM, i.e., approaches that use the health condition of machinery for planning purposes, are required and in turn motivate PdM-IPS.

Publication 2 explores the general formulation of PdM-IPS problem instances using simplified degradation models based on the Weibull distribution. A genetic algorithm was adapted to display its potential to solve PdM-IPS instances in reasonable time. The publication concludes by stating that real PHM models instead of simplified degradation models shall be developed for the PdM-IPS approach to generate value-added for the industry.

Publication 3 develops and implements a PHM model based on a CVAE to assess and predict the health condition of a machine operation-specifically. The developed model is able to quantify the health condition after a specific sequence of operations has been executed or products have been manufactured. The simulated benchmark data set C-MAPSS and real industrial data were used to validate the PHM model.

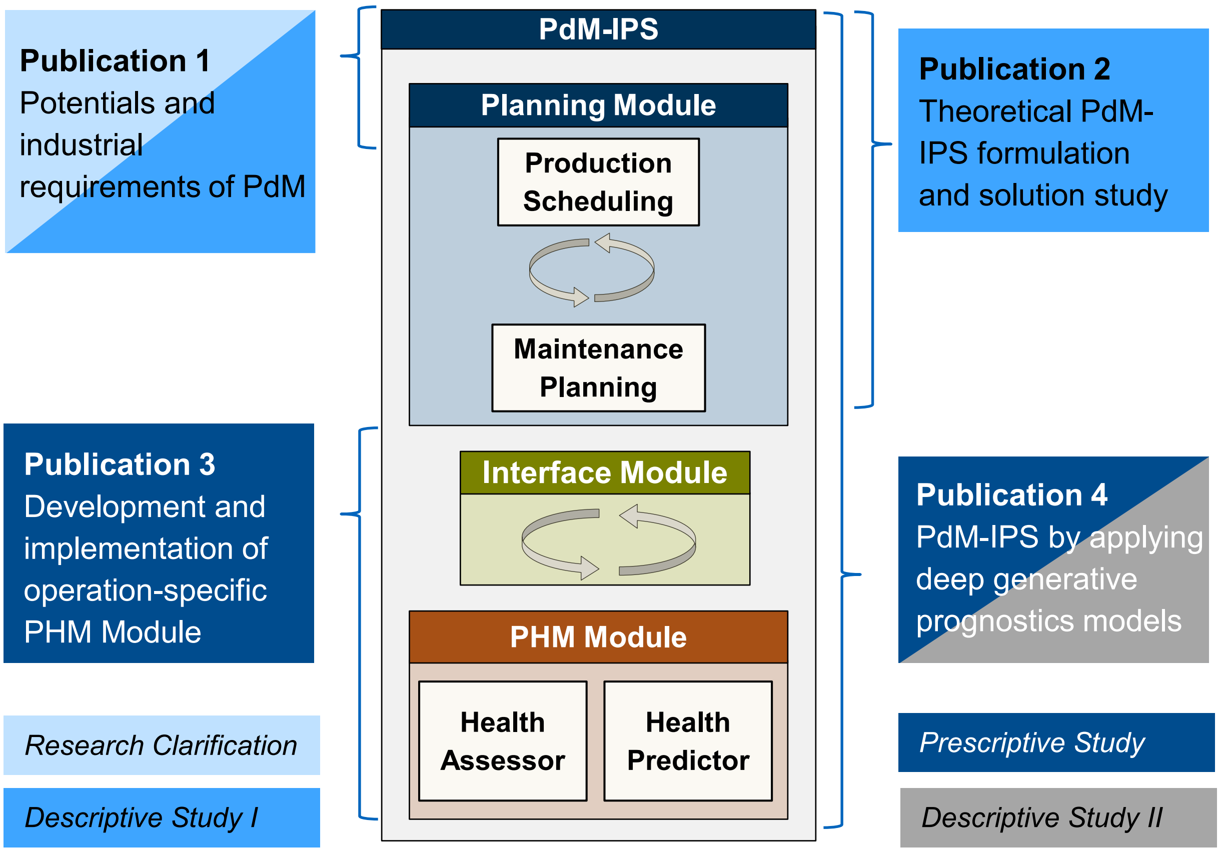

Figure 3-2: Overview of publication and their relationship to the overall PdM-IPS approach as well as to the stages of the DRM.

Publication 4 uses the developed model of publication 3 as the *PHM Module* for IPSMP. A two-stage genetic algorithm was developed to optimally schedule production and PdM actions for the flexible job shop. Together with an interface enabling the exchange of information between the PHM model and the genetic algorithm, the PdM-IPS approach is realized. The PdM-IPS approach is validated in a production line using simulated C-MAPSS as well as real industrial data for the PHM model. Results indicate that the PdM-IPS approach can indeed optimally schedule production and maintenance actions regarding the actual health condition of machines.

The publications on which this dissertation is based were produced in collaboration with other researchers. However, the author of this dissertation was the first author in the creation of all four publications included. In sections 3.2.1 to 3.2.4, following the summary of each publication, the individual contribution of the first author and those of the co-authors are presented.

3.2.1 Publication 1: An Empirical Expert Study on the Status Quo and Potential of Predictive Maintenance in Industry

The first publication focuses on PdM's status quo and potential in the industrial application by conducting an expert study (ZHAI ET AL. 2020). Actions to be taken to successfully develop PdM systems that are feasible to be used industrially are derived from empirical data collected from 62 European manufacturing experts. This publication therefore contributes to the *Research Clarification* and the *Descriptive Study I* of the DRM by identifying the factors for the success of industrial PdM applications (see Figure 1-2).

The study utilized a standardized, anonymized online questionnaire and the data was subsequently retrieved from the online database. Subsequent statistical analysis of the data was conducted offline using Microsoft Excel. Both quantitative and qualitative questions were asked and as such, a mixed-method research approach as outlined by YIN (2014) was followed. Participants were asked whether they have experience in applying PdM in their company. All closed questions had multiple answers to select from, i.e., the questions were multiple-choice. In addition, participants could freely add answers if they perceived that the existing options did not match their opinions. The questionnaire of this study can be found in Appendix 7.3.

Five key findings and resulting possible actions to be taken concerning successful PdM application can be derived from the analysis of the empirical data:

1) **Respondents who stated that they possess PdM experience tended to evaluate the potential of PdM higher, but holistic approaches were still regarded as necessary to fulfill the promise of PdM.**

This finding can be explained by the users' positive experiences with PdM, e.g., by realizing cost savings and reducing downtime. While the potential was rated higher in the PdM experienced group, these respondents noted that potentials are not yet fully exploited. The free text answering section, where participants were asked to add potentials they perceive, lists possible exploitation fields. Responses mostly demanded a holistic approach to PdM, e.g., using PdM information to integrate maintenance and production planning.

2) **A common understanding is required to streamline PdM implementation and application.**

The implementation and application of PdM are highly interdisciplinary. Different understanding of PdM throughout the company hinders the successful application of PdM. The terms CbM and PdM were frequently confused (see section 2.1 for definition), which led to misunderstandings and different expectations.

3) **PdM has a significant positive impact on maintenance processes.**

The retrieved data from the study showed that PdM experienced respondents rate their maintenance processes better than the inexperienced group. In combination with the fact that PdM users were overall satisfied with PdM applications and that they rated the potential of PdM highly, it can be derived that PdM does indeed have a positive impact on the respondent's maintenance processes.

4) **Data is widely available in the industry.**

The study showed that the majority of both PdM experienced and inexperienced respondents acquire data from different sources, albeit PdM experienced respondents stated that they collect more data compared to the inexperienced group. Thus, the first step toward PdM implementation is already taken.

5) **Research should focus on models that use real industrial data.**

The biggest challenge all respondents faced was the lack of know-how concerning value-adding PdM applications (see Figure 3-3). Therefore, research should focus on using real industrial data when developing models. Scientific literature primarily uses simulated datasets to benchmark their models. These datasets do not mirror the industry's challenges in practice, e.g., handling lack of failure data.

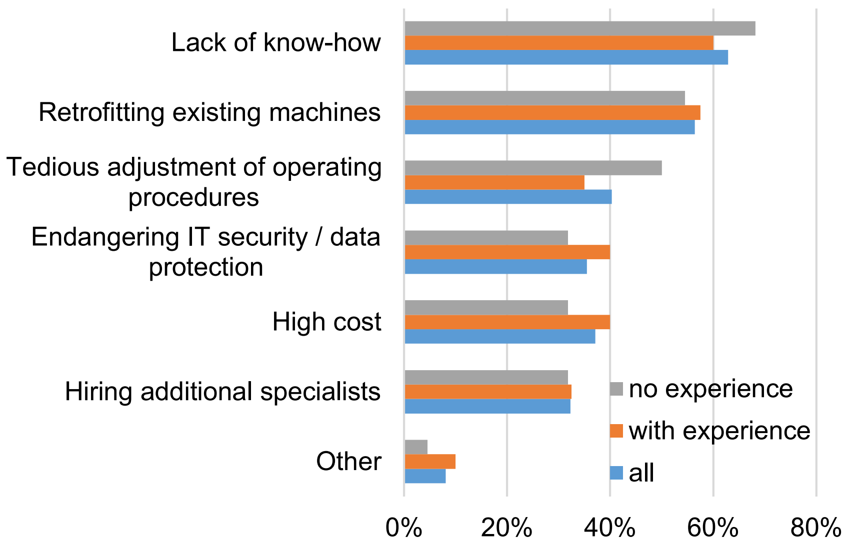

Figure 3-3: Identified challenges of PdM implementation, grouped by PdM experience of participants. Multiple answers were possible.

In conclusion, this empirical study showed that future research should focus more on developing holistic PdM approaches using real industrial data. By doing so, the highly-rated potentials of PdM can be exploited and real value-added can be generated.

Figure 3-4 shows the relative contribution of the author of this dissertation for this publication.

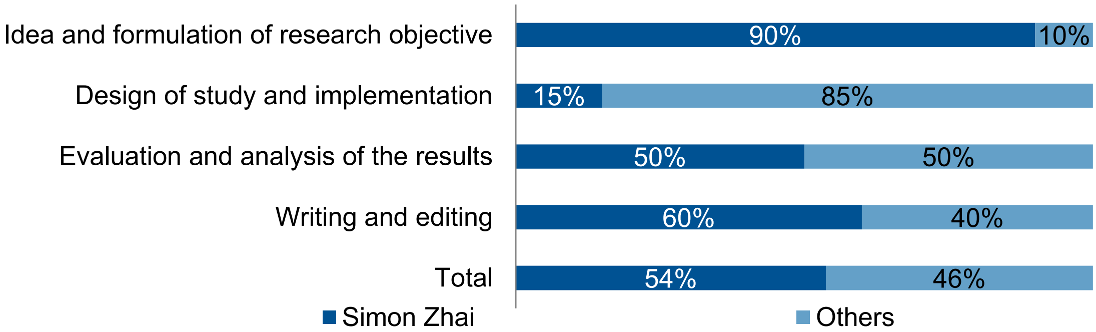

Figure 3-4: Contribution of work for publication 1.

3.2.2 Publication 2: Formulation and Solution of the Predictive Maintenance Integrated Job Shop Scheduling Problem

The second publication explores the formulation of IPSMP problem instances with integrated PdM actions in a job shop setting, i.e., a manufacturing setting where necessary maintenance actions of machines are predicted and the production is scheduled such that minimal downtime occurs (ZHAI ET AL. 2019). Further, the feasibility of genetic algorithms as the solver for such problems is evaluated. Results indicate that the developed genetic algorithm is indeed able to produce high-quality schedules, including PdM actions. The design of the genetic algorithm and its hyperparameters is following the principles laid out by WERNER (2013). By deriving further required success factors and prototyping the solution method, this publication is set at the intersection of the DRM's *Descriptive Study I* and the *Prescriptive Study*.

First, analysis of scientific literature led to the conclusion that a holistic IPSMP formulation, including operation-specific modeling of degradation, is required (see also the first publication in section 3.2.1). Therefore, the formulation of such problem is extended by reliability and machine breakdown prediction. The publication assumes that an arbitrary PHM module supplies information RUL_{ik}, i.e., the RUL of a machine k processing only operation i. To consider operation-specific degradation, the Operation Specific Stress Equivalent (OSSE) is subsequently defined as follows:

$$\delta_{ik} = \frac{p_i}{RUL_{ik}} \tag{3-1}$$

This formula is adapted from LADJ ET AL. (2016) and C. FITOURI ET AL. (2016). p_i describes the processing time for a certain operation O_{ik} running on machine k. For improved comparability between operations, it is assumed that the PHM module provides the RUL_{ik} information on the basis of the machine's *as good as new* condition, meaning that a maintenance action fully resets the RUL to 1. This simplifies the cumulative degradation $\Delta_k = \sum_i \delta_{ik}$ estimation to

$$\Delta_k(t_1) = \Delta_k(t_0) + \Delta_k(t_1 - t_0) = \Delta_k(t_0) + \delta_{ik} \tag{3-2}$$

with $\Delta_k(t_1)$ being the cumulative degradation of machine k at the time t_1, i.e., after running the operation O_1.

The cumulative degradation directly influences the machine's reliability and failure probability. The scientific literature has different measurements and models of reliability, the most frequently used measurement being the failure rate λ (LAWLESS 2003). Following STRUNZ (2012), using the two-parameter cumulative Weibull distribution function $F(t)$ with shape parameter β and the scale parameter η, the reliability $R(t)$ can be modeled as follows:

$$R(t) = 1 - F(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (3\text{-}3)$$

STRUNZ (2012) also denotes the degradation progress can be mathematically expressed as the ratio $\frac{t}{\eta}$ of the operational time t and the remaining operational lifetime η. Following the OSSE introduced in Eq. (3-1), the operational time passed t equals the sum of operation processing times p_i. As described above, the remaining operational life time η is identical to the RUL_{ik} provided by the PHM module, yielding

$$\frac{t}{\eta} = \sum_i \frac{p_i}{RUL_{ik}} = \sum_i \delta_{ik} = \Delta_k(t). \quad (3\text{-}4)$$

Thus, Eq. (3-3) can be reformulated to

$$R(t) = 1 - F(t) = e^{-\Delta_k(t)^{\beta}}. \quad (3\text{-}5)$$

For an exemplary schedule with a sequence of six operations, the reliability and cumulative degradation can be visualized as presented in Figure 3-5.

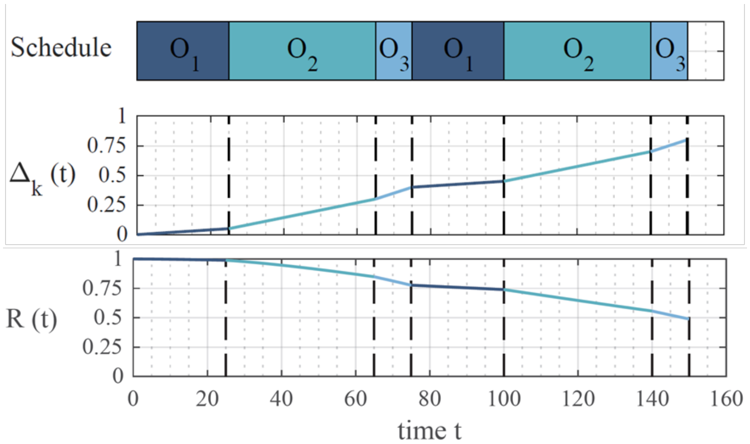

Figure 3-5: Exemplary evolution of $\Delta_k(t)$ and $R(t)$ for $\beta = 1$.

Existing JSSP benchmark instances were adapted within this publication to formulate the maintenance-integrated JSSP using operation-specific degradation information. In particular, the well-known *ft10* benchmark instance of FISHER & THOMPSON (1963), which describes a JSSP instance containing ten machines processing ten jobs with ten operations each, was extended by OSSEs. To account for the operation-specific degradation and its effect on the machine's reliability, a new minimization objective is formulated: the *Reliability Weighted Makespan* C^R_{max}. It is defined as the latest reliability weighted completion time

$$C^R_{max} = \max\left(C^R_1, C^R_2, \dots, C^R_n\right), \text{ and}$$
$$C^R_i = R(t) \cdot C_i + \left(1 - R(t)\right) \cdot (C_i + F) \quad (3\text{-}6)$$

where C_i^R equals the completion time C_i of Job i multiplied by $R(t)$ (i.e., how probable the job can be completed without the machine failing) and a time penalty F, weighted according to the failure probability $F(t) = 1 - R(t)$.

A genetic algorithm (GA) with job-based representation with repetition (YAMADA ET AL. 1997) is designed and validated in a simulation setting. The GA is initialized with the random job selection method (JORAPUR ET AL. 2016) and uses tournament selection, the precedence preserving crossover operator and insertion and shift mutation (WERNER 2013) at a rate of 95 % and 5 %, respectively. The stopping criterion is set to 100 generations. The input is the production demand derived from the *ft10* instance, while the output represents a feasible PdM integrated schedule. A simulation model is created that calculates the failure probability of each machine according to the cumulative degradation imposed by a feasible schedule. Unplanned machine breakdowns are simulated proportionally to the calculated failure probability.

The proposed solution method is validated using the *ft10* instance and benchmarked against results from the literature. Results indicate that the proposed GA is able to produce schedules comparable to the optimal literature schedules. Most notably, the number of machine failures is reduced by planning PdM actions. However, the solved problem instance is based on an arbitrary PHM module supplying simplified operation-specific degradation information that, in turn, is used to simulate machine breakdowns. Future research shall replace this arbitrary PHM module with a realistic PHM module. The publication proves the viability of applying GAs to solve PdM-IPS problem instances and concludes by stating that to realize holistic PdM-IPS, a PHM-module capable of deriving operation-specific degradation estimations from real industrial is required.

Figure 3-6 shows the relative contribution of the author of this dissertation for this publication.

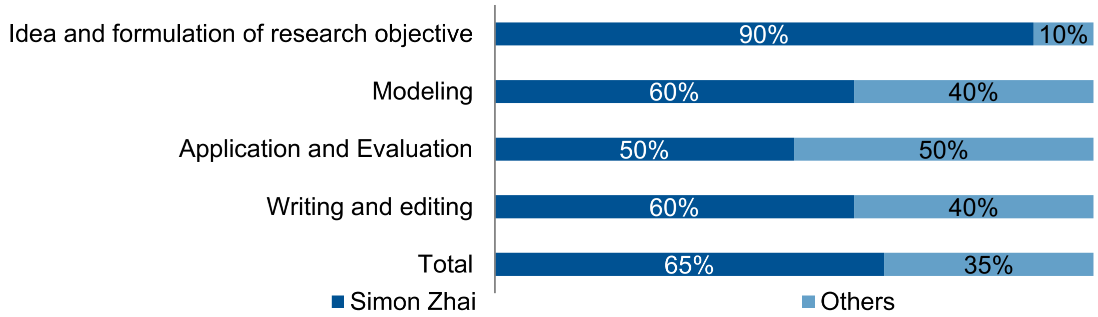

Figure 3-6: Contribution of work for publication 2.

3.2.3 Publication 3: Enabling Predictive Maintenance Integrated Production Scheduling by Operation-Specific Health Prognostics with Generative Deep Learning

The third publication builds upon the findings of the second publication and develops and implements the *PHM Module* of the PdM-IPS approach and as such serves as part of the *Prescriptive Study* of the DRM by developing the support needed for PdM-IPS (ZHAI ET AL. 2021). Within the publication, the DRM was applied as the overarching research methodology while the cross-industry standard process for data mining (CRISP-DM) was chosen for the domain-specific development of industry-viable health models. The *PHM Module* is developed according to the following objectives:

- ability to handle industrial data where labeled failure data is sparse while unlabeled CM data is widely available,
- modeling under time-varying operational conditions and
- supply of product-specific HI for subsequent scheduling.

The publication includes the methodology to develop the *PHM Module,* which includes all necessary steps to generate product-specific HI predictions, i.e., data preparation, and developing a HI model consisting of a health assessor and a data simulator for subsequent health condition prediction. The *PHM Module* has CM sensor data, historical production and operation data and failure events of machines as input. Using a combination of conditional variational autoencoders (CVAE), the output of an operation-specific (and, if needed, product-specific) HI prediction is estimated.

Apart from the usual data preprocessing steps like merging and imputation, operating regime identification (ORI) and operating regime-specific standardization (ORSS) are applied to enable subsequent operation-specific modeling. ORI partitions the CM data into meaningful clusters that represent ORs. Depending on the data, different clustering algorithms are suggested for ORI. Using the identified ORs, ORSS is applied to the CM data to transform the data to a common scale while preserving their inherent variance. The resulting transformation leads to scaled and comparable CM data across different ORs. The reader shall be referred to section 2.5.1 for more information on ORs and their significance in HI modeling. Using the information on failure events of machines, healthy and unhealthy timespans of CM data are labeled: Healthy data accounts for the first 20 % of data since the last maintenance action, while unhealthy data is defined as 80 % of the data leading up to the machine failure. The data preprocessing concludes by splitting the data into training, testing and validation sets.

Two CVAEs are trained: the health assessor CVAE (HA-CVAE) and the data simulator CVAE (DS-CVAE). CVAEs in general consist of an encoder and decoder network and are able to learn the latent representation $\boldsymbol{z}$ of data $\boldsymbol{x}$ (in this case: CM data) conditioned on $\boldsymbol{c}$ (in this case: ORs) and reconstruct the data back to $\hat{\boldsymbol{x}}$, see Figure 3-7. It does so by minimizing the reconstruction error $|\boldsymbol{x} - \hat{\boldsymbol{x}}|$.

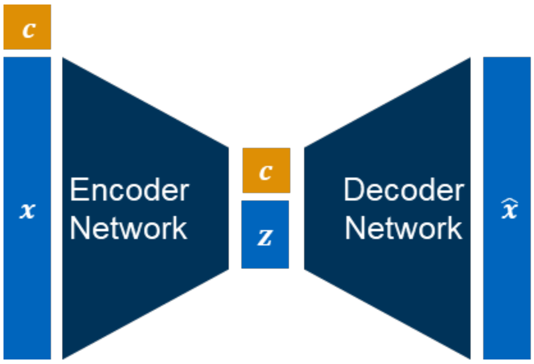

Figure 3-7: Simplified architecture of the CVAE.

Figure 3-8 presents the interaction between DS-CVAE and HA-CVAE and the general procedure of operation-specific HI prediction of the *PHM Module*. The left side represents the mentioned training phase, while the right side depicts the application. The HA-CVAE utilizes the fact that a trained CVAE can only reproduce data it has seen during training well. By training the HA-CVAE with healthy data only, the reconstruction error will increase when CM data behaves differently due to degradation. The HA-CVAE alone is thus able to estimate the condition of the machine given incoming CM data but not able to predict the condition of the machine given a future production schedule since it needs CM data as input. In order to predict the degradation an arbitrary future production schedule induces on machines, the DS-CVAE, which outputs simulated CM data given a future production schedule, is introduced. The DS-CVAE is trained on all data and is therefore also capable of reproducing degraded CM signals.

In application, only the decoder of the DS-CVAE is used to generate simulated CM data conditioned on a given future production schedule. This simulated CM data is fed back to the HA-CVAE, which will return a HI estimate based on the reconstruction error. Therefore, an operation-specific HI prediction for a future production schedule is realized. Apart from using the reconstruction error, other metrics can also be utilized in order to estimate the HI, e.g., the reconstruction probability p_{rec}. Different metrics can lead to improved HI estimations depending on the available data and its characteristics. In evaluations, the metric p_{rec} showed the highest performance when working with industrial data. The application of the CVAE as an underlying unsupervised learning model and the combination of HA-CVAE and DS-CVAE enables the *PHM Module* to generate HI estimations with only a low number of failure observations since the models are trained on widely available CM data.

The *PHM Module* was validated using both NASA's C-MAPSS dataset and industrial dataset originating from a multifunctional machine tool. Being an unsupervised learning task, there is no ground truth available for the evaluation of HI estimates. In line with PHM literature, metrics assessing desired properties of HI trajectories are used to evaluate the HA-CVAE. These metrics are monotonicity, robustness, trendability and inter-unit consistency.

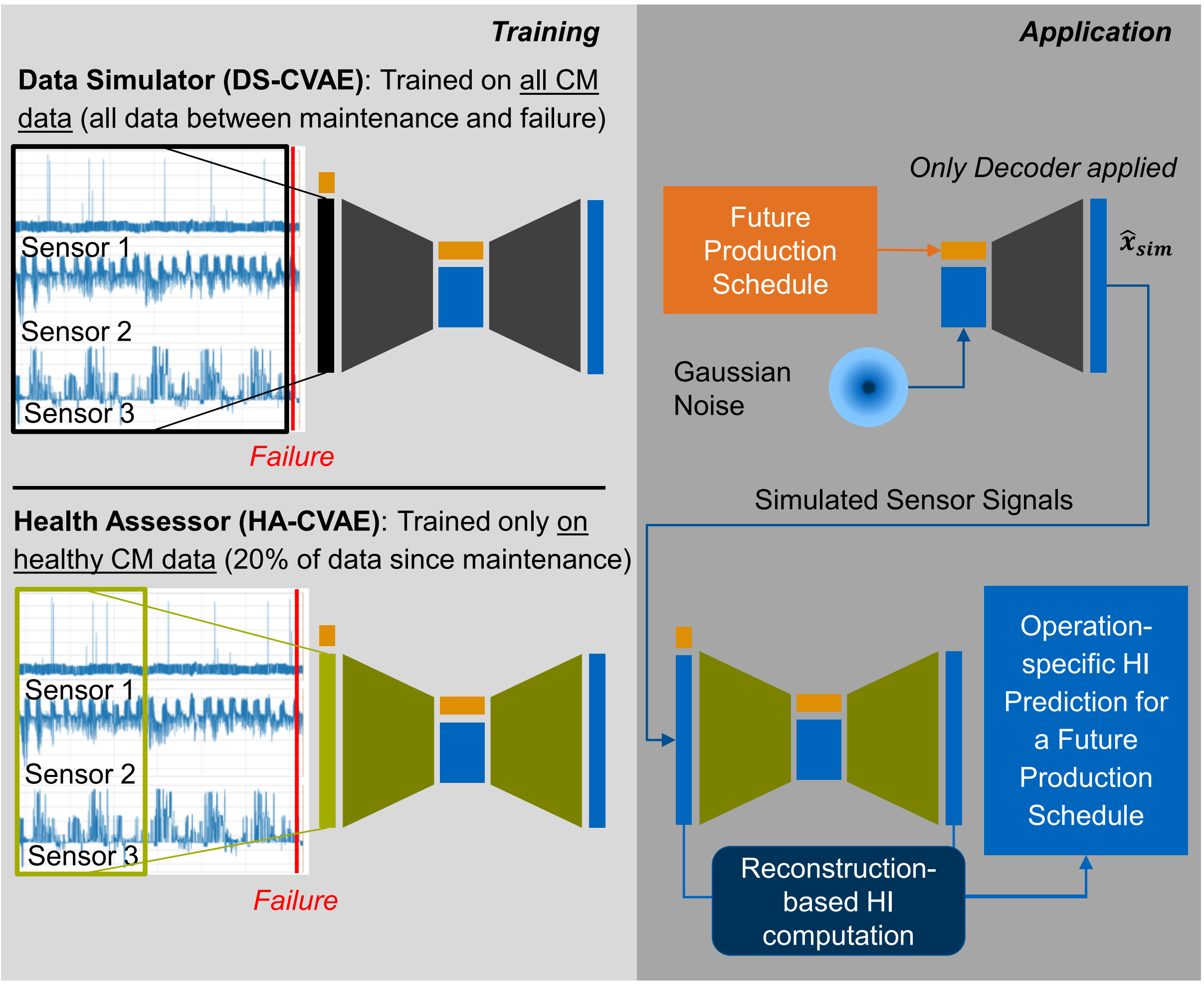

Figure 3-8: DS-CVAE and HA-CVAE during training and their interaction during application.

The evaluation of unsupervised deep generative models as the DS-CVAE is to this day still debated in the scientific community. Simple error measures such as the MSE or MAE between data points do not suffice to capture the generative capabilities of models. Hence, the evaluation takes place by plotting and comparing the probability distributions of the generated sensor data of the DS-CVAE for different discrete periods, i.e., life cycle bins that represent different stages of degradation. A higher overlapping rate between the generated distribution and the real distribution indicates better results since a larger spectrum of the real probability distribution was reconstructed.

While good results were achieved for C-MAPSS and industrial data, the expressiveness of the generated HIs for the industrial data is limited due to limited trendability, i.e., a limited decline of the HI. Explanations for this behavior could be wrongly labeled failure data and limited expressiveness of the recorded CM data. Also, it should be noted that the system-wide calculation of the HI using a mean aggregation implicates the derived HI does not differentiate between components, which especially can impact the HI of multi-functional machine tools. More targeted, component-wise HI modeling and a weighted aggregation can lead to improved results.

Figure 3-9 displays an exemplary output of the *PHM Module*, the predicted HI trajectory based on the metric reconstruction probability p_{rec} for four different future sequences of ORs using real industrial data. Operation-specific degradation is visible, with sequence 1 (green) causing less degradation than sequence 4 (orange).

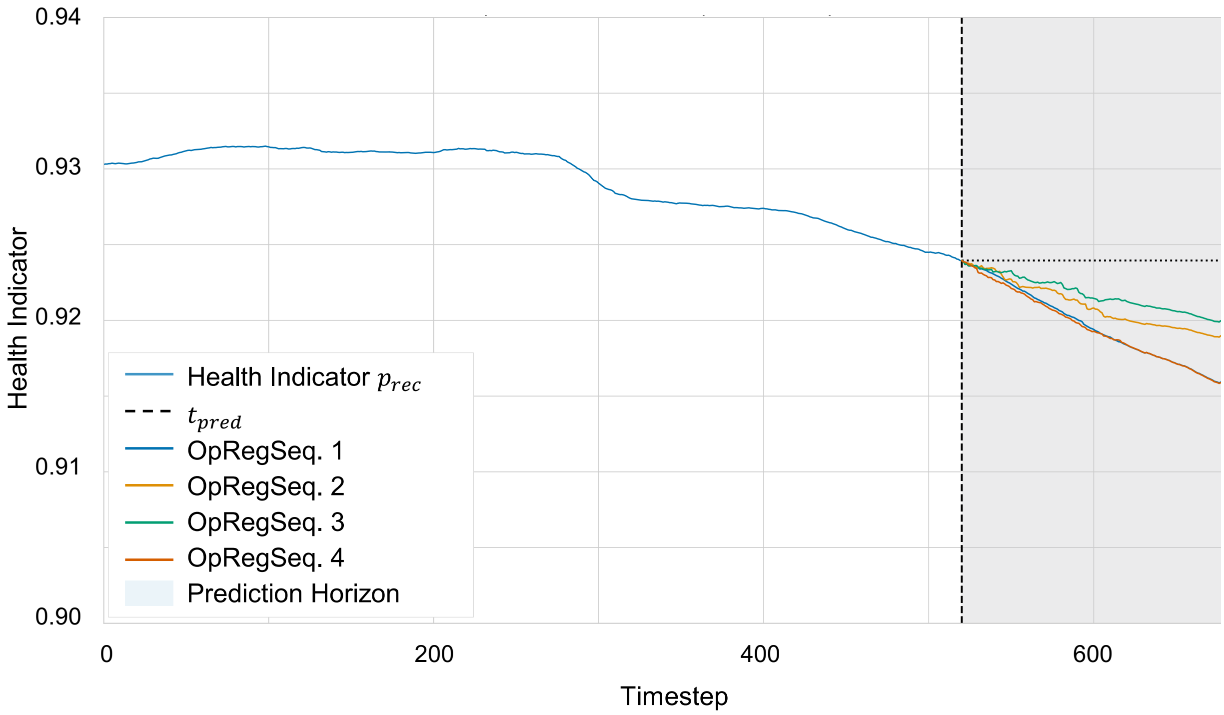

Figure 3-9: Four different HI predictions for four different future OR sequences.

Figure 3-10 shows the relative contribution of the author of this dissertation for this publication.

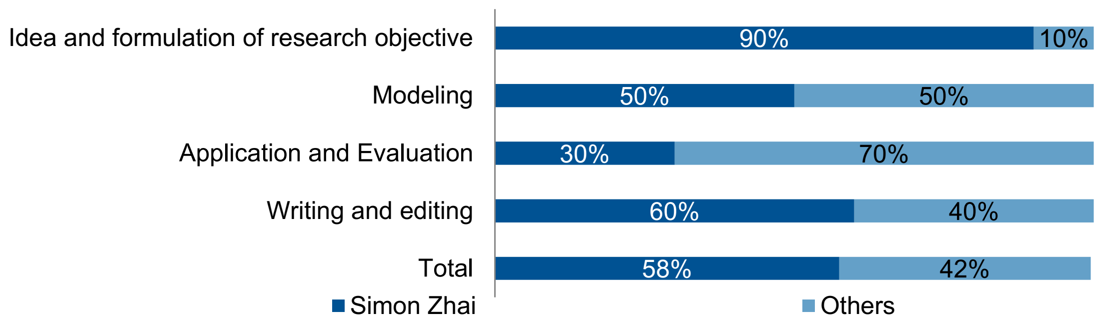

Figure 3-10: Contribution of work for publication 3.

3.2.4 Publication 4: Predictive Maintenance Integrated Production Scheduling by Applying Deep Generative Prognostics Models: Approach, Formulation and Solution

The *Planning Module, Interface Module* and holistic interaction in sync with the *PHM Module* are the focus of the fourth and final publication (ZHAI ET AL. 2022). Using the presented *PHM Module* from publication 3, a two-stage genetic algorithm (TSGA) for the PdM-IPS approach is developed and forms the *Planning Module*. Together with the validation using artificial and industrial data and discussion of resulting PdM integrated schedules, it covers the *Prescriptive Study* and *Descriptive Study II* of the DRM.

After a thorough analysis of the state of the art, it was derived that existing solutions to solving the IPSMP problem have two significant drawbacks. First, integrating PdM in the flexible job shop setting was not thoroughly addressed in the scientific literature; most approaches only focused on single-machine or flow shop settings. Second, existing publications that did address more complex JSSP settings used a simplified linear degradation model and thus did not account for the challenges of industrial data and non-linear PHM models. Consequently, this publication aims at developing an optimization model for the maintenance integrated flexible job shop scheduling problem and the interface of this model to the developed non-linear *PHM Module.*

As shown in both publication 2 (see section 3.2.2) and the scientific literature, genetic algorithms are well-suited to encounter the multi-objective IPSMP using PdM information from a PHM module. As such, this publication proposes a genetic algorithm with *elitist* and *tournament selection* operators as the underlying optimization model for PdM-IPS. In comparison to the developed genetic algorithm in the second publication (see section 3.2.2), changes in algorithm architecture and objective functions were made. Most notably, to improve efficiency, a TSGA was designed. The single-objective first stage S1 aims at generating a high-quality initial population for the multi-objective second stage S2. S1 focuses only on generating an optimal production schedule, while S2 optimizes for both production and maintenance metrics and is thus more computationally intensive. A population consists of a defined number of chromosomes whereby each chromosome represents a different schedule, i.e., a candidate solution. The hyperparameters of the genetic algorithm were retrieved using a full-factorial experiment and the hyperparameter combination yielding the best results was chosen. The flow chart presented in Figure 3-11 provides an overview of the TSGA, the interactions of both stages and the interface with the *PHM Module*.

After generating random populations, S1 optimizes these populations according to the production metrics makespan C_{max} and tardiness T_{total} over generations until the termination criterion is reached. The fittest generations, i.e., the lowest makespan and tardiness populations, are merged for the subsequent S2. By ensuring that S2 starts in promising search regions, S1 thus aims to improve the convergence speed of the multi-objective stage S2.

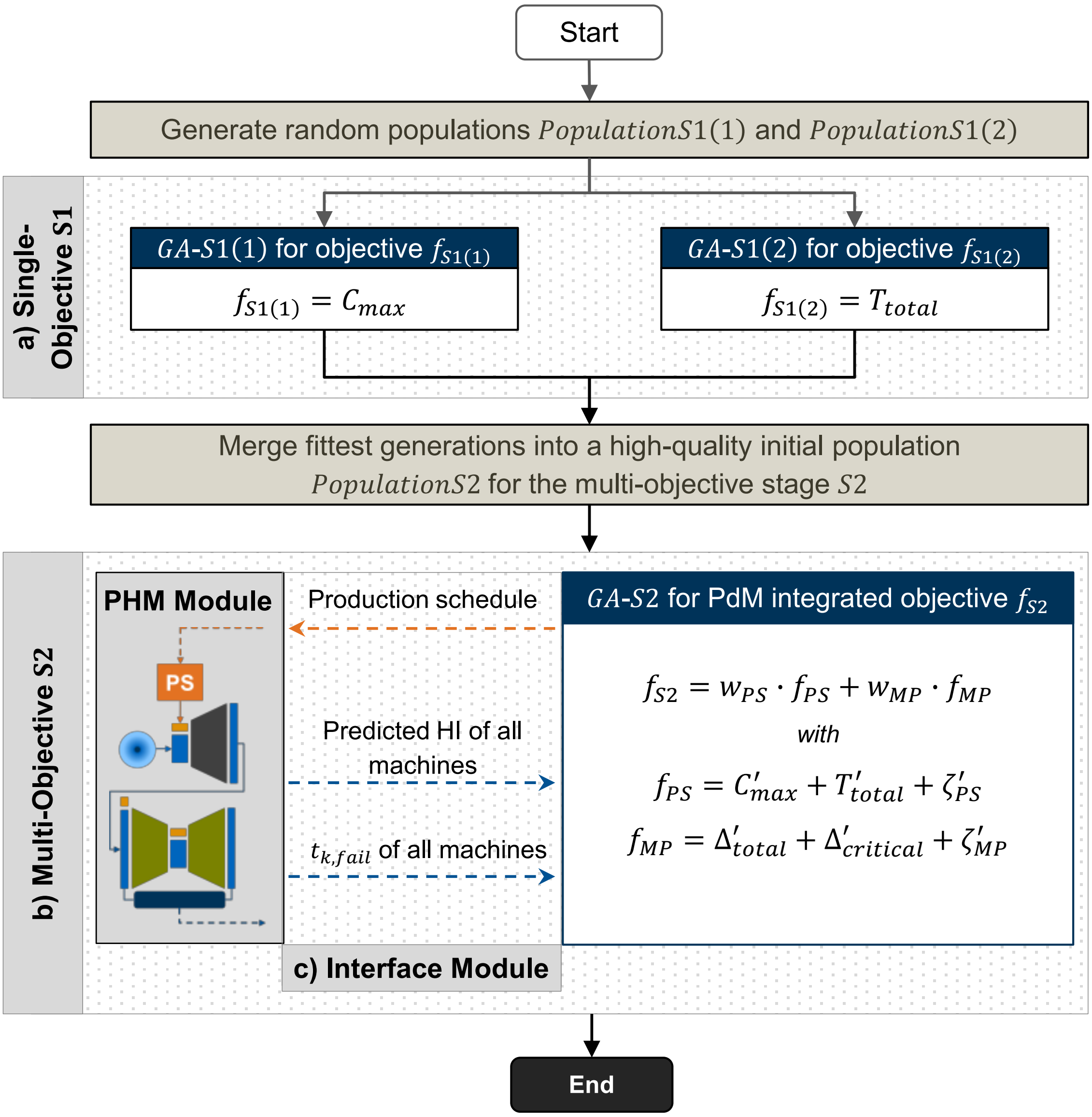

Figure 3-11: Simplified flowchart of the proposed TSGA with a) Single-objective Stage S1, b) Multi-objective Stage S2 and c) Interface between the PHM Module and GA-S2.

S2 aims at the multi-objective optimization of both production and maintenance using the weighted fitness function, and hence, the overall objective function:

$$f_{S2} = w_{PS} \cdot f_{PS} + w_{MP} \cdot f_{MP}, \tag{3-7}$$

where f_{PS} and f_{MP} refer to the fitness functions of the PS and MP, their corresponding weights w_{PS} and w_{MP} (with $w_{PS} + w_{MP} = 1$), see Figure 3-11 b). Production and maintenance metrics have different units, so their values must be scaled to use the weighted sum method. Table 5 presents the components of the fitness function of S2.

f_{PS} consists of the sum of the scaled values of C'_{max}, T'_{max} and the scaled costs associated with transport and set-up of the production schedule ζ'_{PS}. f_{MP} focuses on minimizing the scaled total degradation of all machines Δ'_{total}, the maximum degradation of a single machine $\Delta'_{critical}$ and associated scaled costs of PdM actions ζ'_{MP}. While Δ'_{total} is minimized to minimize the frequency of maintenance actions, the minimization of $\Delta'_{critical}$ ensures the balanced usage of the machines. By assigning infinitive costs to ζ'_{MP} in case a machine is used beyond its failure threshold, PdM actions are guaranteed.

Table 5: Fitness function components of S2.

Fitness function	Scaled parameters to minimize	Description
Production schedule f_{PS}	C'_{max}	Makespan
	T'_{max}	Tardiness
	ζ'_{PS}	Transport and set-up costs
Maintenance planning f_{MP}	Δ'_{total}	Total degradation over all machines
	$\Delta'_{critical}$	Degradation of the machine with the highest degradation
	ζ'_{MP}	Costs of PdM action

To retrieve the values needed for f_{MP}, the *PHM Module* introduced in publication 3 (see section 3.2.3) is applied. Each chromosome, i.e., PdM integrated PS, is fed to the *PHM Module* to estimate the change of the HI, i.e., the degradation the very schedule is expected to cause. The *Interface Module* translates each PS to sequences of ORs that in turn condition the CVAE of the *PHM Module*. The *PHM Module* simulates the specific sequence on each machine and returns the predicted HI and failure threshold $t_{k,fail}$ for all machines. Using this information, Δ'_{total}, $\Delta'_{critical}$ and ζ'_{MP} can be calculated and optimized. Due to the stochastic nature of the *PHM Module*, the predicted values can differ slightly for the same schedule in different simulation runs. In order to limit these effects, multiple runs of the algorithm and the presentation of the top three chromosomes, i.e., schedules, are suggested. The decision-maker thus has the option to choose from multiple different options, thereby also including her or his implicit knowledge. Hence, the PdM-IPS approach serves as a decision support system.

Two scenarios were developed to validate and evaluate the PdM-IPS approach using the developed TSGA, i.e., the *Planning Module*, together with the *Interface Module* and the *PHM Module*. While both scenarios focused on short-term planning, i.e., daily and weekly planning horizons, they differed in terms of data used to train the *PHM Module* and shop floor layout (see Table 6).

Table 6: Scenarios for the validation of the PdM-IPS approach.

No.	Training data of *PHM Module*	Multifunctional machines	Product variants
1	Simulated C-MAPSS data	5	5
2	Real industrial data	3	10

Artificial production lines were modeled using different numbers of multifunctional machines as well as product variants. Figure 3-13 (see next page) features an exemplary user interface and visualization of a developed PdM-integrated production schedule for the first scenario.

With the support of the user interface, the decision-maker can set flexible job shop data (e.g., number of machines, jobs and other constraints), objective parameters regarding costs and time and TSGA hyperparameters by selecting the respective tab. Production times, set-up times, as well as PdM actions, can be retrieved for the fittest three chromosomes. In addition, the cost positions are also presented.

Results indicate that the developed PdM-IPS approach can generate optimal PdM-integrated production schedules for both simulated and real industrial data in reasonable time. In both cases, the TSGA converges, critical machine conditions and potential machine failures can be avoided by scheduling PdM actions.

Figure 3-12 shows the relative contribution of the author of this dissertation for this publication.

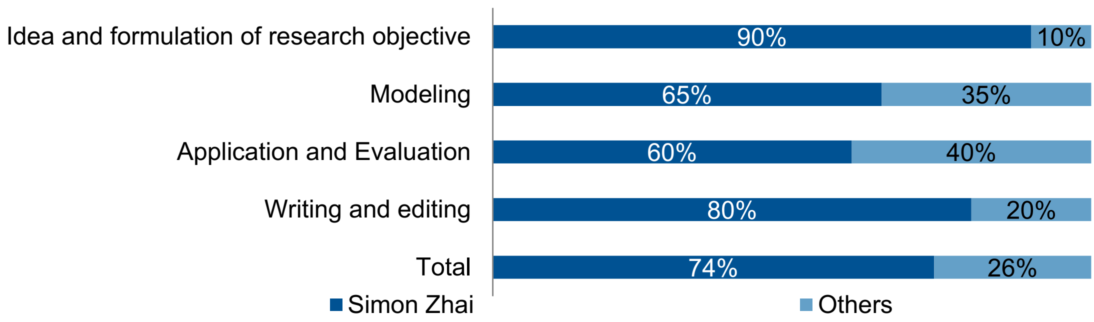

Figure 3-12: Contribution of work for publication 4.

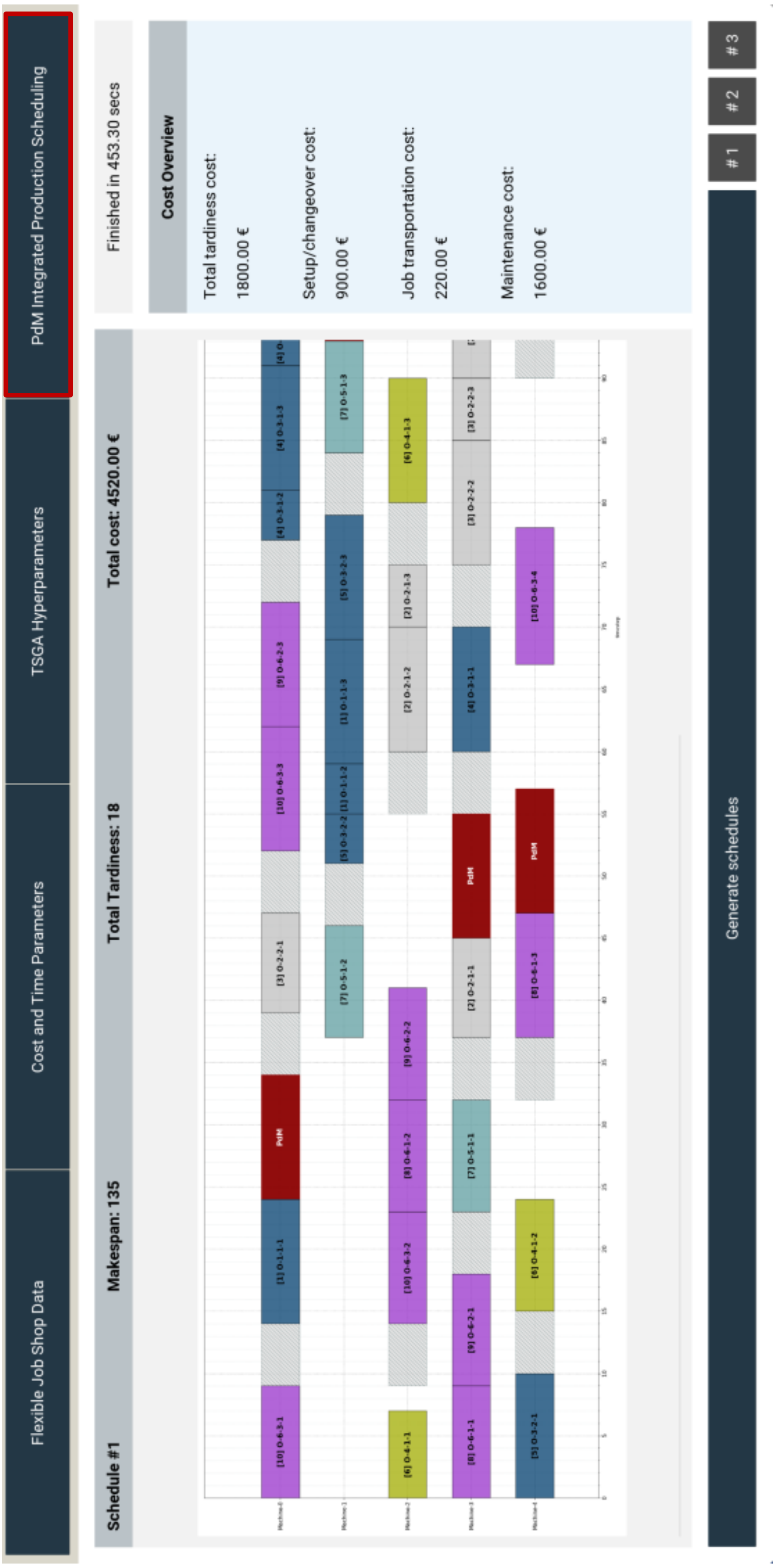

Figure 3-13: Exemplary user interface and the result of the PdM-IPS approach.

4 Validation, Discussion and Reflection of the Results

This chapter focuses on the validation, discussion and reflection of the conducted work and results in both qualitative, i.e., technical, and quantitative, i.e., economical, manner. In previously established terminology, this chapter, therefore, forms the *Descriptive Study II* of the DRM (see Figure 1-2).

As formulated in section 1.2, the main challenge regarding PdM-IPS was identified: the need for operation-specific health modeling in the presence of industrial data with limited quality and availability. Existing IPSMP approaches, such as those proposed by LADJ ET AL. (2016), LADJ ET AL. (2019) and BENAGGOUNE ET AL. (2020) (see section 2.2), are limited in terms of scheduling scope (e.g., focus on single machine scheduling). Therefore, they are not suited for integration with state-of-the-art health modeling approaches such as the model proposed by MICHAU & FINK (2019) (see section 2.5). The assumption of linear degradation development of most IPSMP approaches heavily limits industrial applications where this very assumption rarely holds. While the state of the art does offer non-linear and operation-specific HI modeling as demonstrated by MICHAU & FINK (2019), LI ET AL. (2019) and others (see sections 2.5.1 and 2.5.2), these approaches are not developed with subsequent IPSMP interaction in mind and thus can not be directly utilized for PdM-IPS.

The developed PdM-IPS approach can be clearly delimited from existing methods by focusing on operation-specific health modeling using industrial data for subsequent IPSMP. Existing approaches for operating regime identification (WANG 2010) are adapted so the developed *PHM Module* can operation-specifically estimate degradation caused to machines due to the processing of specific production schedules. Unlike the formulation of KARNER ET AL. (2019), operation-specific and subsequently product-specific changes in HI estimation are explicitly modeled. Hence, PdM actions can be planned according to non-linear HI estimations instead of simplified linear assumptions. The presented PdM-IPS approach includes all necessary steps from industrial CM data preparation and HI estimation to finally develop an optimal PdM integrated production schedule for the flexible job shop.

The following section 4.1 focuses on the technical discussion and fulfillment of requirements by revisiting the requirements formulated in section 1.3 at the beginning of this thesis. Section 4.2 presents the application of the PdM-IPS approach in an industrial use case, including both a technical and economical discussion, in order to validate the overall approach.

4.1 Technical Discussion and Fulfillment of Requirements

This section discusses the fulfillment of the general, PdM-related and IPSMP-related requirements introduced in section 1.3 to develop the PdM-IPS approach. The focus lies on the critical discussion of fulfillment of the requirements and highlighting both achievement and encountered challenges.

4.1.1 Fulfillment of General Requirements

R1 General applicability

The *PHM Module* generated meaningful HI estimations for both simulated and real industrial data, see publication 3 (section 3.2.3). The *Planning Module* is based on a flexible job shop layout, see publication 4 (section 3.2.4). Most other shop floor layouts can be modeled as a variation of a flexible job shop by introducing constraints. Since the developed TSGA is able to solve FJSSPs, it is also able to solve other scheduling problems. The *Interaction Module* is formulated use-case independently and thus can also be generally applied.

R2 Industrial applicability

By validating the PdM-IPS approach using industrial data, the industrial applicability, in general, was proven, see publications 3 and 4 (see sections 3.2.3 and 3.2.4). The preprocessing of the data and the subsequent application of the unsupervised CVAE model enable operation-specific health modeling even when data quality is low and the amount of failure data is scarce. As with all learning approaches, it should be noted that higher data quality and availability lead to better results.

Furthermore, the approach still needs manual adaptation in the implementation: Expert knowledge is necessary to choose those CM signals that reflect the machine's condition and to decide whether a system-wide or component-level HI should be applied. The definition of the threshold is also based on expert knowledge and can differ depending on the use case, e.g., the definition of the critical HI threshold for PdM actions and the splitting proportion of the training data set according to healthy and unhealthy intervals. When failure data is scarce, the splitting of the training data according to these failures is of high significance for the quality of the prediction.

R3 Modularity

The PdM-IPS approach consists of the modules *PHM Module, Interface Module* and *Planning Module.* Using the *Interface Module* to translate products into sequences of operating regimes, the algorithms of the *PHM and Planning Modules* can be adapted and replaced if needed. For example, instead of a CVAE, other artificial neural network architectures can be implemented in the *PHM Module*. In addition, the *PHM Module* and the *Planning Module* can also be adapted for stand-alone usages, e.g., for use cases where only HI estimates or only production schedules are required.

R4 Economic viability

As it will be shown in the following section 4.2.2, the PdM approach is economical since expenses are amortized in reasonable time (around one year in case of a new implementation in an exemplary use case).

4.1.2 Fulfillment of PdM-Related Requirements

R5 Robustness

Robustness towards low data quality (e.g., outliers, missing data, …) is key in industrial applications. By showing the ability to handle industrial data, the proposed PdM-IPS approach is robust and can derive meaningful results even in low data quality circumstances. However, major sensor failures can lead to either unusual behavior or even the absence of sensor readings. A manual or automated system to identify these irregularities is required to prohibit false HI estimations.

R6 Ability to handle high-dimensional data

The developed *PHM Module* can handle high-dimensional data, as shown in section 3.2.3. In the mentioned publication, the *PHM Module* successfully derived HI-estimations using industrial CM data acquired by 140 different sensors.

R7 Ability to handle a low amount of labeled failure data

By applying a CVAE as the underlying model, the *PHM Module* applies unsupervised learning. The design of the *PHM Module* explicitly caters to the industrial reality of having a low number of failure observations by applying the unsupervised learning model CVAE.

The modular design of the whole approach makes it also possible to use other unsupervised models, e.g., generative adversarial networks. Naturally, adaptation and further work are required to implement these models.

R8 Operation-specific health assessment and prediction

Together with the ORI, CVAE enables conditioning of the model to different operation sequences and as such can generate operation-specific health assessments and predictions.

In line with *R2* and *R6*, other artificial neural networks that have the ability to be conditioned can also be applied, e.g., conditional generative adversarial networks (CGAN).

4.1.3 Fulfillment of IPSMP-Related Requirements

R9 Flexibility regarding shop floor layout

As described in section 3.2.4 and in line with *R1*, the *Planning Module* is based on a flexible job shop and is thus representative of many industrial shop floors. Other layouts, e.g., flow shops, can be easily modeled by introducing different constraints.

R10 Time-efficiency

The TSGA ensures time-efficient calculation by both the used metaheuristic and its design in two stages. The first stage ensures that the computationally-intensive second stage starts in a promising search region. In publication 4 (see section 3.2.4.), it was shown that the PdM-IPS approach could run on normal desktop PCs. Higher processing power and memory can further scale the approach's ability and facilitate the usage of CM signals sampled with high frequency.

R11 Multi-objective optimization ability

Genetic algorithms are able to optimize multi-objectively. As such, the implemented TSGA fulfills this requirement.

R12 Consideration of the decision maker's preferences

The decision-maker can set different production and maintenance metrics weights to prioritize the optimization process accordingly. Furthermore, thresholds for critical machine degradation and maximum calculation time, amongst others, can also be chosen.

To conclude, the requirements defined in section 1.3 were explicitly taken into account while developing the PdM-IPS approach and as such, all requirements are fulfilled. Further potentials regarding industrial implementations were identified and are detailed in the following.

4.2 Validation Case Study: The PdM-IPS Approach in Industrial Application

The validation of the PdM-IPS approach took place following a multi-step validation approach. First, separate validation of each module, i.e., the *PHM, Interaction* and *Planning Module,* was conducted in publications 3 and 4. These validations showcased that the *PHM Module* is indeed able to construct meaningful operation-specific HI estimates using industrial data.

Also, it was shown that these estimates could be successfully transferred by the *Interface Module* such that the *Planning Module* can generate PdM-integrated production schedules. Second, this section presents the results of holistic validation of the PdM-IPS approach that took place in a real production setting using a functional prototype.

The prototype was implemented in a production line in the automotive industry for over four months to evaluate the industrial as well as economic viability of the approach. The automotive industry is the most important branch of Germany’s manufacturing industry with the largest revenue of any branch, yielding 411 bil. Euro and while directly employing 786.000 employees in 2021 (BUNDESMINISTERIUM FÜR WIRTSCHAFT UND KLIMASCHUTZ 2023). As such, choosing an automotive company for the validation of PdM-IPS ensures the largest possible impact. In addition, machine tools used in the automotive industry are utilized in other industrial branches and hence, validation results are transferable. For example, a company that manufactures parts for jet engines also utilizes machine tools that are subject to degradation.

It should be noted that due to privacy reasons, no company and personnel names are mentioned. The following sections are based on adapted and abstracted production settings as well as anonymized statements of experts to preserve confidentiality. The observed production line consists of multiple units of the same multi-functional machine tool able to produce different product variants. CM data was acquired from 32 sensors of a representative machine tool and was resampled to 1 Hz. These 32 sensors were preselected from a total of 140 sensors according to expert knowledge and represent six machine tool components. In principle, the PdM-IPS approach is also able to handle the processing of all 140 sensors, as shown in publication 3. However, as the results of the mentioned publication suggest, a preselection of the most meaningful sensor signals and a component-wise HI aggregation can significantly improve result quality.

A combination of qualitative and quantitative methods, i.e., expert interviews and cost-benefit analysis, are applied to ensure multiple perspectives and different levels of abstractions of the validation are considered. It can thus be stated that the validation, in general, follows a *mixed-method* design (KUCKARTZ 2014, p. 33). The qualitative validation is based on expert interviews with six experts working in the mentioned production setting. In order to enable in-depth validation interviews, the number of experts was kept low and was limited to those experts who had in-depth knowledge of the developed PdM-IPS approach. The experts were chosen according to their expertise and experience and to cover the wide range of PdM-IPS: one process expert with more than 25 years of maintenance experience, a specialist for data engineering, development and operations (“DevOps”), an IT specialist responsible for PdM in the department, a specialist for tooling maintenance and two specialists for planning and operational data acquisition. It should be noted that the choice of experts is indeed a limiting factor of the representative population. The statements and results can therefore be seen as valid for other manufacturing companies with similar prerequisites, that is, companies that utilize machine tools subject to degradation which is at least indirectly measurable using an available CM system. Furthermore, maintenance and production are scheduled and documented electronically.

4.2.1 Qualitative Analysis

In order to critically discuss the validity of the developed PdM-IPS approach, the validation methodology of LANDRY ET AL. (1983) was adapted. Landry et al. distinguish five different validities that models in operations research and, more generally, decision support models have to fulfill. Using a structured questionnaire as the basis for expert interviews, the fulfillment of these validities was examined.

Conceptual validity describes "[...] the degree of relevance of the assumptions and theories underlying the conceptual model of the problem situation for the intended users and use of the model" (LANDRY ET AL. 1983, p. 212). In the context of PdM-IPS, conceptual validity guarantees that the user's scope is covered and that the model represents the problem at hand with enough detail.

Logical validity deals with "[...] the capacity of the formal model to describe correctly and accurately the problem situation" (LANDRY ET AL. 1983, p. 213). In other words, logical validity ensures that the problem and its constraints are correctly described. The *experimental validity* focuses "[...] the quality and efficiency of the solution mechanism" (LANDRY ET AL. 1983, p. 213), while the *operational validity* evaluates the "[...] quality and applicability of the solutions and recommendations" (LANDRY ET AL. 1983, p. 214). Finally, the *data validity* rates the "[...] the sufficiency, accuracy, appropriateness, and availability of the data" (LANDRY ET AL. 1983, p. 214).

Interview methodology

Expert interviews are chosen as means for the qualitative analysis since exclusive and often implicit knowledge of the expert is required to provide the information necessary to assess the five dimensions of validity. A semi-structured design is selected for the expert interview, combining multiple open-ended and close-ended questions. The questionnaire and answers can be found in Appendix 7.4. The design of the questionnaire and formulation of questions follow the best-practice recommendations of PORST (2014, 53 f.):

- Question type: Closed, semi-open and open questions can be utilized in questionnaires. Closed questions can be easily interpreted and used for further analysis. However, these questions narrow down the answering possibilities of the interviewees and

might force them to select an answer that does not reflect their respective opinion. Semi-open questions extend closed questions with the answer possibility “other” to enable different answers. Open questions empower the interviewees to voice their opinion freely but come at the price of decreased comparability and difficulty for evaluation and subsequent analysis.
The utilized questionnaire uses closed and open questions. Closed questions are applied for rating defined aspects of the PdM-IPS approach using the Likert scale. This application minimizes the possibility that the interviewee’s opinion is not reflected in the answering possibilities. Furthermore, interviewees are allowed to voice any different opinion or observation to every closed question, thus enabling capturing a holistic view. Open questions are mainly employed to capture the expert’s opinion regarding further chances and risks of the PdM-IPS approach that are not yet mentioned. Selecting experts familiar with the problem at hand ensures that the answers to the open questions are comparable and within the bounds of the use case.

- Scaling of answers: As mentioned, the Likert scale is applied to quantify the personal impression of a described aspect. When applicable, an equal amount of items is given as answering possibilities to prohibit the middle item from being misused as an “escape category.” This effect describes when interviewees choose the middle category to avoid voicing opinions (PORST 2014, p. 83). For questions where experts are asked to quantify an aspect (e.g., estimated savings), the provided items shall represent a realistic distribution.
The applied questionnaire follows these guidelines. Middle items are allowed for questions that concern the evaluation of experimental results but are prohibited when rating concepts. In order to estimate realistic saving potentials, the highest possible answer category is “>20 %”.

- Question formulation: The questions shall be formulated such that their semantic understanding is easy to derive. This entails the explanation of unknown terms and exact specifications of possibly ambiguous vocabulary.
Before answering the questions, all experts receive a thorough presentation about the PdM-IPS approach and related terminology. By doing so, a common understanding is ensured.

The interview is divided into two parts. Part A was conducted between April and May 2021, while part B was conducted from July until October 2021. Part A focuses on the concept of the PdM-IPS approach and starts with an introductory presentation of roughly 30 minutes of PdM-IPS, related terminology and its application in the company. Part B focuses on experimental results. The interviews were held in German language and were subsequently translated into

English. In order to evaluate the different dimensions of validity, multiple questions concerning each dimension were asked. All questions are related to the prototypical implementation of the PdM-IPS.

The first part focuses on the conceptual and operational validity, which were rated using a six-point Likert scale (strongly disagree, disagree, slightly agree, agree, strongly agree), forcing the interviewee to take a non-neutral position so deviations in the concept from reality can be clearly seen. Part B uses a five-point Likert scale (strongly disagree, disagree, undecided, agree, strongly agree) and focuses on experimental, data and logical validity. The interviewee was given the possibility to voice a neutral position because part B incorporates examples of actual PdM-IPS applications. For the final evaluation, answers to the six-point Likert scale were scaled to match the five-point Likert scale to derive the average levels of fulfillment. The experts were asked to elaborate on the question freely and base the rating on their overall thoughts. In addition, the answers were recorded to provide a further basis of corroboration and potential for further improvement.

Figure 4-1 depicts the average fulfillment of each validity class with a scale from 1 (no fulfillment) to 5 (high fulfillment).

Summary of interview results

With a score of 4.6, the conceptual validity of the developed PdM-IPS approach was rated the highest. All respondents agree that integrating machine degradation into production scheduling is essential. Specifically, it was agreed upon that operation-specific modeling of degradation is indeed required to derive meaningful estimations of health conditions. The experts could reflect on PdM-IPS's main components and confirm that the underlying concepts of these components match the requirements of the use case at hand.

The logical validity was rated 4.3 on average. The proposed approach, including the formal model and solution method, as well as assumptions made considering degradation and maintenance, were considered to be following the expert’s expectations. However, experts note that outliers and changes in measurements of condition monitoring data can certainly be caused by degradation, but other causes like sensor malfunctions and human errors should also be considered.

The operational validity was rated with an average score of 3.8. The cause for the slightly lower evaluation is that some experts voiced skepticism concerning the incorporation of product-specific degradation for integrated planning finding its way into their daily operation. This skepticism is caused by existing scheduling constraints such as strict tact times and supply chain restrictions. Integration into daily operations will take time and reorganization of the production might have to take place, which cannot be realized for every manufacturing setting. However, the experts agree that, in principle, the integration of operation-specific and product-specific degradation in production scheduling is important and the prototypical application of the PdM-IPS approach in their setting was successful.

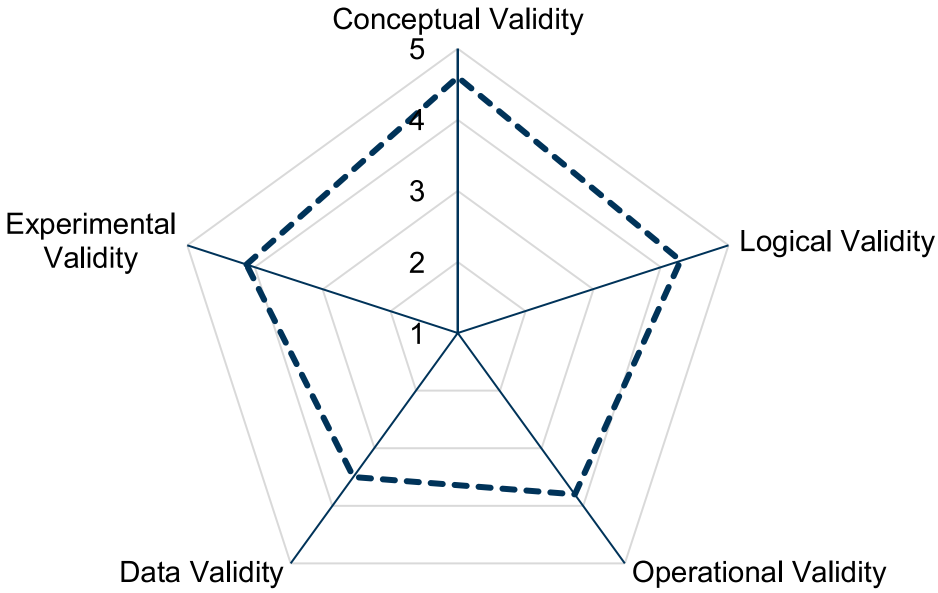

Figure 4-1: Average degree of satisfaction based on expert's evaluation.

Data validity was rated with an average score of 3.5. Although the rating is reasonably high, data validity was rated the lowest among all validities. While experts state that the data acquisition period of four months is satisfactory for a prototypical validation, this period should be prolonged to assure that all eventualities and seasonalities are captured in the data. Furthermore, the need to interpret failure logs that were manually created is not trivial and is a source of errors since maintenance operators do not utilize a standardized language when protocolling failure and maintenance events. This interpretation is needed to label the acquired sensor data as "healthy" or "unhealthy". There is also the possibility of failure events that were not logged due to human error, hence leading to "unhealthy" data being labeled as "healthy". Lastly, faulty sensors could lead to misreading and erroneous data.

Finally, with an average score of 4.1, the experimental validity also received a high rating. Different HI predictions and the corresponding ground truths (see Appendix 7.4.2) of the prototypical application were presented to the experts for evaluation. In particular, operation-specific degradation trends were identified. The presented HI predictions include both good and poor predictions that occurred during the validation phase to enable the experts to voice an unbiased rating. The interviewees recognize the overall prediction performance of the prototypical implementation as being highly satisfactory, albeit mentioning that more testing and optimization are needed for live applications in mass production.

Additionally, possible PdM-integrated production schedules were presented. Experts acknowledge that these schedules have a high potential to improve production and maintenance planning, especially improving communication between production and maintenance personnel. Nevertheless, the realization of such integrated planning is a long-term objective since multiple departments are involved and best suited for flexible production settings, e.g., a matrix production layout envisioned for Industrie 4.0 (KUKA SYSTEMS GMBH 2016).

Overall, the average of 4.1 out of 5 over all validities indicates that the prototypical implementation of the PdM-IPS approach was deemed successful by the experts and thus, the industrial viability of the PdM-IPS approach was proven.

4.2.2 Economic Discussion: Cost-Benefit Analysis

In order to evaluate the economic benefits of the PdM-IPS approach, a cost-benefit analysis is applied. An exemplary manufacturing setting resembling a real production line in the automotive sector consisting of 18 multifunctional machine tools is investigated. These machine tools are equally distributed in three machine parks, each representing one processing step. Products to be manufactured have to visit all three parks. Assumptions similar to the proposed PdM evaluation model of WOLF ET AL. (2019) are applied. The economic discussion is structured as follows: First, costs for developing and implementing the PdM-IPS approach are estimated. Subsequently, the cost-saving potential is analyzed and finally, the amortization period is calculated.

The costs of adapting and implementing the PdM-IPS approach depend on the PdM maturity level the manufacturing company is situated in. As indicated by BUSSE ET AL. (2019), different maturity levels and scenarios shall be examined to make the right investment decision. For example, the costs of implementing the PdM-IPS approach are lower for production sites that already have a CM system and corresponding sensors installed on the machine tools than for a site with no system installed. To account for these differences, different maturity levels are examined: CbM, PdM and PdM-IPS. The maturity levels are considered reached when the tasks listed in Table 7 to Table 9 have been completed. Each level is needed to reach the next one, e.g., in order to realize PdM-IPS, CbM and PdM have to be implemented. It is important to emphasize that the PdM-IPS approach includes models that can be used for each maturity level: the HA-CVAE can be used for CbM, the combination of HA-CVAE and DS-CVAE is required for PdM and finally, the combination of HA-CVAE, DS-CVAE (introduced as *PHM Module*, see section 3.2.3) and the scheduling module enable PdM-IPS.

Estimation of development and implementation costs

Table 7 to Table 9 depict the amount of work and related costs needed to reach the maturity level of CbM, PdM and PdM-IPS, respectively. The amount of work is based on the actual and estimated times needed to develop and implement the approach, the costs per hour are based on estimates of 150 € per hour for researchers and engineers (R/E) (BAYRISCHE INGENIEURKAMMER-BAU 2019) and actual costs of student researchers and interns (S/I) of 35 € per hour. It should be noted that hardware costs are neglected at this stage and will be added to calculate the amortization duration in the subsequent section.

Table 7: Cost estimation for development and implementation of the maturity level "CbM" for the exemplary use case.

Condition-based Maintenance				
Task	**Hours**	**Cost rate [€/h]**		**Costs [€]**
Data Pipeline Set up	30	S/I	35	1,050
	10	R/E	150	1,500
Data Preparation	500	S/I	35	17,500
	40	R/E	150	6,000
Feature Engineering	100	S/I	35	3,500
	20	R/E	150	3,000
Development Health Assessment	700	S/I	35	24,500
	200	R/E	150	30,000
Model Validation	40	S/I	35	1,400
	10	R/E	150	1,500
Online Implementation	60	S/I	35	2,100
	10	R/E	150	1,500
User Interface Development	90	S/I	35	3,150
	10	R/E	150	1,500
Operator Training	16	S/I	35	560
	4	R/E	150	600
Scaling Costs	144	S/I	35	5,040
	36	R/E	150	5,400
Sum				**109,800**

Table 8: Cost estimation for development and implementation of the maturity level "PdM" for the exemplary use case with existing CbM.

Predictive Maintenance				
Task	**Hours**	**Cost rate [€/h]**		**Costs [€]**
Development Data Simulator	800	S/I	35	28,000
	300	R/E	150	45,000
Prediction Validation	140	S/I	35	4,900
	20	R/E	150	3,000
User Interface Extension	36	S/I	35	1,260
	4	R/E	150	600
Operator Training	16	S/I	35	560
	4	R/E	150	600
Scaling Costs	8	S/I	35	5,040
	2	R/E	150	5,400
Sum				**79,360**

Table 9: Cost estimation for development and implementation of the PdM-IPS approach for the exemplary use case with existing CbM and PdM.

PdM-IPS				
Task	**Hours**	**Cost rate [€/h]**		**Costs [€]**
Development Planning Module	800	S/I	35	28,000.00
	300	R/E	150	45,000.00
Development Interface Module	140	S/I	35	4,900.00
	100	R/E	150	15,000.00
Validation	100	S/I	35	3,500.00
	20	R/E	150	3,000.00
User Interface Extension	100	S/I	35	3,500.00
	25	R/E	150	3,750.00
Operator Training	25	S/I	35	875.00
	10	R/E	150	1,500.00
Sum				**109,025**

Estimation of the cost-saving potential

Since estimations for the cost-saving potential of advanced maintenance paradigms are spread widely (THOMAS & WEISS 2021, p. 3), specific experts familiar with the use case at hand were interviewed to receive a realistic and precise estimation. Using financial key performance indicators (KPIs) obtained from the *Kennzahlenkompass* (VDMA VERLAG 2020) of the German

Mechanical Engineering Industry Association (VDMA) and industry-related literature to calculate the base costs of the exemplary use case, transparency and transferability to other manufacturing settings are ensured. Relevant KPIs and calculation formulas can be found in Appendix 7.2.

The cost-saving potential per year of maturity levels of CbM and PdM was estimated by the experts responsible for maintenance and CbM/PdM rollout and is presented in Table 10 and Table 11. It should be noted that the base costs in the following tables are already reduced by the savings realized by the previous maturity level.

Table 10: Estimated cost saving per year of CbM for the exemplary use case.

Condition Based Maintenance			
Position	**Base Costs [€]**	**Saving ratio**	**Savings [€]**
Total costs of unplanned downtime	5,621,465	25 %	1,405,366
Total costs of planned downtime	897,545	15 %	134,632
Costs for internal maintenance	2,448,329	5 %	122,416
Costs for external maintenance	2,448,329	5 %	122,416
Costs for tool replacement	1,370,057	5 %	68,503
Costs for spare parts	1,224,165	5 %	61,208
Costs for rejects due to low quality	4,621,166	15 %	693,175
Sum			**2,607,717**

Table 11: Estimated cost saving per year of PdM for the exemplary use case.

Predictive Maintenance			
Position	**Base Costs [€]**	**Saving ratio**	**Savings [€]**
Total costs of unplanned downtime	4,216,099	5 %	210,805
Total costs of planned downtime	762,913	10 %	76,291
Costs for internal maintenance	2,325,913	5 %	116,296
Costs for external maintenance	2,325,913	5 %	116,296
Costs for tool replacement	1,301,554	0 %	-
Costs for spare parts	1,162,956	10 %	116,296
Costs for rejects due to low quality	4,216,099	5 %	210,805
Sum			**635,983**

To estimate the yearly cost-saving potential of PdM-IPS, the same six experts ranging from production and IT to maintenance in the automotive industry were interviewed (see section 4.2.1). The median saving ratio class was chosen in order to calculate the estimated savings.

If the median was between two classes, the more conservative, i.e., lower class, was chosen. Since each saving ratio class represents a saving range (e.g., 5-10 %), minimum, average and maximum estimated savings are calculated. The results are displayed in Table 12.

Table 12: Estimated cost saving per year of the PdM-IPS approach for the exemplary use case.

PdM-IPS							
Position	**Base Costs [€]**	**Min. saving ratio**	**Average saving ratio**	**Max. saving ratio**	**Min. savings [€]**	**Average savings [€]**	**Max. savings [€]**
Total costs of unplanned downtime	4,005,294	3.0 %	3.0 %	3.0 %	120,159	120,159	120,159
Costs for internal maintenance	2,209,617	5.0 %	7.5 %	10.0 %	110,481	165,721	220,962
Costs for external maintenance	2,209,617	2.5 %	3.75 %	5.0 %	55,240	82,861	110,481
Costs for tool replacement	1,301,554	2.5 %	3.75 %	5.0 %	32,539	48,808	65,078
Costs for rejects due to low quality	4,21,166	2.5 %	3.75 %	5.0 %	115,529	173,294	231,058
Sum					**433,948**	**590,843**	**747,737**

Estimation of the amortization period

By taking costs and yearly savings into account, it is possible to calculate the amortization period. Three Scenarios are investigated, each mirroring a different maturity level of the exemplary manufacturing setting:

- **Scenario A**: Hardware, e.g., sensors, is available and installed, and maturity levels CbM and PdM are already developed and implemented. Only the PdM-IPS approach has to be developed and implemented. This scenario represents companies that already have extensive PdM experience but lack the integration of production and maintenance planning. The exemplary company of the case study can be located in this scenario.

- **Scenario B**: Hardware equipment is available and installed, but all three maturity levels CbM, PdM and the PdM-IPS approach have to be developed and implemented. This scenario represents companies that are preparing to roll out the PdM-IPS approach but have no experience in PdM yet.
- **Scenario C**: Hardware has to be purchased and installed. All three maturity levels CbM, PdM, and the PdM-IPS approach have to be developed and implemented. This scenario represents companies with no experience in PdM which have not yet decided to implement the PdM-IPS approach. The estimated additional hardware costs per machine are 150,000 €, representing a high estimation (CAPGEMINI 2018, p. 7, STRAUSS ET AL. 2018).

Furthermore, yearly operating costs of 100 working hours of engineering personnel per maturity level are assumed, adding 15,000 € per maturity level. For all three maturity levels, the operating costs are equal to 45,000 €.

Table 13 shows the costs and associated saving estimations of each scenario. It should be noted that "best, average and worst-case" scenarios refer to the different expert estimations of savings for the PdM-IPS approach, as presented in Table 12. In line with other studies showing the high saving potential of PdM technologies (THOMAS & WEISS 2021), also the PdM-IPS approach realizes significant reductions in costs with an average savings of around 600,000 € per year for the exemplary use case. Together with the savings realized by CbM and PdM, over 3.8 € million could be saved. By dividing the sum of the development and operating costs by the expected savings, the amortization period is calculated and presented in Table 14 for each scenario. Unsurprisingly, the last scenario features a much higher amortization period than the first two scenarios since hardware costs are included. It is noteworthy that, all in all, even the worst-case scenario possesses an amortization period of around 300 working days. However, it should be highlighted that this calculation assumes the possibility to implement PdM-IPS directly without the eventual costs of organizational change since this cost position is highly dependent on each company in question.

Table 13: Overview of costs and savings for different scenarios.

<table>
<tr><th></th><th>Costs of Development and Implementation [€]</th><th>Operating costs [€/y]</th><th>Savings, best case [€/y]</th><th>Savings, average case [€/y]</th><th>Savings, worst case [€/y]</th></tr>
<tr><td>Scenario A</td><td>109,025</td><td>15,000</td><td>747,737</td><td>590,843</td><td>433,948</td></tr>
<tr><td>Scenario B</td><td>313,185</td><td rowspan="2">45,000</td><td rowspan="2">3,991,437</td><td rowspan="2">3,834,543</td><td rowspan="2">3,677,648</td></tr>
<tr><td>Scenario C</td><td>3,013,185</td></tr>
</table>

Table 14: Overview of amortization periods for different scenarios.

	Amortization period, best case [d]	Amortization period, average case [d]	Amortization period, worst case [d]
Scenario A	54	69	95
Scenario B	29	30	31
Scenario C	279	290	303

4.3 Discussion and Reflection: Conclusion

This chapter critically discussed the fulfillment of requirements and showcased the application of the PdM-IPS approach in an industrial use case. Achievements and challenges were identified using both qualitative and quantitative means of analysis. With an average validation score of 4.1/5, experts considered the prototypical implementation in an industrial setting successful. The expert interviews revealed that the prototypical implementation showed promising results in both monetary and technological terms.

The PdM-IPS approach fully met the experts' expectations in terms of concept, logic and experimental results. HI predictions based on future production sequences were evaluated regarding plausibility. While errors in data due to sensor failures or human mistakes were possible and can lead to low-quality predictions, it was deemed that the PdM-IPS approach itself is industrially viable. The approach can handle typical data inconsistencies, e.g., missing data, by applying data preparation techniques and is also able to work with a limited amount of failure data.

Still, it should be noted that data validity was rated lowest among all validities, which represents one major limitation of the PdM-IPS approach: Ensuring data quality and availability is not trivial, wrong measurements or mislabeling of the failure data due to human error can render the HI less meaningful – or, in the worst case, even give a false sense of security. Thus, the implementation of the PdM-IPS approach requires the interdisciplinary collaboration of different departments to ensure the correct setup of data acquisition and interpretation of the acquired data. Preventing erroneous data from emerging and identifying its root cause are challenges that all data-driven approaches face and are investigated in other research fields, e.g., the application of virtual sensors to identify faulty sensors (DARVISHI ET AL. 2021).

The experts agree that product-specific degradation should be considered when planning production and maintenance. However, it should be noted that a company-wide rollout of the PdM-IPS approach is not yet possible due to operational constraints and should be considered in the future. Operational constraints can be the biggest roadblock for PdM-IPS implementation, e.g., existing manufacturing lines may be limited as to how much they can adapt their current production and maintenance planning.

Nevertheless, the prototypical approach showcases that value-added can indeed be realized. By introducing three exemplary scenarios, each representing a different PdM maturity of the company, potential costs and savings are showcased. It should be noted that all scenarios exclude eventual costs for organizational change since this cost position is highly dependent on the company in question. It is shown that for each scenario high savings can be realized. The amortization period is reasonably low, with an estimation of one year in the most conservative estimation. This knowledge enables future decision-makers to consider introducing the PdM-IPS approach when adapting existing manufacturing sites or when new factories have to be built.

5 Summary and Outlook

The final chapter of this thesis summarizes the work conducted and the main results of this dissertation in section 5.1 and outlines further possible future research areas in section 5.2.

5.1 Summary

Recent developments in AI and condition monitoring (CM) led to the emergence of the new maintenance paradigm *Predictive Maintenance (PdM)*, which enables manufacturing companies to prevent unplanned downtime and achieve significant savings. However, the potential of synchronizing production and PdM actions has yet to be realized, since state-of-the-art approaches cannot product-specifically estimate the degradation of manufacturing equipment and utilize this information for integrated planning purposes.

The first chapter presents the underlying motivation and status quo of PdM. In addition, the underlying research methodology, the DRM, is introduced. By challenging the status quo, the overarching research objective is derived: the development of an industrially viable Predictive Maintenance Integrated Production Scheduling (PdM-IPS) approach. Specifically, this approach shall include the operation-specific modeling of degradation and health condition prediction and the ability to handle industrial data, i.e., data from industrial condition monitoring systems and operating logs. Industrial data is especially challenging for PdM applications due to its high dimensionality and low amount of labeled failure data.

The second chapter introduces PdM-IPS-related terminology, fundamentals and state-of-the-art literature. The research deficit lies in a holistic approach for the industrial application of PdM-IPS, which includes Health Indicator (HI) modeling and scheduling approaches. These must work in sync to optimally plan production and maintenance such that the remaining useful life (RUL) of machines is optimally consumed. In the scientific literature, degradation and RUL consumption are often simplified as linear to the processing time, but this assumption may not accurately reflect the real-life situation in industrial settings.

In order to overcome these shortcomings, the third chapter presents a data-driven approach for PdM-IPS, i.e., an approach to integrating production scheduling and maintenance planning using the potential of recent developments in AI. The development and implementation of the PdM-IPS approach are outlined in four publications. The first publication presents an expert study of European manufacturing companies. The study reveals that a holistic application of PdM, i.e., PdM-IPS, catered to industrial needs and industrial data is required to succeed in PdM rollout.

A simulative PdM-IPS model is developed in the second publication. By assuming arbitrary linear operation-specific degradation, the health of machines was modeled. Subsequently, a GA was applied to schedule production and maintenance according to operation-specific degradation. Results indicate that GAs are indeed suited to schedule PdM-IPS instances optimally.

The holistic PdM-IPS approach is developed in the third and fourth publications and consists of three modules: the PHM Module, the Interface Module, and the *Planning Module.* The *PHM Module* derives product-specific HI estimations which the Planning Module will use to determine the integrated production and maintenance plan. The *Interface Module* facilitates communication between these modules.

As the linear assumption of degradation heavily limits industrial application, the *PHM Module* that derives non-linear operation-specific HIs from industrial data is developed in the third publication. Since failure events are rare and CM data when the machine was in a healthy state is widely available, the unsupervised learning model conditional variational autoencoder (CVAE) is utilized. The CVAE is conditioned to the active operating regime in training, thus enabling operation-specific modeling. Two CVAE models are trained: the Health Assessor (HA-)CVAE, which is trained on healthy CM data only and the Data Simulator (DS-)CVAE, which is trained on all available data. The product-specific HI prediction procedure is realized as follows: The DS-CVAE receives a production sequence as input. It generates corresponding CM data, which in turn is evaluated by the HA-CVAE. The HA-CVAE outputs the estimated HI after the manufacturing of the production sequence. The *PHM Module* is validated using both simulated and real industrial CM data.

The fourth publication seamlessly integrates the *PHM Module* with a *Planning Module*, thus completing the PdM-IPS approach. A flexible job shop IPSMP is modeled and a two-stage genetic algorithm as a solution method is employed to solve the optimization problem. The solution method features two stages to increase efficiency. The first stage schedules only production according to the set constraints and ensures that the more computationally intensive second stage starts in a promising search region. The second stage integrates production and maintenance planning. Production sequences generated by the *Planning Module* are transmitted via the *Interface Module* to the *PHM Module* and the estimated HI is returned during the optimization process. This process is done for every candidate solution, i.e., production sequence. A PdM action is planned when the HI falls below a critical threshold, consequently preventing machine failure. By changing the weights of the objective function, the decision-maker can prioritize maintenance (e.g., frequency of maintenance actions) or production metrics (e.g., makespan). The completed PdM-IPS approach is validated using simulated and real industrial CM data in an artificial production setting.

The fulfillment of requirements is evaluated and a case study is conducted based on a prototypical implementation of the approach in the automotive industry. Experts involved in the implementation and application were interviewed to identify potentials and challenges. These expert interviews and a subsequent cost-benefit analysis deemed the approach industrially viable and profitable. In particular, the PdM-IPS approach was able to identify correct patterns of operation-specific degradation. The amortization period is conservatively estimated to be less than one year for a typical manufacturing setting.

5.2 Outlook

During the development, implementation and validation of the PdM-IPS approach, two core areas for possible further research work are identified and shortly summarized.

Model advancement and improvement of data acquisition

While the CVAE applied in the *PHM Module* is robust and is able to generate meaningful HI prediction, other generative models should also be considered and investigated. The Generative Adversarial Network (GAN) architecture is of high interest since its conditioned version CGAN possesses greater ability than the CVAE to generate more realistic CM signals, especially in generating samples with higher variance. However, the training of GANs can at times be unstable and requires high customization. Recent developments hint at the high potential of CGANs and combinations of CVAE and GANs for generating realistic image data and therefore should be considered for future application in PHM (BAO ET AL. 2017).

Since the database and data acquisition is critical regardless of model architecture, the research shall develop means of identifying erroneous data necessary for PHM applications and include these in the PdM-IPS approach as an additional module. Erroneous data can occur within but is not limited to CM and failure data. Virtual sensors are one concept that distinguishes malfunctioning sensors and their application can prevent erroneous CM data from being included in the model databases. In addition, failure logs shall be standardized and a system that prevents manual logging errors shall be developed. For industrial applications, designing a single source of truth combining all data streams is of vast importance to prevent ambiguous data and thus facilitate interdisciplinary and cross-departmental technologies like PdM-IPS.

Application of the PdM-IPS approach as part of the Smart Factory

Apart from model advancements, research should be conducted on the further potential of applications of PdM-IPS and its integration in current and future manufacturing lines of factories. Since the PdM-IPS approach is best suited for a highly flexible and reconfigurable manufacturing line, research should investigate how the Smart Factory of the future can implement the PdM-IPS approach in accordance with other Industrie 4.0 technologies. New production management paradigms such as Lean 4.0 are emerging and enable new factory structures that facilitate the PdM-IPS approach implementation (DILLINGER ET AL. 2021). Due to the interdisciplinary and cross-departmental character of PdM-IPS, new organizational structures in production and maintenance shall be developed to foster cross-sectional cooperation and create value-added. Research can focus on the combination, reorganization and creation of new departments that facilitate PdM-IPS, or vice versa, is facilitated by PdM-IPS.

6 References

ABELE & REINHART 2011
Abele, E.; Reinhart, G.: Zukunft der Produktion. Herausforderungen, Forschungsfelder, Chancen. München: Carl Hanser Fachbuchverlag 2011. ISBN: 9783446428058.

ASSAF 2018
Assaf, R.: Prognostics and Health Management for Multi-Component Systems. (Dissertation). School of Computing, Science & Engineering, University of Salford Manchester. Manchester (2018) - 21.10.2019.

BABU ET AL. 2016
Babu, G. S.; Zhao, P.; Li, X.-L.: Deep Convolutional Neural Network Based Regression Approach for Estimation of Remaining Useful Life. In: Navathe, S. et al. (Eds.): Database systems for advanced applications. Cham, Heidelberg: Springer 2016, pp. 214-228. ISBN: 978-3-319-32024-3.

BAO ET AL. 2017
Bao, J.; Chen, D.; Wen, F.; Li, H.; Hua, G.: CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training. 2017 IEEE International Conference on Computer Vision (ICCV). Venice, 22.10.2017 - 29.10.2017: IEEE 2017, pp. 2764-2773. ISBN: 978-1-5386-1032-9.

BAYRISCHE INGENIEURKAMMER-BAU 2019
Bayrische Ingenieurkammer-Bau: Stundensätze im Ingenieurbüro. <https://www.bayika.de/bayika-wAssets/docs/beratung-und-service/download/bayika_stundensaetze_im_ingenieurbuero_0025.pdf> - 27.08.2021.

BEKTAS ET AL. 2017
Bektas, O.; Alfudail, A.; Jones, J. A.: Reducing Dimensionality of Multi-regime Data for Failure Prognostics. Journal of Failure Analysis and Prevention 17 (2017) 6, pp. 1268-1275.

BEKTAS ET AL. 2019a
Bektas, O.; Jones, J. A.; Sankararaman, S.; Roychoudhury, I.; Goebel, K.: A neural network framework for similarity-based prognostics. MethodsX 6 (2019), pp. 383-390.

BEKTAS ET AL. 2019b
Bektas, O.; Marshall, J.; Jones, J. A.: Comparison of Computational Prognostic Methods for Complex Systems Under Dynamic Regimes: A Review of Perspectives. Archives of Computational Methods in Engineering 23 (2019) 3.

BEN ALI ET AL. 2011
Ben Ali, M.; Sassi, M.; Gossa, M.; Harrath, Y.: Simultaneous scheduling of production and maintenance tasks in the job shop. International Journal of Production Research 49 (2011) 13, pp. 3891-3918.

BENAGGOUNE ET AL. 2020
Benaggoune, K.; Meraghni, S.; Ma, J.; Mouss, L.; Zerhouni, N.: Post Prognostic Decision for Predictive Maintenance Planning with Remaining Useful Life Uncertainty. 2020 Prognostics and Health Management Conference (PHM-Besançon). Besancon, France, 2020: IEEE 2020, pp. 194-199. ISBN: 978-1-7281-5675-0.

BENBOUZID-SITAYEB ET AL. 2011
Benbouzid-Sitayeb, F.; Guebli, S. A.; Bessadi, Y.; Varnier, C.; Zerhouni, N.: Joint scheduling of jobs and Preventive Maintenance operations in the flowshop sequencing problem: a resolution with sequential and integrated strategies. International Journal of Manufacturing Research 6 (2011) 1, pp. 30-48.

BERRICHI ET AL. 2010
Berrichi, A.; Yalaoui, F.; Amodeo, L.; Mezghiche, M.: Bi-Objective Ant Colony Optimization approach to optimize production and maintenance scheduling. Computers & Operations Research 37 (2010) 9, pp. 1584-1596.

BIAN ET AL. 2015
Bian, L.; Gebraeel, N.; Kharoufeh, J. P.: Degradation modeling for real-time estimation of residual lifetimes in dynamic environments. IIE Transactions 47 (2015) 5, pp. 471-486.

BLESSING & CHAKRABARTI 2009
Blessing, L. T.; Chakrabarti, A.: DRM, a Design Research Methodology. London: Springer London 2009. ISBN: 9781848825864.

BOUGACHA ET AL. 2019
Bougacha, O.; Varnier, C.; Zerhouni, N.; Hajri-Gabouj, S.: Integrated Production and Predictive Maintenance Planning based on Prognostic Information. 2019 International Conference on Advanced Systems and Emergent Technologies (IC_ASET). Hammamet, Tunisia, 2019: IEEE, pp. 363-368. ISBN: 978-1-7281-1317-3.

BUNDESMINISTERIUM DER FINANZEN 2001
Bundesministerium der Finanzen: AfA-Tabelle Maschinenbau. <https://www.bundesfinanzministerium.de/Content/DE/Standardartikel/Themen/Steuern/Weitere_Steuerthemen/Betriebspruefung/AfA-Tabellen/AfA-Tabelle_Maschinenbau.pdf?__blob=publicationFile&v=3> - 04.11.2021.

BUNDESMINISTERIUM FÜR WIRTSCHAFT UND KLIMASCHUTZ 2023
Bundesministerium für Wirtschaft und Klimaschutz: Automobilindustrie. <https://www.bmwk.de/Redaktion/DE/Textsammlungen/Branchenfokus/Industrie/branchenfokus-automobilindustrie.html> - 15.01.2023.

BUSSE ET AL. 2019
Busse, A.; Metternich, J.; Abele, E.: Evaluating the Benefits of Predictive Maintenance in Production: A Holistic Approach for Cost-Benefit-Analysis. In: Schmitt, R. et al. (Eds.): Advances in Production Research. Cham: Springer International Publishing 2019, pp. 690-704. ISBN: 978-3-030-03450-4.

C. FITOURI ET AL. 2016
C. Fitouri; N. Fnaiech; C. Varnier; F. Fnaiech; N. Zerhouni: A Decison-Making Approach for Job Shop Scheduling with Job Depending Degradation and Predictive Maintenance (2016).

CAPGEMINI 2018
Capgemini: Automotive Smart Factories. <https://www.capgemini.com/it-it/wp-content/uploads/sites/13/2018/04/dti-automotive-smart-factories_report-10.pdf>.

CHEN ET AL. 2014
Chen, X.; Xiao, L.; Zhang, X.: A production scheduling problem considering random failure and imperfect preventive maintenance. Journal of Risk and Reliability 229 (2014), pp. 26-35.

DA ET AL. 2016
Da, W.; Feng, H.; Pan, E.: Integrated preventive maintenance and production scheduling optimization on uniform parallel machines with deterioration effect. 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM). Bali, Indonesia, 2016: IEEE, pp. 951-955. ISBN: 978-1-5090-3665-3.

DARVISHI ET AL. 2021
Darvishi, H.; Ciuonzo, D.; Eide, E. R.; Rossi, P. S.: Sensor-Fault Detection, Isolation and Accommodation for Digital Twins via Modular Data-Driven Architecture. IEEE Sensors Journal 21 (2021) 4, pp. 4827-4838.

DENKENA ET AL. 2012
Denkena, B.; Bluemel, P.; Kroening, S.; Roebbing, J.: Condition based maintenance planning of highly productive machine tools. Production Engineering 6 (2012) 3, pp. 277-285.

DENKENA ET AL. 2020
Denkena, B.; Dittrich, M.-A.; Keunecke, L.; Wilmsmeier, S.: Continuous modelling of machine tool failure durations for improved production scheduling. Production Engineering 14 (2020) 2, pp. 207-215.

DILLINGER ET AL. 2021
Dillinger, F.; Kagerer, M.; Reinhart, G.: Concept for the development of a Lean 4.0 reference implementation strategy for manufacturing companies. Procedia CIRP 104 (2021), pp. 330-335.

DIN EN 13306 2018
Deutsches Institut für Normung e.V. EN 13306, ICS 01.040.03; 03.080.10: Instandhaltung – Begriffe der Instandhaltung; Dreisprachige Fassung EN 13306:2017. Berlin: Beuth Verlag GmbH 2018.

DUSCHEK ET AL. 2021
Duschek, F.; Blameuser, R.; Gehrmann, S.: BearingPoint: Predictive Maintenance Studie 2021. 2021.

ELMARAGHY 2012
ElMaraghy, Hoda A. (Ed.): Enabling Manufacturing Competitiveness and Economic Sustainability. Berlin, Heidelberg: Springer Berlin Heidelberg 2012. ISBN: 978-3-642-23859-8.

FELDMANN ET AL. 2017
Feldmann, S.; Herweg, O.; Rauen, H.; Synek, P.-M.: Predictive Maintenance. Service der Zukunft - und wo er wirklich steht. München 2017.

FISHER & THOMPSON 1963
Fisher, H.; Thompson, G.: Probabilistic learning combinations of local job-shop scheduling rules. Industrial Scheduling (1963).

GHALEB ET AL. 2020
Ghaleb, M.; Taghipour, S.; Sharifi, M.; Zolfagharinia, H.: Integrated production and maintenance scheduling for a single degrading machine with deterioration-based failures. Computers & Industrial Engineering 143 (2020).

GLAWAR ET AL. 2018
Glawar, R.; Karner, M.; Nemeth, T.; Matyas, K.; Sihn, W.: An Approach for the Integration of Anticipative Maintenance Strategies within a Production Planning and Control Model. Procedia CIRP 67 (2018), pp. 46-51.

GUGULOTHU ET AL. 2018
Gugulothu, N.; Malhotra, P.; Vig, L.; Shroff, G.: Sparse Neural Networks for Anomaly Detection in High-Dimensional Time Series. <https://www.zurich.ibm.com/AI4IoT/2018/> - 20.04.2019.

HADIDI ET AL. 2012
Hadidi, L. A.; Turki, U. M.; Rahim, A.: Integrated models in production planning and scheduling, maintenance and quality: a review. International Journal of Industrial and Systems Engineering 10 (2012) 1, p. 21.

HARRATH ET AL. 2012
Harrath, Y.; Kaabi, J.; Ben Ali, M.; Sassi, M.: Multiobjective genetic algorithm-based method for job shop scheduling problem: Machines under preventive and corrective maintenance activities. 2012 4th Conference on Data Mining and Optimization (DMO). Langkawi, 2012: IEEE, pp. 13-17. ISBN: 978-1-4673-2718-3.

JOHANSEN 1994
Johansen, T. A.: Operating Regime based Process Modeling and Identication. Department of Engineering Cybernetics, The Norwegian Institute of Technology Universityof Trondheim. Trondheim (1994). <http://folk.ntnu.no/torarnj/dring.pdf> - 28.11.2019.

JORAPUR ET AL. 2016
Jorapur, V. S.; Puranik, V. S.; Deshpande, A. S.; Sharma, M.: A Promising Initial Population Based Genetic Algorithm for Job Shop Scheduling Problem. Journal of Software Engineering and Applications 09 (2016) 05, pp. 208-214.

KACEM ET AL. 2002
Kacem, I.; Hammadi, S.; Borne, P.: Approach by localization and multiobjective evolutionary optimization for flexible job-shop scheduling problems. IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews) 32 (2002) 1, pp. 1-13.

KARNER ET AL. 2018
Karner, M.; Glawar, R.; Sihn, W.; Matyas, K.: Integrating machine tool condition monitoring and production scheduling in metal forming. Proceedings of MOTSP 2018 (2018).

KARNER ET AL. 2019
Karner, M.; Glawar, R.; Sihn, W.; Matyas, K.: An industry-oriented approach for machine condition-based production scheduling. Procedia CIRP 81 (2019), pp. 938-943.

KENNEDY & EBERHART 1995
Kennedy, J.; Eberhart, R.: Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks. Perth, WA, Australia, 27 Nov.-1 Dec. 1995: IEEE, pp. 1942-1948. ISBN: 0-7803-2768-3.

KIM ET AL. 2017
Kim, N.-H.; An, D.; Choi, J.-H.: Prognostics and health management of engineering systems. An introduction. Cham, Switzerland: Springer 2017. ISBN: 978-3-319-44742-1.

KUCKARTZ 2014

Kuckartz, Udo (Ed..): Mixed Methods. Wiesbaden: Springer Fachmedien Wiesbaden 2014. ISBN: 978-3-531-17628-4.

KUKA SYSTEMS GMBH 2016

KUKA Systems GmbH: Industrie 4.0_Matrix-Produktion. <https://www.kuka.com/-/media/kuka-downloads/imported/2d0d7c7d6573491a8b43eb5f66aec596/kuka_matrixproduktion_screenpdfs_de_160419.pdf> - 02.11.2021.

LADJ ET AL. 2016

Ladj, A.; Varnier, C.; Tayeb, F. B.-S.: IPro-GA. An integrated prognostic based GA for scheduling jobs and predictive maintenance in a single multifunctional machine. IFAC-PapersOnLine 49 (2016) 12, pp. 1821-1826.

LADJ ET AL. 2017a

Ladj, A.; Benbouzid-Si Tayeb, F.; Varnier, C.; Dridi, A. A.; Selmane, N.: A Hybrid of Variable Neighbor Search and Fuzzy Logic for the permutation flowshop scheduling problem with predictive maintenance. Procedia Computer Science 112 (2017), pp. 663-672.

LADJ ET AL. 2017b

Ladj, A.; Varnier, C.; Benbouzid Si Tayeb, F.; Zerhouni, N.: Exact and heuristic algorithms for post prognostic decision in a single multifunctional machine. International Journal of Prognostics and Health Management (2017).

LADJ ET AL. 2019

Ladj, A.; Tayeb, F. B.-S.; Varnier, C.; Dridi, A. A.; Selmane, N.: Improved Genetic Algorithm for the Fuzzy Flowshop Scheduling Problem with Predictive Maintenance Planning. 2019 IEEE 28th International Symposium on Industrial Electronics (ISIE). Vancouver, BC, Canada, 2019: IEEE, pp. 1300-1305. ISBN: 978-1-7281-3666-0.

LANDRY ET AL. 1983

Landry, M.; Malouin, J.-L.; Oral, M.: Model validation in operations research. European Journal of Operational Research 14 (1983) 3, pp. 207-220.

LANZA ET AL. 2009

Lanza, G.; Niggeschmidt, S.; Werner, P.: Optimization of preventive maintenance and spare part provision for machine tools based on variable operational conditions. CIRP Annals 58 (2009) 1, pp. 429-432.

LAWLESS 2003

Lawless, J. F.: Statistical models and methods for lifetime data. 2. ed. Hoboken, N.J.: Wiley-Interscience 2003. ISBN: 0471372153. (Wiley series in probability and statistics).

LEI ET AL. 2018
Lei, Y.; Li, N.; Guo, L.; Li, N.; Yan, T.; Lin, J.: Machinery health prognostics: A systematic review from data acquisition to RUL prediction. Mechanical Systems and Signal Processing 104 (2018), pp. 799-834.

LI ET AL. 2019
Li, N.; Gebraeel, N.; Lei, Y.; Bian, L.; SI, X.: Remaining useful life prediction of machinery under time-varying operating conditions based on a two-factor state-space model. Reliability Engineering & System Safety 186 (2019), pp. 88-100.

LIAO ET AL. 2018
Liao, Y.; Zhang, L.; Liu, C.: Uncertainty Prediction of Remaining Useful Life Using Long Short-Term Memory Network Based on Bootstrap Method. IEEE International Conference on Prognostics 2018 2018, pp. 1-8.

LUO ET AL. 2019
Luo, B.; Wang, H.; Liu, H.; Li, B.; Peng, F.: Early Fault Detection of Machine Tools Based on Deep Learning and Dynamic Identification. IEEE Transactions on Industrial Electronics 66 (2019) 1, pp. 509-518.

MALHOTRA ET AL. 2016
Malhotra, P.; TV, V.; Ramakrishnan, A.; Anand, G.; Vig, L.; Agarwal, P.; Shroff, G.: Multi-Sensor Prognostics using an Unsupervised Health Index based on LSTM Encoder-Decoder. <https://doi.org/10.48550/arXiv.1608.06154> - 12.12.2022

MÄRZ 2017
März, M.: Instandhaltungsmanagement für die Fabrik der Zukunft. ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb 112 (2017) 10, pp. 690-694.

MICHAU ET AL. 2018
Michau, G.; Hu, Y.; Palmé, T.; Fink, O.: Feature Learning for Fault Detection in High-Dimensional Condition-Monitoring Signals. <https://doi.org/10.48550/arXiv.1810.05550> - 10.12.2022

MICHAU & FINK 2019
Michau, G.; Fink, O.: Fully Unsupervised Feature Alignment for Critical System Health Monitoring with Varied Operating Conditions.

PAN ET AL. 2012
Pan, E.; Liao, W.; Xi, L.: A joint model of production scheduling and predictive maintenance for minimizing job tardiness. The International Journal of Advanced Manufacturing Technology 60 (2012) 9-12, pp. 1049-1061.

PEYSSON ET AL. 2019
Peysson, F.; Leon, D.; Lafuste, Q.; Armendia, M.; Mutilba, U.; Guruceta, E.; Kortaberria, G.: Behaviours Indicators of Machine Tools. In: Armendia, M. et al. (Eds.): Twin-Control. A Digital Twin Approach to Improve Machine Tools Lifecycle. Cham: Springer International Publishing 2019, pp. 137-154. ISBN: 978-3-030-02202-0.

PINEDO 2016
Pinedo, Michael L. (Ed.): Scheduling. Theory, Algorithms, and Systems. 5th ed. 2016. Cham, Heidelberg, New York, Dordrecht, London: Springer 2016. ISBN: 978-3-319-26578-0.

PORST 2014
Porst, R.: Fragebogen. Ein Arbeitsbuch. 4., erweiterte Aufl. 2014. Korr. Nachdruck 2013. Wiesbaden: Springer Fachmedien Wiesbaden 2014. ISBN: 9783658021184. (SpringerLink Bücher).

REINHART 2017
Reinhart, Gunther (Ed.): Handbuch Industrie 4.0. Geschäftsmodelle, Prozesse, Technik. München: Hanser 2017. ISBN: 978-3-446-44642-7.

ROSHANAEI ET AL. 2013
Roshanaei, V.; Azab, A.; ElMaraghy, H.: Mathematical modelling and a meta-heuristic for flexible job shop scheduling. International Journal of Production Research 51 (2013) 20, pp. 6247-6274.

SANKARARAMAN & GOEBEL 2014
Sankararaman, S.; Goebel, K.: Uncertainty in Prognostics and Health Management: An Overview. Second European Conference of the Prognostics and Health Management Society 2014 (2014).

SAXENA ET AL. 2008
Saxena, A.; Celaya, J.; Balaban, E.; Goebel, K.; Saha, B.; Saha, S.; Schwabacher, M.: Metrics for evaluating performance of prognostic techniques. 2008 International Conference on Prognostics and Health Management (PHM). Denver, CO, USA: IEEE 2008, pp. 1-17. ISBN: 978-1-4244-1935-7.

SAXENA & GOEBEL 2008
Saxena, A.; Goebel, K.: Turbofan Engine Degradation Simulation Data Set. NASA Ames Prognostics Data Repository. <http://ti.arc.nasa.gov/project/prognostic-data-repository>. - 05.06.2019.

SCHNIEDERJANS 1995
Schniederjans, M. J.: Goal programming. Methodology and applications / by Marc J. Schniederjans. Boston, London: Kluwer Academic 1995. ISBN: 9780792395584.

SCHREIBER 2022
Schreiber, M.: System zur integrierten Produktions- und Instandhaltungsplanung. (Dissertation)Technische Universität München. München (2022). <https://nbn-resolving.org/urn/resolver.pl?urn:nbn:de:bvb:91-diss-20220318-1624848-1-3> - 10.12.2022.

SI ET AL. 2011
Si, X.-S.; Wang, W.; Hu, C.-H.; Zhou, D.-H.: Remaining useful life estimation – A review on the statistical data driven approaches. European Journal of Operational Research 213 (2011) 1, pp. 1-14.

STAUFEN AG 2018
Staufen AG: Deutscher Industrie 4.0 Index 2018. 2018.

STRAUSS ET AL. 2018
Strauss, P.; Schmitz, M.; Wostmann, R.; Deuse, J.: Enabling of Predictive Maintenance in the Brownfield through Low-Cost Sensors, an IIoT-Architecture and Machine Learning. 2018 IEEE International Conference on Big Data (Big Data). Seattle, WA, USA, 10.12.2018 - 13.12.2018: IEEE 2018, pp. 1474-1483. ISBN: 978-1-5386-5035-6.

STRUNZ 2012
Strunz, M.: Instandhaltung. Grundlagen - Strategien - Werkstätten. Berlin, Heidelberg: Springer Vieweg 2012. ISBN: 9783642273896.

THOMAS & WEISS 2021
Thomas, D. S.; Weiss, B.: Maintenance Costs and Advanced Maintenance Techniques: Survey and Analysis. International Journal of Prognostics and Health Management 12 (2021) 1.

VDMA VERLAG 2020
VDMA Verlag: Kennzahlenkompass 2020. Benchmarks und Informationen des Maschinen- und Anlagenbaus. Frankfurt a. M.: Verband Deutscher Maschinen- und Anlagenbau 2020.

WANG ET AL. 2008
Wang, T.; Yu, J.; Siegel, D.; Lee, J.: A similarity-based prognostics approach for Remaining Useful Life estimation of engineered systems. International Conference on Prognostics and Health Management (2008), pp. 1-6.

WANG 2010
Wang, T.: Trajectory Similarity Based Prediction for Remaining Useful Life Estimation. (Dissertation). School of Dynamic Systems, College of Engineering and Applied Science, University of Cincinnati. Cincinnati (2010).

WARNECKE ET AL. 2003
Warnecke, G.; Aurich, J. C.; Hiller, M.: Multiprojektmanagement - Synergien in der Vielfalt. In: Reinhart, G. et al. (Eds.): Marktchance Individualisierung. Berlin: Springer 2003, pp. 129-140. ISBN: 978-3-642-624568.

WERNER 2013
Werner, F.: A Survey of Genetic Algorithms for Shop Scheduling Problems. Heuristics: Theory and Applications (2013), pp. 161-222.

WOLF ET AL. 2019
Wolf, C.; Kirmse, A.; Burkhalter, M.; Hoffmann, M.; Meisen, T.: Model to assess the Economic Profitability of Predictive Maintenance Projects. 2019 International Conference on High Performance Computing & Simulation (HPCS). Dublin, Ireland, 15.07.2019 - 19.07.2019: IEEE 2019, pp. 976-981. ISBN: 978-1-7281-4484-9.

YAMADA ET AL. 1997
Yamada, T.; Nakano; R.: Job-shop scheduling. In: Zalzala, A. M. S. et al. (Eds.): Genetic algorithms in engineering systems. London: Institution of Electrical Engineers 1997, pp. 134-160. ISBN: 0852969023. (IEE control engineering series 55).

YAN ET AL. 2017
Yan, J.; Meng, Y.; Lu, L.; Li, L.: Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance. IEEE Access 5 (2017), pp. 23484-23491.

YE & MA 2015
Ye, J.; Ma, H.: Multiobjective Joint Optimization of Production Scheduling and Maintenance Planning in the Flexible Job-Shop Problem. Mathematical Problems in Engineering 2015 (2015) 7, pp. 1-9.

YIN 2014
Yin, R. K.: Case study research. Design and methods. 5. edition. Los Angeles, London, New Delhi, Singapore, Washington, DC: SAGE 2014. ISBN: 9781483302003.

ZANDIEH ET AL. 2017
Zandieh, M.; Sajadi, S. M.; Behnoud, R.: Integrated production scheduling and maintenance planning in a hybrid flow shop system: a multi-objective approach. International Journal of System Assurance Engineering and Management 8 (2017) S2, pp. 1630-1642.

ZHAI ET AL. 2019
Zhai, S.; Riess, A.; Reinhart, G.: Formulation and Solution for the Predictive Maintenance Integrated Job Shop Scheduling Problem. 2019 IEEE International Conference on Prognostics and Health Management (ICPHM) 2019, pp. 1-8.

ZHAI ET AL. 2020
Zhai, S.; Achatz, S.; Groher, M.; Permadi, J.; Reinhart, G.: An Empirical Expert Study on the Status Quo and Potential of Predictive Maintenance in Industry. International Conference on Sensing, Diagnostics, Prognostics, and Control (2020), pp. 125-130.

ZHAI ET AL. 2021
Zhai, S.; Gehring, B.; Reinhart, G.: Enabling predictive maintenance integrated production scheduling by operation-specific health prognostics with generative deep learning. Journal of Manufacturing Systems 61 (2021) 12, pp. 830-855.

ZHAI ET AL. 2022
Zhai, S.; Kandemir, M. G.; Reinhart, G.: Predictive maintenance integrated production scheduling by applying deep generative prognostics models: approach, formulation and solution. Production Engineering - Research and Development 16 (2022) 1, pp. 65-88.

ZHAI & REINHART 2018
Zhai, S.; Reinhart, G.: Predictive Maintenance als Wegbereiter für die instandhaltungsgerechte Produktionssteuerung. ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb 113 (2018) 5, pp. 298-301.

7 Appendix

7.1 Embedded Publications

Publication 1

ZHAI ET AL. 2020

Zhai, S.; Achatz, S.; Groher, M.; Permadi, J.; Reinhart, G.: An Empirical Expert Study on the Status Quo and Potential of Predictive Maintenance in Industry. International Conference on Sensing, Diagnostics, Prognostics, and Control 2020, pp. 125-130.

Publication 2

ZHAI ET AL. 2019

Zhai, S.; Riess, A.; Reinhart, G.: Formulation and Solution for the Predictive Maintenance Integrated Job Shop Scheduling Problem. IEEE International Conference on Prognostics and Health Management (ICPHM) 2019, pp. 1-8.

Publication 3

ZHAI ET AL. 2021

Zhai, S.; Gehring, B.; Reinhart, G.: Enabling predictive maintenance integrated production scheduling by operation-specific health prognostics with generative deep learning. Journal of Manufacturing Systems 61 (2021) 12, pp. 830-855.

Publication 4

ZHAI ET AL. 2022

Zhai, S.; Kandemir, M. G.; Reinhart, G.: Predictive maintenance integrated production scheduling by applying deep generative prognostics models: approach, formulation and solution. Production Engineering - Research and Development 16 (2022) 1, pp. 65-88.

7.2 Formulas and Key Performance Indicators

The following section presents the formulas and KPIs used to calculate the base costs and amortization period of the exemplary use case for the cost-benefit evaluation (see section 4.2.2).

Notation	Description	Value	Reference
$c_{planned}$	Cost for planned downtime	10 €/min	WOLF ET AL. (2019, p. 980)
$c_{unplanned}$	Cost for unplanned downtime	50 €/min	WOLF ET AL. (2019, p. 980)
$r_{planned}$	Ratio of planned downtime to total downtime	9.5 %	VDMA VERLAG (2020, p. 169)
$r_{unplanned}$	Ratio of unplanned downtime to total downtime	11.9 %	VDMA VERLAG (2020, p. 169)
$r_{c,\ non-material}$	Ratio of non-material related costs to all costs	52.5 %	VDMA VERLAG (2020, p. 69)
$r_{c,Q}$	Ratio of defective quality-induced costs to the company's revenue	1.2 %	VDMA VERLAG (2020, p. 147)
r_{output}	Ratio of total output to total expenditure	104 %	VDMA VERLAG (2020, p. 65)
$r_{c,\ T\&E}$	Ratio of costs for tools and additional production equipment (e.g., electricity) to all costs	3.7 %	VDMA VERLAG (2020, p. 67)
$r_{T\&E,T}$	Ratio of tools costs to all costs for tools and additional production equipment	10 %	Estimation
r_{DT}	Downtime ratio	24.3 %	VDMA VERLAG (2020, p. 169)
r_{depr}	Ratio of depreciation costs to all costs	2.9 %	VDMA VERLAG (2020, p. 79)
τ_m	Average age/useful life of machine derived from depreciation time	10 years	VDMA VERLAG (2020, p. 39), BUNDESMINISTERIUM DER FINANZEN (2001)
$r_{maintenance}$	Ratio of maintenance costs to replacement costs	5.7 %	VDMA VERLAG (2020, p. 171)

$r_{spare\ parts}$	Ratio of spare parts costs to all maintenance-related costs	20 %	Estimation
r_{intern}	Ratio of internal maintenance costs to total maintenance costs	50 %	Estimation
r_{extern}	Ratio of external maintenance costs to total maintenance costs	50 %	Estimation

Item	Formula
Total costs of planned downtime per year	$C_{planned,DT} = r_{planned} \cdot r_{DT} \cdot c_{planned} \cdot 255[\frac{d}{y}] \cdot 16[\frac{h}{d}] \cdot 60[\frac{min}{h}]$
Total costs of unplanned downtime per year	$C_{unplanned,DT} = r_{unpplanned} \cdot r_{DT} \cdot c_{unplanned} \cdot 255[\frac{d}{y}] \cdot 16[\frac{h}{d}] \cdot 60[\frac{min}{h}]$
Yearly non-material related costs of N machines due to unplanned downtime	$C_{yearly} = \frac{N}{r_{c,non-material}} \cdot c_{unplanned} \cdot 255[\frac{d}{y}] \cdot 16[\frac{h}{d}] \cdot 60[\frac{min}{h}]$
Costs for rejects due to quality	$C_Q = r_{output} \cdot C_{yearly} \cdot r_{c,Q}$
Costs for tool replacement	$C_T = C_{yearly} \cdot r_{T\&E,T} \cdot r_{c,T\&E}$
Replacement value of N machines	$V_{replacement} = r_{depreciation} \cdot \tau_m \cdot C_{yearly}$
Overall costs for maintenance, including spare parts	$C_M = r_{maintenance} \cdot V_{replacement}$
Costs for spare parts	$C_{M,SP} = r_{spare\ parts} \cdot C_M$
Costs for internal maintenance	$C_{M,int} = (1 - r_{spare\ parts}) \cdot C_M \cdot r_{intern}$
Costs for external maintenance	$C_{M,int} = (1 - r_{spare\ parts}) \cdot C_M \cdot r_{extern}$
Amortization period	$t_a = \frac{Costs\ of\ Development\ and\ Implementation}{Yearly\ Savings - Operation\ Costs}$

7.3 Questionnaire of Publication 2: An Empirical Expert Study on the Status Quo and Potential of Predictive Maintenance in Industry

1. **Which department of the company do you belong to?**

☐ Research/Development
☐ Production
☐ Management
☐ Maintenance
☐ IT
☐ Logistic
☐ Marketing
☐ Human resources
☐ Quality management
☐ Administration
☐ Other

2. **In which industry segment is your company active?**

☐ Automotive
☐ Chemical and process industry
☐ Consulting
☐ Electronic Industry
☐ Energy
☐ Wood or Metal Construction
☐ IT
☐ Food Industry
☐ Aerospace
☐ Mechanical Engineering
☐ Medicine Technology
☐ Pharmaceutical Industry
☐ Other

3. **How many employees are working in your company?**

☐ < 50

☐ 50 to 250

☐ > 250

4. **What is the annual turnover of your company?**

☐ <= 50 mil. Euro

☐ > 50 mil. Euro

☐ No information

5. **Which of the following would you associate with the term "predictive maintenance"?**

Please choose **all** that apply:

☐ Acquisition of machine operating data

☐ Use of mathematical models to determine the machine condition

☐ Maintenance actions when the predetermined thresholds were exceeded

☐ Prediction of the instant (date) of failure of a machine

☐ Optimization of machine maintenance dates

☐ Continuous monitoring of machine operation

☐ I am not familiar with the term

☐ Other:

Predictive maintenance is a core competence of Industry 4.0 for predicting machine failures. Based on the evaluation of various machine and process data, impending plant failures can be forecast and thus foresightful (predictive) maintenance strategies can be developed. In contrast to "condition monitoring", data is used to predict downtimes and does not simply react to limit values being exceeded.[1]

[[1] Zhai, S.: Predictive Maintenance als Wegbereiter für die instandhaltungsgerechte Produktionssteuerung. ZWF 113 (2018) 5, S. 298-301]

The following questions should be answered considering this definition for the term "predictive maintenance"!

The questions in this section are aimed at <u>assessing predictive maintenance in industry in general.</u> The <u>implementation</u> of predictive maintenance <u>in your company</u> can <u>still be neglected.</u>

6. **How do you generally assess the potential of predictive maintenance?**

	Very low	**Low**	**Adequate**	**High**	**Very high**
The potential seems ...					

7. **How do you assess the potential of predictive maintenance with regard to the following criteria?**

Please choose the appropriate response for each item:

	Very low	Low	Ade-quate	High	Very high
Cost savings					
Increase competitiveness					
Increase the degree of automation					
Increase in machine utilization					
Development of new business models					
Increase operational efficiency					
Avoidance of unplanned down-times					
Increase the machine availability					

Multiple entries are possible.

8. **In addition to these criteria, do you see other areas for which predictive maintenance has great potential?**

☐ Yes, see the comment on the right:

☐ No

Comment on your choice here:

9. **What risks and challenges do you associate with predictive maintenance?**

Please choose **all** that apply:

☐ Hiring additional specialists

☐ Retrofitting existing machines

☐ High costs

☐ Lack of know-how

☐ Threats to IT security/data protection

☐ Lengthy adjustment of business processes

☐ Other:

10. **How would you rate the efficiency of current maintenance processes in your company on a scale of 1 to 10?** (1 = inefficient, 10 = very efficient)
11. **Does your company already have experience with predictive maintenance?**

☐ Yes

☐ No

If you have answered yes, continue this questionnaire for questions 12-16. If you answered no, continue with questions 16-20.

If question 10 was answered with “yes”, continue here:

12. **What is your company's experience with predictive maintenance?**

Please choose the appropriate response for each item:

	Very bad	Bad	Neutral	Good	Very good
The experiences are ...					

13. **Which of the following describes best the current status of your company's predictive maintenance initiatives?**

Please choose **only one** of the following:

☐ Predictive maintenance applications are in the planning and evaluation phase

☐ Predictive maintenance applications are in the test phase

☐ First projects with business effects have already been started

☐ Predictive maintenance applications are already in use

☐ Other

14. **In which areas is predictive maintenance used in your company?**

Please choose **all** that apply:

☐ In the manufacturing process of your products

☐ In the end product itself

☐ Other:

If predictive maintenance has not yet been used in your company, please answer this question in the sense: "For which areas in your company are there (concrete) considerations to introduce predictive maintenance?"

15. **What data do you collect as part of the current maintenance processes in your company?**

Please choose **all** that apply:

☐ Current operating parameters of the systems (target values and their compliance, e.g., speed)

☐ Other sensor values that describe the state of the system in operation (e.g., vibrations, temperature development, ...)

☐ Data describing the current value/overall condition of the system (e.g., wear of tools, ...)

☐ Data on the machine's time utilization

☐ Ambient data (e.g., temperature or humidity in the vicinity of the system)

☐ Maintenance history data (e.g., when was the maintenance? How often? What was checked/replaced? ...)

☐ Other:

If question 10 was answered with „no”, continue here:

16. **What types of external support would be of great use to your company as you develop predictive maintenance strategies?**

Please choose **all** that apply:

☐ General provision of information (e.g., information events)

☐ Support with the introduction of predictive maintenance applications

☐ Support in the redesign of existing maintenance processes

☐ Support in the collection and management of machine data

☐ Support in the analysis of machine data

☐ Other:

17. **Why has predictive maintenance not been used in your company so far?**

Please choose **all** that apply:

☐ Implementation costs are too high

☐ Lack of know-how

☐ No application options

☐ Profitability too low

☐ Previous maintenance processes were satisfactory

☐ Other:

18. **Can you imagine using predictive maintenance in your company?**

☐ Yes

☐ No

19. **If your company decides to implement predictive maintenance, what types of external support would help develop predictive maintenance strategies?**

Please choose **all** that apply:

- ☐ General provision of information (e.g., information events)
- ☐ Support with the introduction of predictive maintenance applications
- ☐ Support in the redesign of existing maintenance processes
- ☐ Support in the collection and management of machine data
- ☐ Support in the analysis of machine data
- ☐ Other:

20. **What data do you collect as part of the current maintenance processes in your company?**

Please choose **all** that apply:

- ☐ Current operating parameters of the systems (target values and their compliance, e.g., speed)
- ☐ Other sensor values that describe the state of the system in operation (e.g., vibrations, temperature development, ...)
- ☐ Data describing the current value/overall condition of the system (e.g., wear of tools, ...)
- ☐ Data on the machine's time utilization
- ☐ Ambient data (e.g., temperature or humidity in the vicinity of the system)
- ☐ Maintenance history data (e.g., when was the maintenance? How often? What was checked/replaced? ...)
- ☐ Other:

7.4 Expert Interview

Excerpts of the expert interview conducted with six experts are presented in the following. Part A of the interview took around 50 min and Part B around took 30 min. For the sake of brevity, only questions whose answers were summarized in chapter 4 are listed. Also, it should be noted that personal and confidential information is omitted. For multiple-choice questions, the respective number of responses per choice is listed.

7.4.1 Expert Interview Part A

---

1. **Personal Background**

[…]

---

2. **Conceptual Validity**

The concept of the PdM-IPS approach is presented using a prepared Powerpoint-presentation.

1. I understood the presentation's content well.

	Strongly Disagree	Disagree	Slightly Disagree	Slightly Agree	Agree	Strongly Agree
Number of responses					3	3

2. I can reflect on key components of PdM-IPS.

	Strongly Disagree	Disagree	Slightly Disagree	Slightly Agree	Agree	Strongly Agree
Number of responses				1	4	1

The expert has the chance to ask questions concerning the concept and reflect on the concept's validity.

---

3. Operational Validity

[…]

1. It is important to incorporate machine degradation in production scheduling.

	Strongly Disagree	Disagree	Slightly Disagree	Slightly Agree	Agree	Strongly Agree
Number of responses					5	1

2. I am confident that machine degradation will be incorporated into future production scheduling.

	Strongly Disagree	Disagree	Slightly Disagree	Slightly Agree	Agree	Strongly Agree
Number of responses	1		1	1	3	

[…]

3. Please justify your answers to questions 4 and 5.

---

4. Opportunities and Risks

1. What are the chances of PdM-IPS?

2. What are the risks of PdM-IPS?

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5. Economical Aspects

The expert shall consider the cost-saving potential of the following aspects given PdM-IPS implementation in their company.

1. Synchronized time of maintenance when service is provided by a non-company provider.

Response Class	1	2	3	4	5	6
	X < 2,5 %	2,5 % ≤ X < 5 %	5 % ≤ X < 10 %	10 % ≤ X < 15 %	15 % ≤ X < 20 %	20 % < X
Number of responses	3		2		1	

Median response class: 2,5 % ≤ X < 5 %

2. Extended durability of tools due to optimized production scheduling.

Response Class	1	2	3	4	5	6
	X < 2,5 %	2,5 % ≤ X < 5 %	5 % ≤ X < 10 %	10 % ≤ X < 15 %	15 % ≤ X < 20 %	20 % < X
Number of responses		3	2	1		

Median response class: 2,5 % ≤ X < 5 %

3. Deliberate induce degradation (i.e., by rescheduling products that induce higher degradation) of certain machines when a production break, including planned maintenance, is coming up. A higher maintenance efficiency can thus be ensured due to the full utilization of the components' RUL.

Response Class	1	2	3	4	5	6
	X < 2,5 %	2,5 % ≤ X < 5 %	5 % ≤ X < 10 %	10 % ≤ X < 15 %	15 % ≤ X < 20 %	20 % < X
Number of responses	1	1	2	2		

Median response class: 5 % ≤ X < 10 %

4. Rescheduling of products with higher manufacturing tolerances according to machine health to reduce quality rejections. Products with strict manufacturing tolerances are produced on machines with high HI, while products with less strict tolerances are produced on slightly degraded machines.

Response Class	1	2	3	4	5	6
	X < 2,5 %	2,5 % ≤ X < 5 %	5 % ≤ X < 10 %	10 % ≤ X < 15 %	15 % ≤ X < 20 %	20 % < X
Number of responses	2	1	1	2		

Median response class: 2,5 % ≤ X < 5 %

7.4.2 Expert Interview Part B

1. Logical validity

Assessment of the capability of the formal model to describe correctly and accurately the problem solution. Do the simplifications and assumptions during model development process hold?

1. Machine failures are classified into two different groups. There exist non-predictable failure events and predictable failure events.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses				1	5

2. During maintenance, only degraded or broken components are replaced. A high HI is assumed for not replaced components and is still functional because a strong HI decrease is observed only close to the system's end of life. Therefore, the influence of imperfect maintenance is rather small.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses			2	3	1

3. Measuring outliers with increasing frequency is an indicator of degradation.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses			2	4	

4. Inter-component correlation of health states exists. This relation can also be unidirectional.

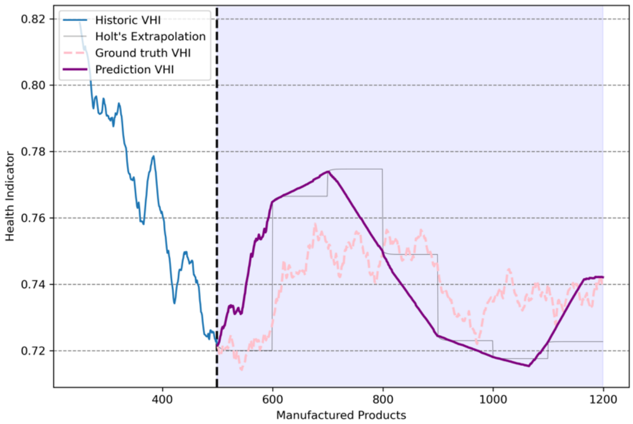
	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses				1	5

2. Experimental validity

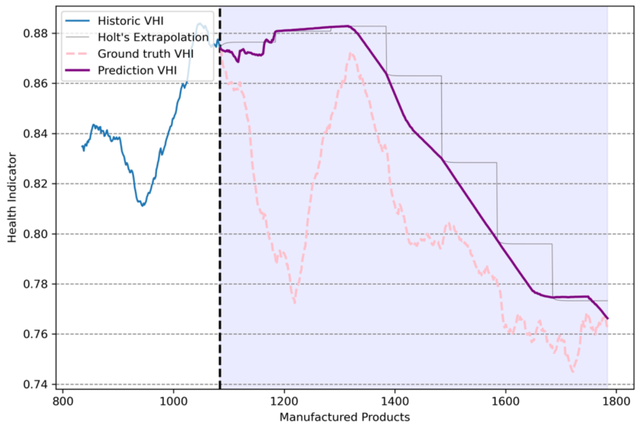
To demonstrate the capabilities of the machine health prediction module, two production intervals are identified. These production intervals feature the same variant and amount of manufactured products in order to take the product-specific wear into account. A prediction horizon of 700 products is chosen.

Promising prediction results are shown for VHI 2 for both production intervals:

Production interval 1

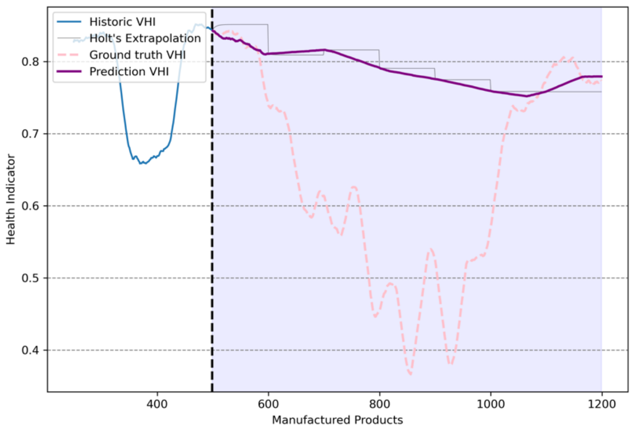


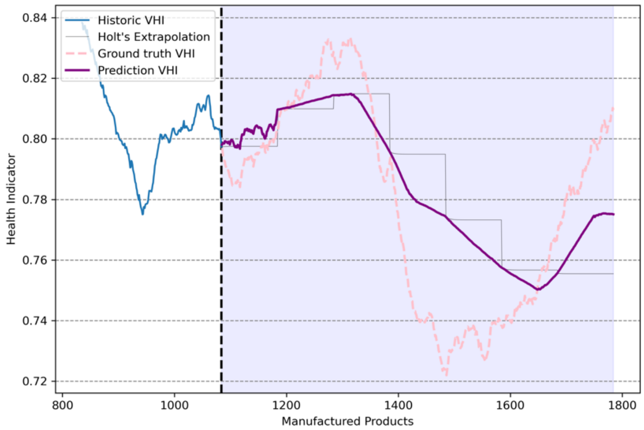
Production interval 2



The malfunction of component 4 during production period 1 is not predictable due to its stochastic character. Thus, a deviation between prediction and ground truth is given.

In addition, two poor predictions of an arbitrary production interval are shown:

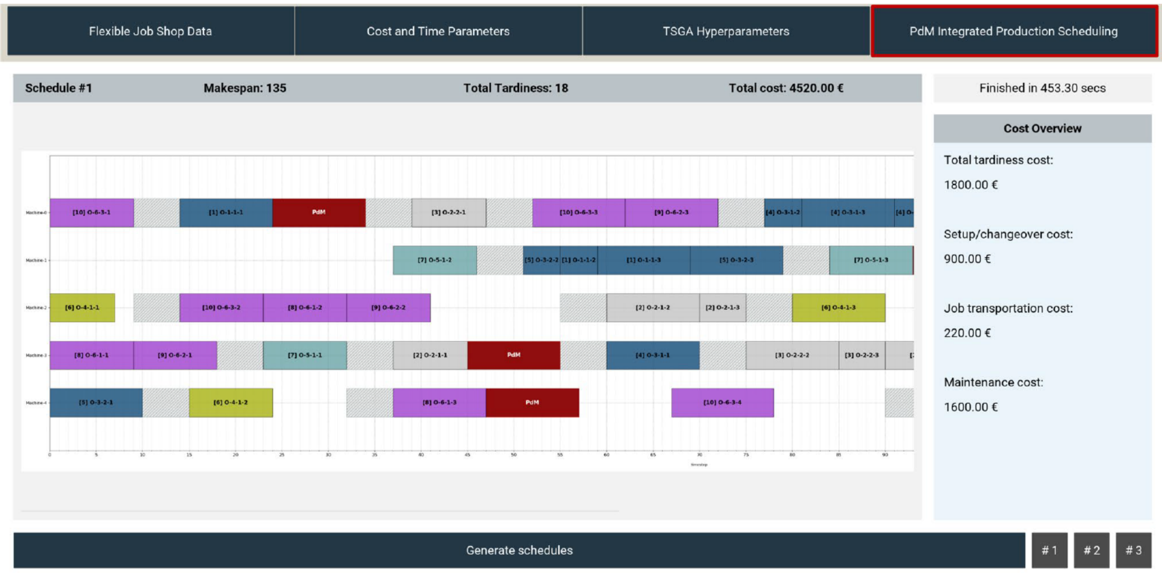




1. The overall performance of the machine health prediction module is promising.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses			1	4	1

The following figure shows an exemplary production schedule resulting from PdM-IPS. In contrast to normal production schedules, time slots for maintenance, shown in red, are explicitly displayed.



2. The displayed exemplary production schedule can in general support production and maintenance planning.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses				4	2

3. The displayed exemplary production schedule can be employed in an adapted version for production and maintenance planning in your company.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses	1		1	2	2

4. The displayed exemplary production schedule can be employed in an adapted version for production and maintenance planning in a different manufacturing company that uses a matrix production system.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses				3	3

3. Data validity

Assessment of the sufficiency, accuracy, appropriateness, and availability of the data. Do the employed data fulfill the mentioned properties to a certain degree to solve the problem?

1. An observation period of 4 months is suitable to train a sophisticated machine-learning model.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses		2	2	1	1

2. Only data from "healthy" machine conditions are required for model training and no further knowledge of different failure causes is needed.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses		2	2	1	1

3. Operator logs offer the opportunity to assess the machine's health implicitly.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses			3	2	1

4. The failure classification requires no increased quality of the operator logs and is based on the logs' raw version.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses			5		1

5. The sampling rate of 1 Hz for condition monitoring data is sufficient for promising model deployment.

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Number of responses		1	1		4

7.5 List of Supervised Student Research Projects

In the context of the research performed by the author, various student research projects were intensively supervised concerning the methodology, problem statements, modeling, approach and the interpretation and documentation of the results. The supervision took place at the Institute for Machine Tools and Industrial Management (*iwb*) of the Technical University of Munich (TUM). The findings and results of the student research projects listed below have contributed to this dissertation. The author would like to express his sincere gratitude for the remarkable commitment of all supervised students and their relevant and important contributions.

BUTZHAMMER, M. 2019

Development of a Methodology for Data-Driven Risk Analysis of Systems for Maintenance Planning Support. Master's Thesis (TUM).

DUNKER, P. *2019*

Data-driven modeling of a Health Indicator for product-specific Predictive Maintenance. Master's Thesis (TUM).

GEHRING, B. 2020

A Generative Deep Learning Approach for Unsupervised Operation-specific Machine Health Prognostics. Master's Thesis (TUM).

KANDEMIR, M. 2021

Design and Implementation of a Genetic Algorithm for Predictive Maintenance Integrated Production Scheduling. Master's Thesis (TUM).

RIESS, A. 2018

Development of a Predictive Maintenance Information Integration Model for Scheduling Optimization. (Master's term paper, TUM).

RIESS, A. 2019

A Deep Learning Approach to Operation Specific Predictive Maintenance of Machine Tools. Master's Thesis (TUM).

SCHATZ, M. 2021

Unsupervised Learning and Feature Engineering for Industrial Predictive Maintenance. Master's Thesis (TUM).

SCZESNY, P. 2020

Predictive Maintenance in Existing Manufacturing Companies: Potential Analysis of the Integration and Application. Bachelor's Thesis (TUM).

WU, Y. 2021

An Advanced Deep Generative Model for Enhancing Health Prognostics and Data Augmentation in Predictive Maintenance. Master's Thesis (TUM).

The students GEHRING, B.; KANDEMIR, M. and RIESS, A. are also co-authors of the embedded publications of this dissertation listed in Appendix 7.1.

8 List of Figures

9 List of Tables