Diplomarbeit

Integrative condition-based production scheduling and maintenance planning:

Development of a procedural model and a physical demonstrator

ausgeführt zum Zwecke der Erlangung des akademischen Grades eines

Diplom-Ingenieurs

unter der Leitung von

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Wien, im Oktober 2021

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TECHNISCHE UNIVERSITÄT WIEN

Ich habe zur Kenntnis genommen, dass ich zur Drucklegung meiner Arbeit unter der Bezeichnung

Diplomarbeit

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Wien, im Oktober 2021

Gabriel Meier

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Abstract

The progressive development of condition monitoring systems, as well as the necessary sensor technologies and IoT-platforms used for information processing, enable data-driven approaches in production planning, maintenance, and quality management. Considering the keywords “predictive maintenance” and “prescriptive maintenance” and the research area prognostics and health management (PHM), maintenance is already discussed in detail regarding the utilization of condition data. Nevertheless, such approaches remain limited in production planning and control. The research areas of condition-based production scheduling and its integration with condition-based maintenance are still in an early stage.

This thesis focuses on integrating condition data in production planning and a holistic view of production planning and maintenance. The goal is to show improvements for existing approaches by bringing together cross-disciplinary knowledge and making it usable. The approaches, models, and methods analyzed are incorporated into the procedural model presented, which intends to facilitate the implementation of condition-based production planning in practice. The presented model is then applied to a use case in the form of a physical demonstrator. The results obtained allow conclusions to be drawn about optimization potential for the integrative consideration of production planning and maintenance, as well as data-driven methods for condition determination.

For further work, the approach presented provides an orientation to the cross-disciplinary state-of-the-art. It can serve as a basis for developing new models and methods that focus on the holistic consideration of new production systems. Implementing a condition data-driven production planning and its holistic integration with maintenance planning holds greater cost reduction potentials than the separate optimization of these disciplines. Furthermore, the approach could support implementing approaches already discussed in the literature into practical applications.

Kurzfassung

Die fortschreitende Entwicklung von Zustandsüberwachungssystemen, sowie dafür notwendigen Sensortechnologien und zur Informationsverwertung verwendeten IoT-Plattformen ermöglichen datengeriebene Ansätze in der Produktionsplanung, Instandhaltung und im Qualitätsmanagement. Während der Bereich der Instandhaltung mit den Schlagwörtern „predictive maintenance“ und „prescriptive maintenance“, sowie dem Forschungsbereich prognostics and health management (PHM) bereits ausführlich in Bezug auf Verwertung von Zustandsdaten diskutiert wird, bleiben solche Ansätze für die Produktionsplanung- und Steuerung überschaubar. Die Forschungsbereiche der zustandsbasierten Reihenfolgeplanung, sowie deren Integration mit zustandsbasierter Instandhaltung stehen noch am Anfang.

Diese Arbeit fokussiert sich auf die Integration von Zustandsdaten in der Produktionsplanung und eine ganzheitliche Betrachtung von Produktionsplanung und Instandhaltung. Ziel ist es, Verbesserungen für bestehende Ansätze aufzuzeigen, indem Fachgebietsübergreifendes Wissen zusammengeführt und nutzbar gemacht wird. Die analysierten Ansätze, Modelle und Methoden fließen in das vorgestellte Vorgehensmodell ein, das die Implementierung einer zustandsbasierten Produktionsplanung in der Praxis erleichtern soll. Das vorgestellte Modell wird dann auf einen Anwendungsfall in Form eines physischen Demonstrators angewendet. Die erhaltenen Ergebnisse lassen Rückschlüsse auf Optimierungspotentiale für die integrative Betrachtung von Produktionsplanung und Instandhaltung, sowie datengetriebene Methoden zur Zustandsermittlung zu.

Für weiterführende Arbeiten bildet der vorgestellte Ansatz eine Orientierung am Stand der Technik und kann als Grundlage für die Entwicklung neuer Modelle und Methoden dienen, die die ganzheitliche Betrachtung neuer Produktionssysteme fokussieren. Die Implementierung einer zustandsdatengetriebenen Produktionsplanung und deren ganzheitliche Integration mit der Instandhaltungsplanung birgt größere Kostensenkungspotentiale als die getrennte Optimierung dieser Fachgebiete. Darüber hinaus könnte der Ansatz verwendet werden, um in der Literatur bereits diskutierte Ansätze in praktische Anwendungen zu bringen.

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1 Introduction

1.1 Condition monitoring and production planning

Digitization is anchoring itself ever more deeply in the industry. The massive increase of sensorization and thing-to-thing information transfer is often referred to as industry 4.0, which started as “a German initiative for improving manufacturing technologies”[1]. It is characterized by merging the operational and information technology layers, which link the physical world with the virtual world and create so-called cyber-physical systems (CPS).

Real-time-based information technologies connecting devices over the internet form the internet of things (IoT). “The increasing advances of information technology and the internet of things have made real-time data easily accessible.”[2] It enables a new level of automation, control, and knowledge distribution. The physical devices participating in the network are often described as smart or intelligent things/devices. By 2025 30 billion IoT devices are expected to be connected to the internet[3] and actively participate in communication processes. Those numbers are mainly driven by the booming consumer market for connected devices, especially in home automation. However, the increasing trend is the same in the industry. “The share of electronics and software in terms of value has risen steadily in recent years and is now around 40 percent in vehicle construction, for example.”[4]

The progress of IoT has been fueled in recent years by technological advances and favorable price trends in sensors, internet protocols, microcomputers (embedded systems), wireless systems, and database systems. Communication protocols, distributed systems, and cloud computing are examples of enablers for the internet of things and are described by the collective term IoT-technologies.

In the industry, the field of maintenance is impacted by the rise of those technologies. As sensors and monitoring systems developed, new data-driven maintenance strategies emerged as an alternative to conventional rule-based approaches.[5] Inexpensive sensors and increasing computing power drive the implementation of condition monitoring systems in various applications. Machines are equipped with sensors to provide data on their condition. Nevertheless, the presence of information alone does not provide added value unless it is utilized to, for example, improve maintenance activities. Also, “in practice, the state of degradation is neither available nor measurable in the majority of cases. It must be deducted from the physical

[1] Xhafa et al. 2017, p. 5.
[2] cf. Malekpour et al. 2021, p. 2.
[3] see https://www.statista.com/statistics/1101442/iot-number-of-connected-devices-worldwide/.
[4] Eigner et al. 2017, p. 5.
[5] cf. Matyas 2019, p. 300.

knowledge, expert knowledge, and available measurements."[6] This fact displays one of the biggest challenges regarding data quality in fault prognosis. Nevertheless, data-driven approaches have the advantage of not being dependent on human perception and can make use of the advancing computing and processing tools. The most dominant use case for condition monitoring is to use the acquired data to improve the planning of necessary maintenance activities. Using data-driven predictions to enable acting before machine failures occur is often described as predictive maintenance. As maintenance activities represent a significant cost driver for production facilities, typically causing between 15-40% of total expenses, it seems evident that improvement potential may have a considerable impact on the industry.[7] Also, "over 80% of surveyed manufacturing companies are aware of the enormous upside potential of predictive maintenance and are currently elaborating their opportunities intensively".[8] In the field of maintenance, the integration of machine condition data therefore has been widely researched within the last decade and has already found its way to numerous applications in the industry.

In production planning and control (PPC), however, this information remains largely unused.[9] In production, the condition of machines and tools can be decisive for whether a production order can be executed or not. If a machine's condition deteriorates, it may still be able to execute specific processing steps before maintaining the machine. The solutions are either to maintain the machine as soon as possible or to adjust the production sequence so the machine only operates on process steps that can be executed with its deteriorated condition. This insight opened the door to the research field of condition-based scheduling and sequencing. Another approach recently proposed in the literature is called condition-based production (CBP) and describes adapting production rate to control the deterioration of a machine. Nevertheless, CBP is largely dismissing production scheduling and is mainly addressed separately to condition-based maintenance.[10] Both approaches require the machine's condition data that can be utilized for maintenance planning as well.

In a perfect factory, production and maintenance would require an interconnected planning process for operating ideally. Therefore, joint optimization of production and maintenance extends those mostly isolated considered research areas and deals with mostly very complex optimization problems. This research area is not yet widespread in literature especially when considering the utilization of a machine's condition data.

[6] Djeziri et al. 2020, p. 2.
[7] cf. uit het Broek et al. 2021, p. 1.
[8] Zhai et al. 2019 - 2019, p. 1.
[9] cf. Karner 2019, p. 2.
[10] cf. uit het Broek et al. 2021, p. 1.

1.2 Problem statements, objectives, and research questions

In this thesis, the impact of utilizing condition data in production planning and control is discussed. In particular, the thesis focuses on the research area of condition-based scheduling and the integration of condition monitoring, maintenance, and production planning. While the individual parts of mentioned topics are partly well-represented research areas already, their integration is not yet widespread in the literature and lacks practical examples for conveying knowledge on the topic.

Problem statements:

P1: Condition monitoring data of machines and equipment is already commonly used for maintenance purposes but largely neglected in production planning.

P2: Systems for determining a health index (HI) for a machine's condition are therefore mainly designed for maintenance purposes.

P3: The research area on condition-based scheduling lacks practical examples for conveying knowledge on the topic.

P4: The research areas of production and maintenance scheduling are mainly discussed isolated. Therefore, joint optimization of both is underrepresented in the literature.

P5: The economic benefit of utilizing condition data for PPC, maintenance, or both depends on the observed machine(s). Also, the possibilities for how this data can be utilized depends on the case at hand, hindering the generalization of models and methods on the topic.

Objectives:

O1: Determine the state-of-the-art of condition-based production scheduling, joint optimization of PPC and maintenance, and focus on machine and equipment condition in both cases.

O2: Create a practical example for demonstrating condition-based scheduling and conveying knowledge on the topic.

O3: Develop and evaluate an artifact[11] for integrative condition-based PPC and maintenance planning.

Non-objectives:

- Developing a new production and maintenance scheduling optimization algorithm or method.
- Developing a new algorithm for machine or equipment fault prognosis.

Research questions:

Q1: How can machine and equipment conditions be determined and utilized for condition-based production scheduling?

Q2: How can knowledge on condition-based scheduling be effectively conveyed?

Q3: How can machine and equipment condition be utilized for integrated PPC and maintenance?

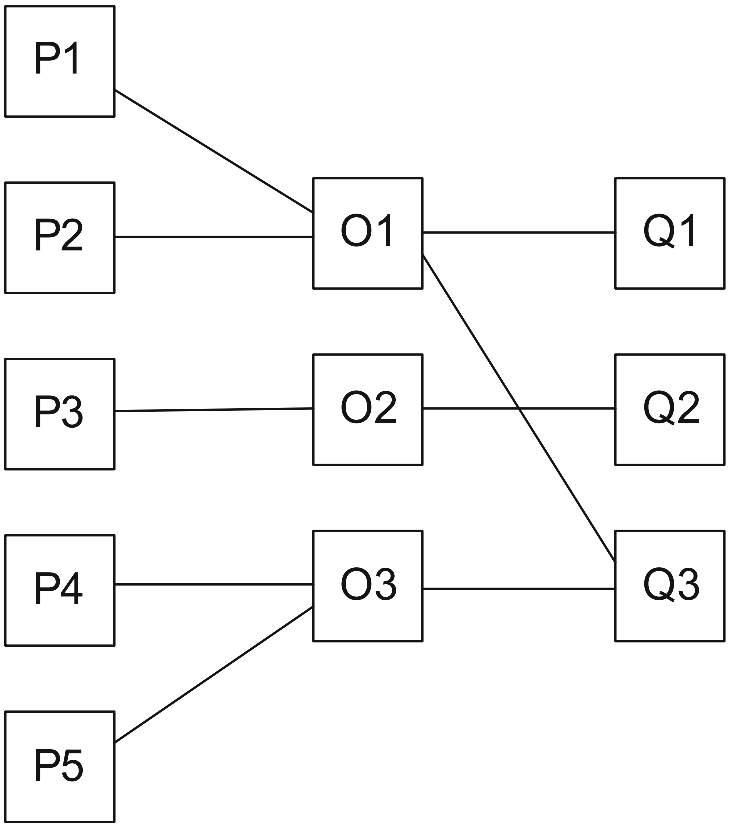


Figure 1: Relations between problem statements, objectives, and research questions

[11]The definition of an artifact follows Hevner et al. 2004 (p. 2.) and comprehends "constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems)".

1.3 Solution approach

The thesis' research methodology is based on the design science in information systems framework by Alan Hevner[12], as described in chapter 4.

To answer the first research question, the underlying theoretical foundations are first explained in Chapter 2. The theoretical foundations for integrating condition data into production planning can mainly be found in the broad areas of industrial maintenance and production planning and control. A discussion on the state-of-the-art is covered within the systematic literature review in chapter 3.

Research question two is answered by providing a demonstrator on condition-based scheduling with a dedicated use case for demonstration purposes. The product development part of the physical demonstrator is supported by the iterative procedure model, according to VDI 2221 (Part 1[13] and Part 2[14]).

To answer research question three, the literature review findings in chapter 3 are incorporated into the design of a procedural model in chapter 6. As provided in the design science method, an artifact in the form of a model is presented, describing the possibilities for integrating condition monitoring, maintenance and PPC in a case study. A use case to support the design phase and the evaluation of the procedural model is defined in chapter 5 by developing a physical demonstrator.

[12] Hevner et al. 2004.
[13] VDI Society Product and Process Design 2019a.
[14] VDI Society Product and Process Design 2019b.

1.4 Thesis structure and design

1) Introduction
• Condition monitoring and production planning • Problem statement, objective, and research question • Solution approach • Thesis structure and design
2) Theoretical foundations
• Industrial maintenance • Production planning and control • Prognostics and health management
3) Practical application of condition data in the context of production planning: State of the art
• Planning a systematic literature review • Conducting the review • Summary of the literature review
4) Applied methodologies
• Research methodology: Design science • Product development • Systematic literature review
5) Physical demonstrator for condition-based scheduling
• Definition of the use-case • Modification of demonstrator • Demonstrator evaluation
6) Design and implementation of a procedural model
• Overview of the procedural model • Model evaluation
7) Summary and consolidation of key findings
• Results of applied methods • Results with respect to research questions
8) Outlook and limitations

Table 1: Thesis structure

Figure 2 shows the research design. The tasks displayed in Figure 2 are mapped to the chapters in table 1 by color:

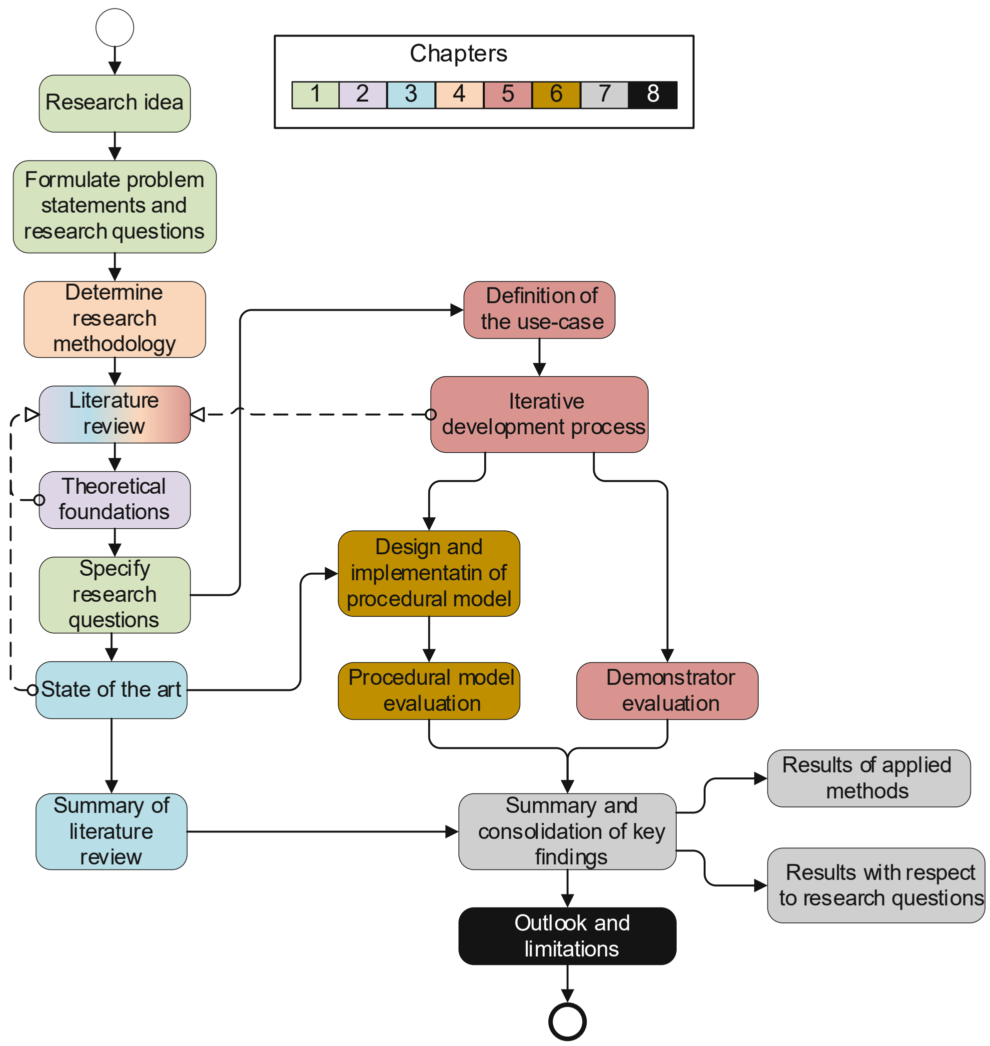


Figure 2: Thesis design

The iterative development process is executed according to guidelines for the product design of technical products and systems. It is described in more detail in chapter 4 and is based on the following foundational schematic:

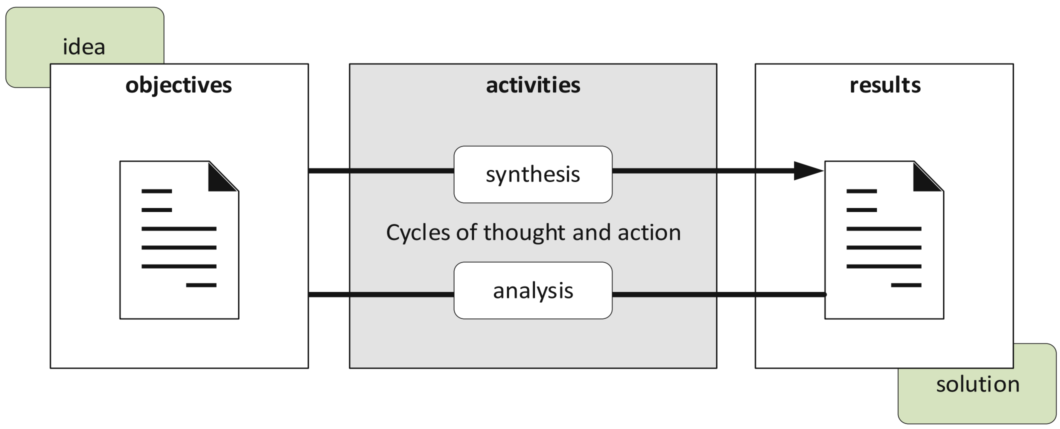


Figure 3: Iterative development process[15]

[15] cf. VDI Society Product and Process Design 2019a, p. 17.

2 Theoretical foundations

2.1 Industrial maintenance

2.1.1 Foundations of maintenance

Objectives

"The purpose of maintenance is to preserve the function and performance of a machine or plant."[16] The importance of maintenance increases because of the growing complexity of production and transport, including automation and interlinking. Today, in order to maintain the highest possible availability of production equipment, it is no longer sufficient to repair after failure occurrences (reactive maintenance). Planned and preventive measures are necessary to avoid expensive failures and risks to safety and the environment.[17]

The main goals of maintenance are to minimize overall operational costs and to maximize reliability and safety.[18] A notable research area therefore is midterm maintenance scheduling (MMS), which aims to maximize the return of investment of equipment for its entire life cycle by optimizing maintenance activities.[19] The two goals of optimizing overall costs and reliability are interlinked, as a safety risk is usually also a cost risk. Machines and equipment that either have very high production numbers (in most manufacturing companies today) or whose failure can have drastic consequences (e.g., aircraft, vehicle, medical technology) require well-planned maintenance.

In any case, it is necessary to find an optimum between the costs of preventive maintenance and the costs of machine breakdowns with the help of a suitable strategy.[20]

The following statements quotes are intended to illustrate the importance of maintenance costs:

> "In typical manufacturing companies, maintenance costs are between 15 and 40 percent of total production costs."[21]

[16] Matyas 2016, p. 27.
[17] cf. Matyas 2016, p. 27.
[18] cf. Ibid., p. 32.
[19] cf. Xu et al. 2020, p. 1.
[20] cf. Matyas 2016, p. 28.
[21] cf. uit het Broek et al. 2021, p. 1.

"Around 140 billion euros are spent annually by German companies on the maintenance of machinery and equipment, experts estimate."[22]

Maintenance costs

A lack of maintenance means high unplanned maintenance costs, whereas excessive maintenance means excessively high planned maintenance costs. The model, according to Hahn and Lassmann (1993), illustrates this relationship:

One can split the total maintenance costs (K_I) into planned maintenance costs (K_{VI}) and unplanned maintenance costs (K_S). These include planned costs for machine downtime, inspection, investment and repair, and unplanned costs for machine downtime, machine failure (and their consequences), and repair. Also, not directly quantifiable cost factors (adherence to schedules, maintenance of product quality, risk reduction,...) should be considered.[23] It is evident that with more frequent maintenance, planned costs increase, and unplanned costs decrease. If we denote the intensity of maintenance activities by (n), then (K_I)=(K_{VI})+(K_S) for the total maintenance costs (K_I) results in a higher-order curve with a global minimum.

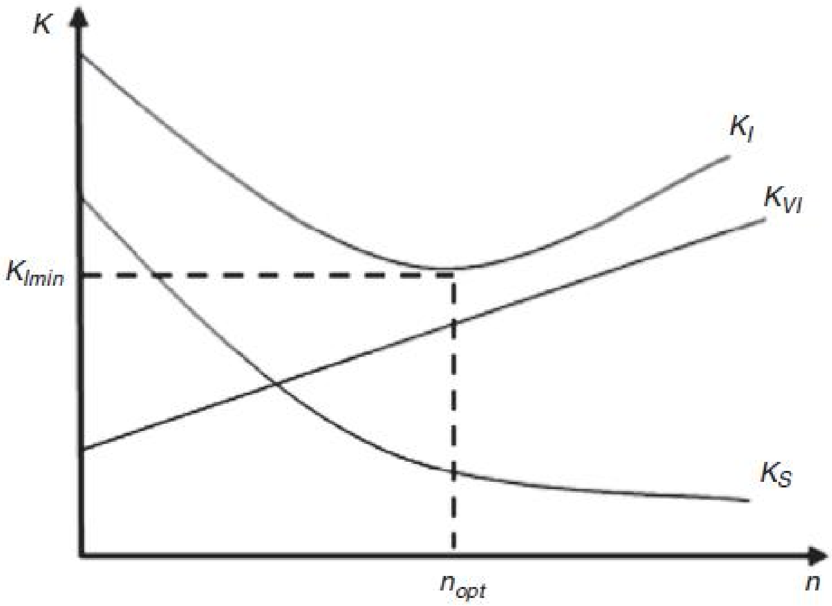


Figure 4: Planned and unplanned maintenance costs[24]

These relationships seem trivial. However, what is not trivial is whether one is currently "to the left or the right" of this minimum since the costs of a lack of maintenance are often not realized until years later. The exact correlation between maintenance activity

[22] Matyas 2016, p. 28.
[23] cf. Ibid., p. 32.
[24] cf. Hahn and Lassmann 1993, p. 353.

and improved machine life would have to be given to make this statement accurately.[25] However, this is not the case in a practical application.

Measures

The following measures can be taken to maintain the functional condition:

<table>
<tr><td>Service</td><td colspan="2">Has the goal of maintaining the target condition (cleaning, adjusting, calibrating). The main objective is to maintain the wear margin.[26]</td></tr>
<tr><td>Inspection</td><td colspan="2">Includes checking for wear, corrosion, leakage points, loosened connections, and periodic or continuous measurement and evaluation, as well as any other activities that determine and evaluate the equipment’s current condition and determine follow-up steps.</td></tr>
<tr><td rowspan="3">Overhaul</td><td colspan="2">Process of making components and machine parts accessible in order to replace them if necessary.</td></tr>
<tr><td>Repair</td><td>Modifies a component so that it restores the functional state. The same level as before a failure is restored. Improvements are excluded from this.[27]</td></tr>
<tr><td>Improvements</td><td>Combines technical changes with administrative changes to the system or component, aiming for assured function, but does not change the function.</td></tr>
</table>

Table 2: Measures of maintenance

The German Institute for standardization provides a similar structure of maintenance measures:

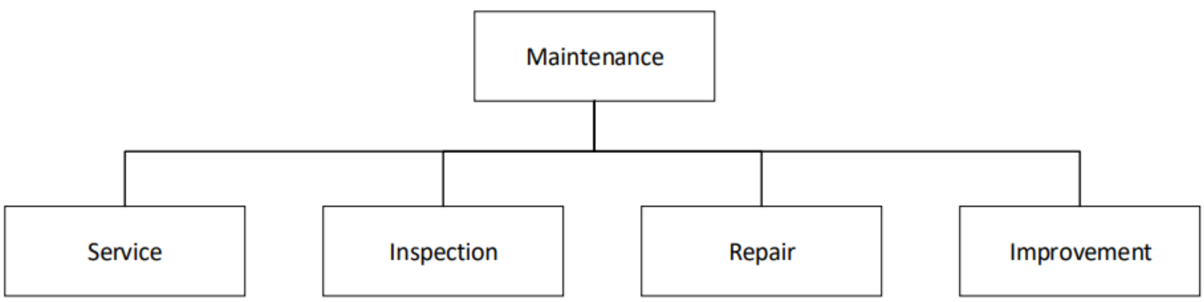


Figure 5: Measures of maintenance[28]

[25] cf. Matyas 2016, p. 49.
[26] cf. Bertsche 2004, pp. 338–339.
[27] cf. DIN31051 2018, p. 5.
[28] cf. Ibid., p. 4.

2.1.2 Maintenance strategies

„Maintenance strategies are rules that specify at which times which actions are to be performed on which units or components. The task is to make the right decisions in the conflicting areas of the economy, safety, and availability in order to minimize costs and maximize machine availability.“[29]

Various definitions of maintenance strategies can be found in the literature. In the following section, the maintenance strategies, according to Matyas (2016), are presented, and reference is made to other standard terms in the relevant literature:

Reactive maintenance (corrective maintenance)	The machines are operated until damage occurs and maintenance takes place in response to a defect. The consequences associated with the damage are therefore accepted. However, since every shutdown is unexpected, no planned measures can be taken for maintenance activities, which results in a lengthy repair time. However, since maintenance is only performed in the fault condition, maintenance cannot be scheduled “earlier than necessary,” which allows for a maximum maintenance interval. This strategy only makes sense in exceptional cases. For example, it is suitable for small, non-critical units and a low probability of failure.
Preventive maintenance (time-based, periodic maintenance)	In time-controlled periodic maintenance, machines are maintained preventively at a particular time interval, regardless of their condition. In this case, an optimal maintenance interval must be found to prevent failures and, at the same time, to not perform maintenance activities “earlier than necessary.” Without being able to infer the machine’s condition, an exact determination of an optimal interval is only possible to a limited extent or not at all, which is why a good failure safety and good utilization of the wear margin cannot be realized simultaneously with this strategy. This strategy is a common maintenance method and is useful when safety or environmental impacts are possible, or the machine’s approximate life is known.
Condition-based maintenance	Condition-based maintenance offers a solution to the problem of maintenance interval optimization in time-controlled periodic maintenance. With proper monitoring and diagnostic systems, information about the current machine condition can be obtained, enabling more targeted maintenance activities to make the best possible use of the machine’s wear stock.
Predictive maintenance	Predictive maintenance extends condition-based maintenance by data analytics methods and incorporates other data sources (environmental data, historical data, third party data) to provide a more accurate condition determination and a forecast for the machine’s remaining useful life.

Table 3: Maintenance strategies[30]

[29] Matyas 2016, p. 119.
[30] cf. Ibid., pp. 120–124.

Table 4 provides an overview of similar terms on maintenance strategies used in the literature:

R2F – run-to-failure	Equals reactive/corrective maintenance
PvM – preventive maintenance	Equals time-based and periodic maintenance
PdM – predictive maintenance	In the literature, there is often no precise distinction between a condition-based and a predictive maintenance strategy (since condition monitoring is a prerequisite for predictive maintenance). The terms condition monitoring (CM) or condition-based monitoring (CbM) are often used to describe condition-based maintenance.

Table 4: Maintenance strategies[31] [32] [33]

The progress on maintenance strategies by utilizing data from condition monitoring systems is often referred to as smart maintenance or maintenance 4.0.

2.1.3 Condition Monitoring and predictive maintenance

A prerequisite for predictive maintenance is the monitoring of a machine's condition. This monitoring can take place continuously or at periodic intervals. "The increasing popularity of sensor technology for recording the condition of tools and machines is driven by the change in maintenance strategies."[34] The appropriate selection of sensors (and test equipment) is crucial to cover all relevant fault conditions while keeping the investment costs low and not generating irrelevant data. Since the prices for sensors and wireless systems have dropped considerably in the last years (tendency further decreasing), it is nowadays possible to find cost-effective solutions for many applications.

„Condition-based maintenance is based on the assumption that most machine failures do not occur suddenly but develop over a period of time and are announced by specific warning signals before they occur. These signals are called potential failures. They can be graphically represented in a so-called PF-curve. P is the point at which a potential fault is detected, and F is the failure time."[35] The PF-interval is defined as the time between potential failure and functional failure[36] and therefore describes the available timeframe for generating proactive recommendations about maintenance actions.

[31] cf. Susto et al. 2012, p. 638.
[32] cf. Mobley 2002, pp. 3–6.
[33] cf. Susto et al. 2015, p. 812.
[34] Karner 2019, p. 24.
[35] Matyas 2016, p. 125.
[36] cf. Bousdekis et al. 2021, p. 2.

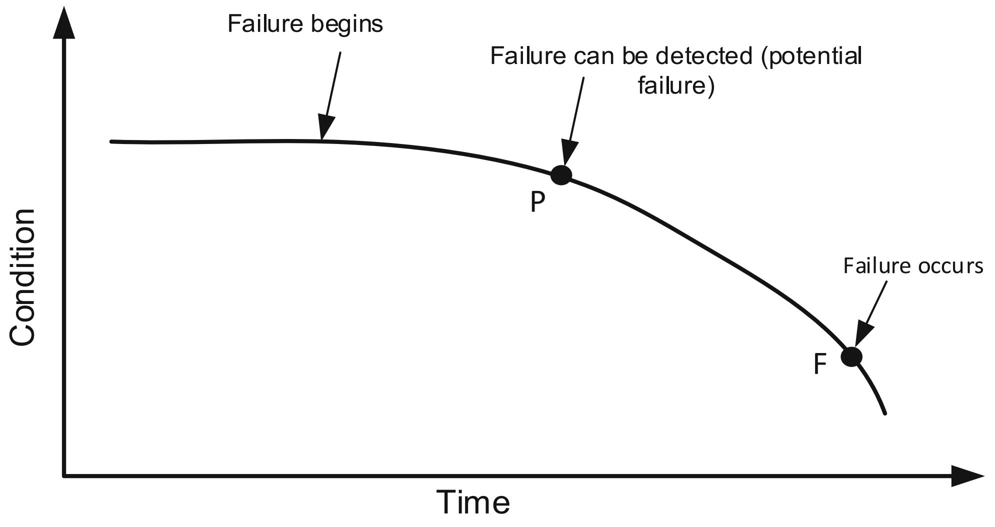


Figure 6: PF-curve[37,38]

If we consider the condition as a health index between 100% and 0%, where 0% of the health index means machine failure, we can visualize the maintenance strategies in analogy to the PF-curve:

[37] cf. Matyas 2016, p. 125.
[38] cf. Bousdekis et al. 2021, p. 2.

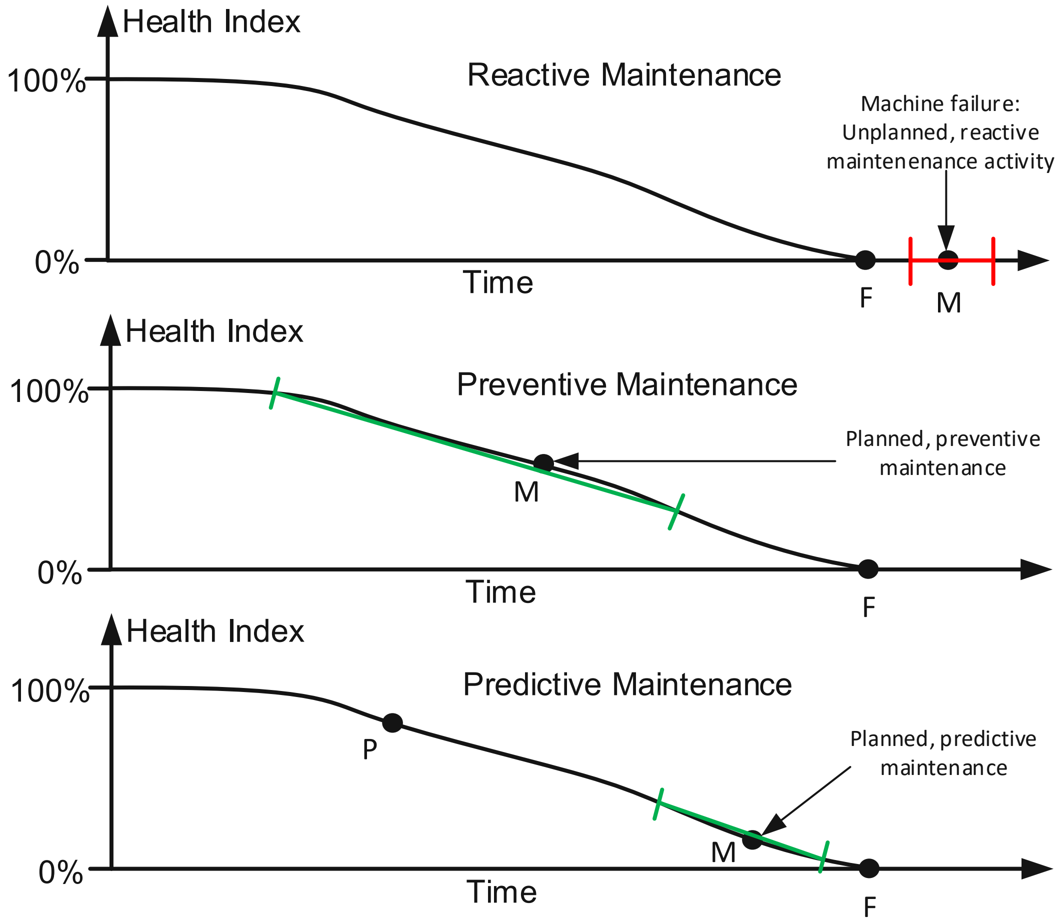


Figure 7: Maintenance strategies on PF-curves[39]

The time interval between the P and F points (Figure 6) is called PF-interval and indicates the advance warning time. A bigger interval means more time for corrective measures to prevent a failure occurrence. As the PF interval is usually unknown, condition monitoring aims to improve the early recognition of potential failures and thereby increase the PF interval.[40]

Thus, once a potential failure is detected, there is a certain amount of time to perform maintenance activities (see M points in Figure 7) before the failure occurs. This period can last "from a few milliseconds to months or years."[41] The red and green intervals indicate corrective and preventive maintenance activities, respectively. For a reactive maintenance strategy, maintenance activities occur only after a failure has been recognized. In a preventive maintenance strategy, maintenance activities usually take place long before the machine's condition is strongly deteriorated to ensure the prevention of machine failure and avoidance of corrective maintenance activities. Therefore, by utilizing condition data for condition-based or predictive maintenance,

[39] cf. Hoffmann et al. 2020, p. 2.
[40] cf. Matyas 2019, p. 129.
[41] cf. Matyas 2016, p. 125.

preventive maintenance tasks can be scheduled at a later point in time while still avoiding machine failure.

The simplest possibility of condition-based maintenance would be to equip a machine with a single sensor and initiate a maintenance activity when a certain threshold is reached. Example: A spindle is equipped with a sensor for measuring the wear margin, and a tool change takes place at a defined level.

The more complex the machine to be monitored, the more sensors can be effectively fitted to predict a specific fault condition. This quickly results in a massive amount of data, which, on the one hand, requires a sufficient infrastructure and, on the other hand, has to be processed. Therefore, the PF-curve can be modeled as a function that depends on many variables (some of which influence each other).

As described, condition-based maintenance uses information that can be obtained directly from a condition monitoring system. However, depending on the problem’s type and complexity, this approach cannot always guarantee the required system reliability. Predictive maintenance requires processing and storing data of the monitored machine. Data analysis methods are used to predict fault conditions based on anomalies in the measurement data or by means of classification of known fault conditions. Thus, a machine-specific model is created, which analyzes current and historical data and provides conclusions about the remaining useful life (RUL). It should be noted that such a model can (and should) not only process the data of the condition monitoring system, but all possible influencing variables can be taken into account in the form of data. E.g., include expert knowledge, human experience data, and third-party data.

2.2 Production planning and control

Scheduling and sequencing are subareas of the production planning and control area. Therefore, this chapter starts with a review of the history and the foundations of production planning and control. The main focus is on the relevance to condition-based scheduling and sequencing.

2.2.1 History on production planning and control (PPC)

The introduction of automation technology in the industry, referred to as the third industrial revolution, led to a massive reduction of routine production activities. Before this, attempts were made to separate simple physical routine activities from mental activities to increase productivity through easier learning and a higher degree of specialization. As these routine activities became automated to a higher degree, the complexity of humans’ work content increased. Also, the machine hours of the ever-improving systems became more valuable, while the production halls’ complexity also increased. Further development of production planning systems became inevitable. As a result, approaches for holistic production planning systems and approaches for lean production arose. “Concepts such as the Toyota production system (kanban and pull principle), just-in-time (JIT), and just-in-sequence (JIS), and later the holistic Aachner PPC model emerged.”[42] Today, enterprise resource planning (ERP) and supply chain management (SCM) are well-established terms within production planning and control, supporting holistic cross-company approaches.[43]

The focus of production planning and control has shifted from singular production plants to cross-company value chains in the last decades. However, while today the focus is still primarily on rigid and linear supply chains, the specific framework conditions of temporary production networks will gain more importance in the future. Current concepts and instruments of supply chain management mainly address the design, operation, and optimization of long-term value creation structures, such as those common in the automotive or consumer goods industries. Project-related cooperation in temporary production networks in mechanical and plant engineering poses challenges that are not adequately met by the current state of business research and operational information systems.[44]

2.2.2 Foundations of production planning and control (PPC)

Production planning and control (PPC) is the process of ensuring the availability of all resources at the right time, place, and quantities to ensure the progress of operation according to predetermined schedules at the minimum possible costs. Production planning and control still forms the core of every industrial company today and is an essential component of the production system.[45] The core task of production planning and control is coordinating the competing orders under consideration of the subordinate production-economic target system.[46] As it is inevitable that plans have to be adopted in some circumstances, PPC is a dynamic process. Some of the main objectives of PPC are minimizing idle times, minimizing inventory turnover, maximize product quality, and keeping inventory levels low.[47]

Production planning is carried out based on customer orders or sales forecasts for the product types to be manufactured in the planning period and is therefore closely linked to sales planning. The result is determining the planned primary requirements, e.g., the finished products and spare parts to be sold on the market. Based on the production plan, the determination of requirements is carried out as part of quantity

[42] Karner 2019, p. 18.
[43] cf. Schuh and Stich 2012a, pp. 3–5.
[44] cf. Schuh and Stich 2012b, p. 61.
[45] cf. Schuh 2006, p. 26.
[46] cf. Vahrenkamp 2008, p. 196.
[47] cf. KIRAN 2019, pp. 1–2.

planning. This comprises the raw materials, vendor parts, and semi-finished products needed to produce the primary requirements. Quantity planning also includes the planning of order quantities, order dates, and order frequencies (optimum order quantity). While quantity planning can also be assigned to procurement or materials management, scheduling is closely related to process planning and is therefore strongly dependent on the organizational type of production (flow production, shop floor production, etc.).

Production planning

According to Kiran, production planning can be split into six basic functions:[48]

1. Product planning
2. Forecast planning
3. Process planning
4. Equipment planning
5. Materials planning
6. Production planning

The first two focus on product design/development and forecasting demands. Process planning includes selecting the technology, processes, machines, and tools used. Equipment planning includes selecting equipment types, numbers, and maintenance plans, whereas material planning includes materials specifications & volumes and planning for inventory and store. Production planning focuses on machine loading, operations scheduling, and job sequencing. Implementing condition-based scheduling and sequencing will affect this function of the production planning process firsthand, as it aims to optimize operations scheduling and job sequencing. However, changes in the production planning function may also open the door to improvements in materials planning, equipment planning, and process planning. For example, the equipment planning process is affected due to the impact of condition-based scheduling on maintenance activities.

Production control

Production controlling must enable two views of production. From the order point of view, the focus is on lead time and adherence to delivery dates. From the resource point of view, the focus is on throughput or capacity utilization and inventories. Control consists of comparing actual and planned values based on key figures. More in-depth analyses are required if there are serious deviations. It is often a good idea to start by analyzing the throughput behavior of the orders. If this reveals an intolerable level of

[48] cf. KIRAN 2019, p. 5.

delivery capability or reliability, the causes can be uncovered by means of further analyses at the work system level.[49]

According to Kiran, production control can be split into five basic functions:[50]

1. To give directives so that the products can proceed without hindrance and interruptions.
2. To deliver orders to the workforce so that the production can be carried out as planned.
3. To make available necessary resources (machines, materials, workers, jigs and fixtures, tools,…) in the right time.
4. To monitor the progress for ensuring the quality and quantity to be as per the specifications.
5. To achieve all these at optimal cost.

Challenges

On the one hand, it is increasingly necessary to ensure not only resource planning in a narrow sense, but also complete order processing along the entire supply chain. On the other hand, maximum compatibility must be achieved with the system landscape of the network partners.

Schuh and Stich (2012b) cite the poor organization of inter-firm order processing and weaknesses in the software systems used as one of the main challenges. The highly complex production network structures in mechanical and plant engineering often encounter interface problems in the software systems used. First of all, this concerns the multitude of different types of software used within an individual company. Practical experience shows that in order to process a specific customer order, software solutions from different providers as well as numerous proprietary solutions are often used within the departments of a single company.[51]

Those challenges could be overcome by standardizing data models and defining reference processes for intercompany order processing in mechanical and plant engineering. A corresponding data standard would enable the integration of order processing, and a process standard would significantly increase the efficiency and transparency of order processing. This arises from the different levels of confidentiality in inter-company order processing, which inevitably characterize business relationships in temporary production networks. Data exchange and processes of inter-company order processing must be differentiated according to the confidentiality level of a business relationship.[52]

[49] cf. Schuh and Stich 2012b, p. 24.
[50] cf. KIRAN 2019, p. 9.
[51] cf. Schuh and Stich 2012b, pp. 64–65.
[52] cf. Ibid., pp. 73–74.

2.2.3 Production scheduling

Production scheduling and sequencing are subareas of the production planning and control area. Scheduling determines when an operation has to be performed in order to meet the desired delivery dates. It is a timetable for the use of resources and processes. Scheduling allocates resources, applying the limiting factors of time and cost. Starting and completion times are assigned to the operations to be performed. Therefore, production is systematically arranged by due dates and priorities.[53]

“Scheduling is the most important function of production planning and control activity in manufacturing and engineering.”[54]

Achieving inventory optimization under the focus of a logistics chain-oriented view requires the use of scheduling strategies in line with requirements. This means that corresponding storage and retrieval quantities and times, as well as minimum and safety stocks, must be harmonized, considering the structural setup of the logistics chain on the one hand and the item-specific requirements on the other.[55]

Two basic strategies for manufacturing settings can be differentiated: Job shop and flow shop. A job shop environment is suitable for low-quantity, high-variety custom products that require unique setups, production sequences, and priorities. On the other hand, flow shop systems utilize mostly linearly designed production process structures to achieve a smooth, less interrupting production flow.[56]

2.3 Prognostics and health management (PHM)

„Three main approaches can be distinguished in the literature for failure prognosis: model-based fault prognosis, data-driven fault prognosis, and experience-based fault prognosis.”[57] Experience-based fault prognosis is the simplest procedure of the three. It considers a relationship between observed situations and a history of failure data. The experience of domain experts and operators thereby is the primary source of information for deriving a model, mainly in the form of if-then rules. An obvious disadvantage of this method is the factor of human perception. The most used methods nowadays are data-driven. The ongoing technological advancements regarding sensors and tools for processing and computing data further drives the usage of data-driven methods. A downside of data-driven approaches is that data quality is crucial for model performance. In fault prognosis, data points along with the degradation profile of the machine, especially in fault conditions, are often rarely available. Another

[53] cf. KIRAN 2019, pp. 321–322.
[54] Ibid., p. 321.
[55] cf. Schuh and Stich 2012b, p. 391.
[56] cf. Moghaddam 2020, p. 85.
[57] Djeziri et al. 2020, p. 1.

challenge is that the practical use of monitoring tools showed that the real degradation of a system might involve different profiles that can shift or variate abruptly.[58]

The research area of prognostics and health management focuses on monitoring a machine's or system's condition in the actual operating environment in real-time and predict its future state based on up-to-date information. Thereby, predictive maintenance is the underlying maintenance strategy that utilizes the information acquired by techniques from prognostics and health management. The main tasks of prognostics are state estimation, state prediction, and remaining useful life (RUL) prediction. State estimation and prediction describe the estimation/prediction of the health or degradation state of the system based on historical data. In contrast, RUL prediction describes determining the time left before failure (or exceeding a set degradation threshold) occurs. Different operational conditions are an obstacle for PHM because they result in different states of sensor signals that need to be treated accordingly. Also, varying the operational condition can speed up machine deterioration and cause sudden signal changepoints and, therefore, high variance in raw sensor values. Another challenge for data-based RUL prediction is the scarcity of labeled failure data needed for incorporating supervised machine learning. Nevertheless, machine learning is commonly used in prognostics as supervised, semi-supervised, and unsupervised machine learning.[59]

Since machine learning can be successfully applied in the industry, publications in this field have ever increased. Also, “the trend has been recently fueled by many government initiatives, like Industry 4.0 (Germany), Smart Factory (South Korea), and Smart Manufacturing (USA), calling for a radical change in the manufacturing paradigm.”[60]

2.3.1 Data mining (DM) and knowledge discovery in databases (KDD)

The KDD process includes the six phases of selection, preprocessing, transformation, **data mining**, interpretation, and evaluation. The CRISP-DM (Cross Industry Standard Process for Data Mining) comprises the six phases of domain understanding, data understanding, data preparation, modeling, evaluation, and deployment.[61]

Preprocessing

Data preprocessing is a fundamental step in data analysis. Since much low-quality information is available in various data sources and the Internet, many organizations

[58] cf. Djeziri et al. 2020, pp. 1–2.
[59] cf. Zhai et al. 2021, p. 2.
[60] Bertolini et al. 2021, p. 2.
[61] cf. Runkler T. A. 2015, p. 3.

or companies are interested in putting this data into a cleansed form and thus profit from it. This goal creates the need to target raw data cleansing with data analytics. In practice, it has been found that data cleansing and pre-processing accounts for about 80% of the total effort in the data engineering process.[62]

3 aspects for the importance of data preprocessing[63]

1. Data from real-world applications can be incomplete, noisy, and inconsistent, which can obscure meaningful patterns. This is caused by:

- Incomplete data: Missing attribute values, Missing attributes of interest, or contains only aggregated data.
- Noisy data: Contain errors and outliers.
- Inconsistent data: Contain discrepancies in the code or the name.

2. Data preprocessing generates a smaller and more refined data set than the original one, which can significantly improve the efficiency of data mining. This process includes:

- Select relevant data: Attribute selection, remove anomalies and eliminate duplicate data.
- Reduce data: Sampling or sample selection.

3. Data preparation generates qualitative data, which leads to patterns. For example, one can:

- Improve incomplete data: Fill in missing values, reduce ambiguities.
- Clean data: Correct errors, remove outliers.
- Resolve data conflicts: Using expertise or domain expert knowledge to mitigate discrepancies.

From the above three observations, we can derive that data preparation, in general, is a comprehensive task. While data mining technologies support data analysis applications, it must be possible to prepare qualitative data from the raw data to enable efficient and qualitative knowledge extraction from the given data.[64]

Data Mining

Data mining is the process of discovering interesting knowledge from large amounts of data stored in databases or other information repositories.[65]

[62] cf. Zhang S., Zhang C., Yang Q. 2003, p. 375.
[63] cf. Ibid., p. 377.
[64] cf. Ibid., p. 377.
[65] cf. Han J., Kamber M., Pei J 2012, p. 1.

Cross-Industry Standard Process for Data Mining (CRISP-DM)[66]

A widely used procedure model for data mining processes is the Cross-Industry Standard Process for Data Mining (CRISP-DM), which was developed in 1996 as part of an EU-funded project.

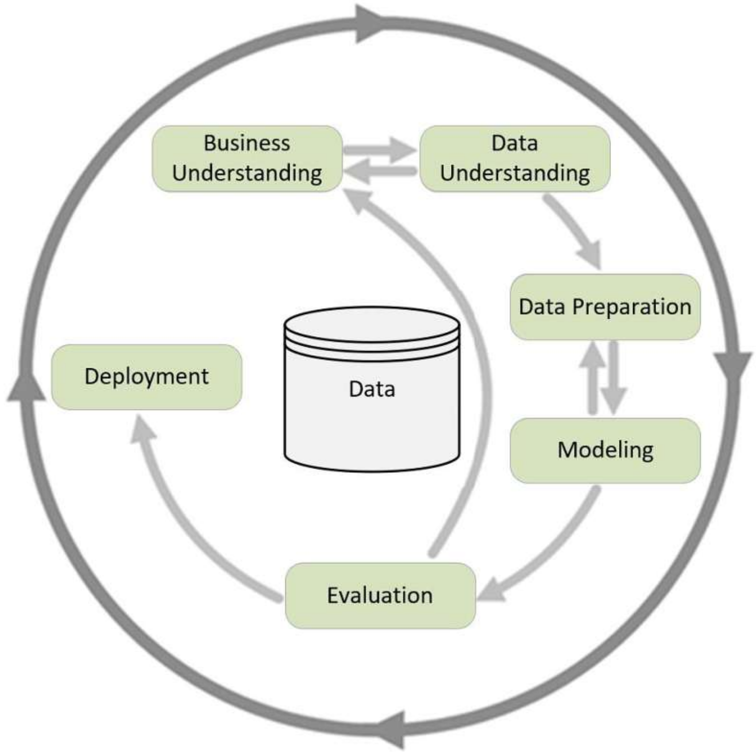


Figure 8: Cross-industry standard for data mining (CRISP-DM)[67]

Business understanding: Before applying data mining, it is necessary to understand the goals of this implementation. The business goals and requirements are examined to determine if data mining can be applied to achieve them. It is determined what data can be collected to create an implementable model.

Data understanding: An initial data set is defined and examined to determine if it is suitable for subsequent processes. If the data quality is poor, it may be necessary to collect new data using more stringent criteria. It is also possible that new insights from the data will lead to a new perspective on the data mining goals of the use case at hand. Thus, a renewed domain understanding phase may be triggered.

Data Preparation: This phase involves preprocessing the raw data into a form from which machine learning algorithms can create a model. This data preprocessing may

[66] cf. Chapman 2000, pp. 13–34.
[67] cf. Ibid, p. 13.

also include model creation, as many preprocessing tools create a model for (automatic) data transformation.

Modeling: Creating a data mining model, possibly by application of machine learning algorithms. Data preparation and modeling go hand in hand. New insights from a created model can influence decisions around data preparation process, which is why an iterative cycle of these two phases is almost always practical.

Evaluation: The importance of this phase cannot be emphasized strongly enough. It must be determined whether the structural description derived from the data contains any prognostic added value at all, which is not necessarily the case. The model may just as well reflect only distorted or incorrect features/regularities from the data. Suppose it is determined in this step that the model is poor/useless. In that case, it may be necessary to revisit the entire project and define more appropriate goals during domain understanding or to enable the acquisition of more valuable data.

Deployment: Once the model has sufficient accuracy, it must be implemented in practice. Typically, it must be integrated into a more extensive software system. Here it depends on the detailed implementation of the model and how it can be transferred into the software system (possibly in another programming language).

2.3.2 Machine Learning (ML)

Machine learning is one of the oldest and most important sub-disciplines of artificial intelligence, but it can also be seen (at least when stochastic processes play a role in it) as a further development of classical statistical decision and classification methods. This is because machine learning, unlike most statistical methods, generally does not require any particular assumptions about the nature of the statistical distributions of the underlying data.[68]

There are two types of learning:

1. Supervised learning,

where the classifications of the training data set are already known. The learning algorithm can therefore check its own decisions. The training data set contains input variables x and output variables y. The goal of the learning procedure is to approximate a function f -which can calculate the output variables from the input variables [y=f(x)]- as accurately as possible from the data set. The predicted output variables can be compared with the actual ones in order to improve the model iteratively.

2. Unsupervised learning,

[68] cf. Wysotzki F. 1997, p. 526.

where the classifications of the training data set are unknown, and the number of classes to be learned are not necessarily known in advance. Thus, input variables x are given without associated output variables y. It is tried to assign groups of similar data points to new classes.

In practice, problems often arise where a mixture of these two types of learning is required. This is called semi-supervised machine learning. In this case, a large data set is available, which for the most part, does not contain any output variables.

Selection of algorithms

Choosing a suitable machine learning algorithm can seem complicated. There are dozens of supervised and unsupervised machine learning algorithms, with each algorithm taking a different approach to learning. There is no best method or one-for-all solution. Finding the correct algorithm happens through systematic trial and error. Even highly experienced data analysts cannot predict (without trial and error) which algorithm will produce the best results. Highly flexible models tend to over-interpret the data ("overfitting") so that even slight variations are modeled that could just be measurement noise. Simpler models are easier to interpret but may have lower accuracy. Therefore, choosing a suitable algorithm means making a trade-off between different advantages such as model speed, accuracy, and complexity. Systematic trial and error is part of machine learning - if one approach does not work, try another.[69]

We can foremost distinguish between classification problems, regression problems, and clustering problems:

1. Regression:

To predict a continuous value. Example:

- Based on the size of a house, predict its value.

2. Classification:

Predict a discrete value or assign it to a finite number of classes. Examples:

- Classify whether a picture contains a dog or a cat.
- Predict whether an e-mail is a spam or not.

3. Clustering:

[69] see https://de.mathworks.com/help/stats/machine-learning-in-matlab.html.

Formation of groups (clusters) based on similarities in the input data. It differs from classification primarily in that the classes themselves are not known in advance and are therefore formed in the learning process.

1) Regression[70]

Regression analysis estimates functional dependencies between characteristics to understand and target relationships. The following three are examples for regressions:

- **Linear regression:** Linear regression provides linear functional relationships between characteristics. The approximation $x^{(i)}$ of a characteristic by a linear function f of another characteristic $x^{(j)}$ can be formulated as:

$$\boldsymbol{x_k^{(i)} \approx a * x_k^{(j)} + b}$$

Equation 1: Linear regression

Linear regression estimates the parameters a and b of this linear function from X by minimizing a suitable error function.

- **Linear regression with nonlinear substitution:** If the nonlinear functions are given for nonlinear regression models, they can be determined efficiently with linear regression methods. For example, if a quadratic relationship is known, its square can be considered instead of considering a feature itself, and the associated coefficient can be determined using linear regression.
- **Robust regression:** The quadratic error function of ordinary linear regression is very sensitive to outliers since they strongly influence the error. Robust error functions try to reduce the influence of outliers

2) Classification[71]

„Classification is a supervised learning method that uses labeled data to assign objects to classes.“[72]

Data classification is a process that consists of two steps: Learning (where the classification model is constructed) and classifying (where the model is used to predict the classes of existing data).[73]

In order to evaluate a classifier, its classification quality must be determined. For this purpose, the possible correct and incorrect statements have to be distinguished. In the case of two classes, these can be described as:

- TP – True Positive: Positive output correctly predicted

[70] cf. Runkler T. A. 2015, pp. 67–69.
[71] cf. Ibid., pp. 89–106.
[72] Ibid., p. 89.
[73] cf. Han J., Kamber M., Pei J 2012, p. 328.

- TN – True Negative: Negative output correctly predicted
- FP – False Positive: Negative output incorrectly predicted
- FN – False Negative: Positive output incorrectly predicted

Therefore, two or more classification criteria are usually considered when evaluating classifiers.

One way of doing this is the receiver operating characteristic (ROC) curve. This is a scatter plot of true-positive rate (TPR) and false-positive rate (FPR). [y-TPR; x- FPR] The classifier's quality can be represented as a point in the ROC diagram. Thus, the more one approaches the upper-left corner in the ROC diagram, the better the classifier's goodness (TPR →1, FOR →0). Another possibility is offered by the accuracy-hit rate diagram (PR - Precision-Recall), a scatter plot of accuracy (Positive Predictive Value) TP/P, and hit rate (True Positive Rate). A good classifier maintains high accuracy even for increasing hit rate. The intersection of the PR curve with the main diagonal is called the Precision-Recall Breakeven Point. This value should be as high as possible. A test data set (independent of the training data set) is used to estimate the learned classification accuracy. The reason for this is a possible "overfitting" of the training data set, which means that during the learning process, certain anomalies from the training data set can also be included, which are not present in the general data set.[74]

The following three are examples for classifications:

- **LDA – Linear Discriminant Analysis**
  Linear discriminant analysis is a method to distinguish between two or more sample groups. For this purpose, a discriminant line is calculated (can also be a plane or hyperplane), which results in the best possible separation of the classes present. One can consider the discriminant line as a boundary between the classes, where it is written in normal form as follows:

$$\boldsymbol{w} * \boldsymbol{x}^T + b = 0, \qquad \boldsymbol{w} \in \mathbb{R}^p, \qquad b \in \mathbb{R}$$

Equation 2: Linear discriminant analysis

[74] cf. Runkler T. A. 2015, pp. 90–93.

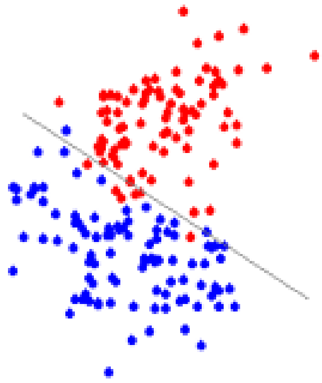


Figure 9: Linear discriminant analysis

For a given data set, linear discriminant analysis determines the parameters w and b of a discriminant line such that a given criterion is optimized.

- **SVM – Support Vector Machine**

  As in linear discriminant analysis, linear class boundaries are also used in the support vector machine. However, it is required that the data keep a minimum distance b>0 from the class boundary. Accordingly, for two classes, it is required that:

$$w * x_k^T + b \geq +1 \;\; falls \;\; y_k = 1$$
$$w * x_k^T + b \leq -1 \;\; falls \;\; y_k = 2$$

Equation 3: Support vector machine for two classes

If several solutions exist for these boundary conditions, the SVM searches for the solution with minimum

$$\boldsymbol{J} = \|\boldsymbol{w}\|^2$$

Equation 4: SVM maximization of distance

which corresponds to a maximization of the distance b.

Using the so-called "kernel trick," data with nonlinear bounds can be transformed into a higher-order with approximately linear bounds, allowing support vector machines to find nonlinear class boundaries as well.

- **NN – Nearest Neighbor**

  A simple classification method is the nearest neighbor classifier. This assigns an object with a given feature vector to the class of the training object with the most similar feature vector. Thus, for a given feature vector x, the nearest neighbor classifier returns class y_k, if

$$\|x - x_k\| = min_{j=1,\dots,n}\|x - x_j\| \,, \qquad \|.\| \dots appropriate\ dissimilarity\ measure$$

Equation 5: Nearest neighbor classifier

In cases of multiple minima, a random selection can be made from these.

The nearest neighbor classifier is poorly suited near noisy data or overlapping class boundaries. Here, the nearest-k-neighbor classifier (k-NN) provides better results. This considers the k nearest neighbors instead of just the nearest neighbor and returns their most frequent class. For two classes, a unique class assignment can be ensured if k is odd.

3) Clustering

Clustering is an unsupervised learning procedure in which unlabeled data are assigned to clusters. If the data to be clustered is also assigned to classes, then the obtained cluster memberships may correspond to the class memberships. However, cluster and class memberships can also be different.[75]

An example for clustering methods would be the k-means algorithm, where the data set is divided into (a predefined number of) k partitions such that the sum of squared deviations from the cluster centroids is minimal.

[75] cf. Runkler T. A. 2015, p. 109.

3 Practical application of condition data in the context of production planning: State-of-the-Art

3.1 Planning a systematic literature review

The state-of-the-art is analyzed by conducting a systematic literature review of research regarding the integration of condition monitoring in production planning. The research methodology is designed along the lines of Tranfield et al.[76], as described in chapter 4.3. The state-of-the-art analysis covers the execution and the results of the systematic literature, as discussed below.

The systematic literature review aims to answer the research question Q1 and provide the necessary knowledge for answering research questions Q2 and Q3.

3.2 Conducting the review

The systematic literature review was conducted in the Scopus[77] database, which is one of the most extensive databases for scientific publications worldwide.

3.2.1 Keywords and search terms

The goal for the keywords is to identify publications that combine content about production planning and control (ID “P”) and condition monitoring (ID “C”). A first research on how many results potential keywords deliver showed that including the terms “production planning” and “production control” as such would lead to more results than the scope of this work allows for analyzing. Also, in a previous systematic literature review, the combination of “production planning and control” or “PPC” with one of the C keywords delivered relatively few relevant results.[78] Therefore, the keywords on production planning are chosen with more detail towards scheduling.

[76] Tranfield et al. 2003.
[77] https://scopus.com.
[78] cf. Karner 2019, p. 169.

ID	Keywords
P1	„Detailed production planning“
P2	„Scheduling and sequencing“
P3	„Production scheduling“
P4	„Production sequencing“
P5	“Job-shop scheduling”
C1	“Condition” AND “maintenance”
C2	“Condition-based monitoring” OR “condition based monitoring” OR “condition monitoring”
C3	“Predictive maintenance”
C4	“Machine condition”
C5	“Tool condition”

Table 5: Keywords for literature review

As there are five different keywords for each category, there are 25 possible ways to combine P keywords with C keywords. However, the Scopus database allows for writing complex search queries. Therefore, all the publications that can be found by searching for the 25 combinations can be found with one longer search query as well. The advantage of this procedure is that there are no duplicate results that need to be sorted out.

Search query:

> ("condition monitoring" OR "predictive maintenance" OR "condition based monitoring" OR "condition-based monitoring" OR (condition AND maintenance) OR "machine condition" OR "tool condition") AND ("detailed production planning" OR "production scheduling" OR "production sequencing" OR "scheduling and sequencing" OR "job-shop scheduling")

Looking at the results, we see a substantial increase in the number of publications on the topic in recent years. Notably, the search was conducted in mid-2021. Therefore, the following graph allows for predicting an even stronger increase by the end of 2021:

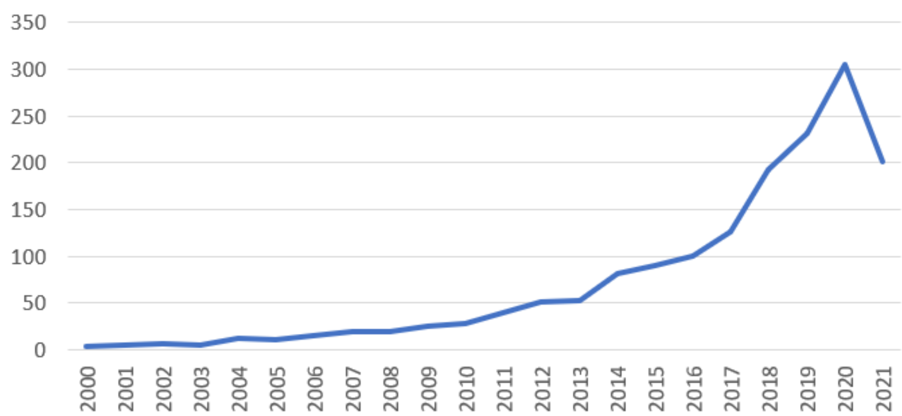


Figure 10: Search query results by June 2021

3.2.2 Classification of publications

The total number of search results is 1684. In the work of Karner[79], a systematic literature review with similar search terms was performed for publications between the years 2000 and mid-2018. The results of that work and its sources have been analyzed according to the topic at hand. Therefore, the timeframe of the literature review conducted in this thesis extends the work of Karner and emphasizes literature published in 2018 and later. After limiting the results to the publication year 2018 and newer, and only publications in English and German language, the remaining results include 878 publications.

The following criteria were applied to the publications:

- Inclusion criteria: Considers condition data for PPC or maintenance or deals with integrative consideration of machine condition, PPC, and maintenance.
- Exclusion criteria: Not a scientific article or published before 2018.

Therefore, these 878 publications were analyzed by their title and filtered to a number of 119 documents. Sixty-one of those did not meet the inclusion criteria at first analysis. For the literature review discussion, the remaining 58 publications were reduced to a number of 40 by considering the relevance to research questions and novelty of content.

Those publications were classified by the following categories, referencing the previous literature review of Karner:[80]

1. Type of publication:

- Review: Publications that focus on analysis and discussion of already existing literature
- Concept: Publications that focus on a conceptual presentation of approaches, models, and methods for integrating condition data, production planning, and maintenance.
- Case-study: Publications that focus on applying existing approaches, models, methods for the integration of condition data, production planning, and maintenance.

2. Type of solution:

- Approach: A not very concrete idea for solving the problem. Under this category are classified publications that identify the problem and present conceptual ideas for its solution.

[79] Karner 2019.
[80] cf. Ibid., pp. 165–172.

- Model: Publications that present models for application-specific or general solutions
- Method: Publications that propose a new method for the utilization of a particular model.

3. Scope

- Specific: Publications in this category involve the development of solutions for specific use cases. Thereby, it specifically refers to the initial problem definition.
- General: Solutions are considered general if they can be applied to similar problems with little effort.

4. Focus:

- Condition Monitoring: The publication focuses on CM.
- Maintenance: The publication focuses on maintenance.
- PPC: The publication focuses on production planning and control.
- CM & maintenance: The publication focuses on condition monitoring and its integration into maintenance
- Maintenance & PPC: The publication focuses on maintenance and its integration in production planning and control.

5. Maintenance strategy:

- Reactive: The publication considers maintenance activities only due to machine failure.
- Preventive: The publication considers time-based, simple models to carry out maintenance preventively.
- Predictive: The publication considers a maintenance strategy that utilizes prediction models for predicting machine or equipment failure.
- Prescriptive: The publications consider not only predicting failure times, but also derives plans or suggestions from the gained information.

6. Production planning

- Production planning: This category includes those publications that incorporate CM systems into long-term production planning.
- Detailed production planning: Publications in this category deal with the integration of CM into detailed production planning (short-term).
- Production control: This category includes those publications that integrate CM as part of production control.

7. Condition monitoring:

- None: Condition monitoring is not described explicitly. Machine condition is considered as given or derived from mathematical models.
- Offline: The machine condition evaluation is not conducted continuously, for example, within the scope of inspections.
- Online: The evaluation of the machine condition happens continuously.

8. Evaluation:

- None: The proposed solution is not validated within the publication.
- Theoretical: The proposed solution is evaluated by utilizing theoretical methods (e.g., simulation)
- Practical: The proposed solution is evaluated by conducting a case study.

9. Algorithm:

The proposed solution utilizes algorithms according to the following table:

Abbreviation	Algorithm
SA	Simulated annealing
MP	Markov Process
RA	R-Algorithm
RL	Reinforcement Learning
H	Heuristic
SW	swarm algorithm
TLB	teaching-learning-based algorithm
NDBM	nonlinear drifted Brownian motion
PA	pareto algorithm
BHA	black hole algorithm
HS	harmony search
TS	tabu search

Table 6: Abbreviations of algorithms

Table 7 shows the classification of publications analyzed in this literature review:

ID	Publication (Author, year)	Type of publication			Type of solution				scope		Focus					maintenance strategy				production planning			condition monitoring			evaluation			Algorithm
		review	concept	case study	approach	model	method	instantiation	specific	general	condition monitoring	maintenance	PPC	CM & maintenance	maintenance & PPC	reactive	preventive	predictive	prescriptive	production planning	detailed production planning	production control	none	offline	online	none	theoretical	practical	
2	Malekpour et al. (2021)			x			x			x			x			x					x		x						SA
3	Yang et al. (2021)		x				x			x					x		x				x		x				x		MP, RA, RL
4	uit het Broek et al. (2021)		x			x				x				x				x		x					x		x		MP
5	Viharos er al. (2021)		x		x					x			x										x						
6	Levitin et al. (2021)			x			x		x						x		x					x	x					x	
7	Mohammadi et al. (2021)			x			x		x					x															H
8	Li and Lei (2021)		x			x				x			x																
9	Peng et al. (2021)			x		x				x				x															MP
10	Motamedi et al. (2021)		x							x		x					x						x						GA, SW
11	Bertolini et al. (2021)	x																											
12	Hadian et al- (20221)		x			x				x					x	x	x			x			x				x		GA
13	Sharifi et al. (2021)		x	x			x		x					x	x	x	x	x			x				x		x		GA, SA, TLB
14	Guo et al. (2021)			x					x					x			x	x							x				NDBM
15	Ait-El-Cadi et al (2021)		x				x			x					x		x			x			x						
16	Wu et al. (2021)			x	x				x						x					x									
17	Alarcon et al. (2021)			x			x		x			x																	

Table 7: Classification of publications

ID	Publication (Author, year)	Type of publication			Type of solution				scope		Focus					maintenance strategy				production planning			condition monitoring			evaluation			Algorithm
		review	concept	case study	approach	model	method	instantiation	specific	general	condition monitoring	maintenance	PPC	CM & maintenance	maintenance & PPC	reactive	preventive	predictive	prescriptive	production planning	detailed production planning	production control	none	offline	online	none	theoretical	practical	
18	Zhou et al. (2021)		x							x		x				x	x						x				x		
19	Lo et al. (2021)	x			x					x																			
20	Zhang et al. (2021)		x			x			x						x	x	x			x			x				x		PA
22	Bousdekis et al. (2021)	x			x					x					x											x			
25	Le et al. (2021)		x			x			x						x		x				x		x						BHA
26	Dutta et al. (2021)			x			x		x						x		x			x			x						
27	Wang et al. (2021)																x				x		x						
29	Zhang X., Xia T. et al. (2021)		x			x				x					x	x	x			x			x				x		GA
30	Moghaddam et al. (2020)			x			x		x			x				x	x			x			x					x	PA
31	Noman et al. (2021)																												
32	Zhang Y. Sun M. et al. (2021)												x										x						SW
33	Meissner et al. (2021)		x		x				x			x							x						x		x		
34	Zhai et al. (2021)		x	x										x	x			x		x					x		x	x	DL
35	Hermann et al. (2021)	x																											
36	Antonella et al. (2021)		x				x			x					x		x			x			x				x		GA, HS
37	Hajej et al. (2021)		x		x					x					x		x				x		x				x		

Table 7: Classification of publications (continued)

ID	Publication (Author, year)	Type of publication			Type of solution				scope		Focus					maintenance strategy				production planning			condition monitoring			evaluation			Algorithm
		review	concept	case study	approach	model	method	instantiation	specific	general	condition monitoring	maintenance	PPC	CM & maintenance	maintenance & PPC	reactive	preventive	predictive	prescriptive	production planning	detailed production planning	production control	none	offline	online	none	theoretical	practical	
43	Shi et al (2020)			x		x				x				x			x								x			x	
45	Kolus et al. (2020)		x			x				x					x		x			x			x				x		
51	Hu et al. (2020)		x			x				x					x		x				x		x						GA
58	Ghaleb et al.		x			x			x						x			x		x					x			x	GA
61	AlShayea et al. (2020)																												TS
77	Takeda et al. (2020)		x			x				x			x							x			x			x			
80	Zhai et al. (2020)		x			x				x				x	x			x		x					x		x		
82	Ansari et al. (2019)		x			x				x				x					x						x			x	

Table 7: Classification of publications (continued)

3.2.3 Discussion of literature review

The world experiences a shift in industrial maintenance: By the increasing popularity of machine learning algorithms and tools for deploying them, preventive maintenance is being replaced by predictive maintenance more and more often, as the required technology becomes easier accessible.[81] Due to the emergence of cyber-physical production systems Ansari et al. go one step further by defining prescriptive maintenance.[82] However, predictive or prescriptive maintenance does not always have to make economic sense. This can depend on several factors, such as the degree of complexity of the machine, the operating mode, and whether it is a series device. Either way, integrating a predictive maintenance system into a production system remains a complex task. In practice, some potential for optimization is lost because production planning is not linked to the machine's condition.[83] In the literature review conducted by Karner, over 60% of the analyzed publications that discuss integrating condition data into production planning are based on preventive maintenance, where condition monitoring is used as thresholds for triggering alarms for preventive maintenance actions.[84] This indicates a lack of connection between predictive maintenance and production planning and control.

Sharifi and Taghipour also state that production scheduling and maintenance planning are interdependent, but this dependency is ignored in most research work.[85] They propose a single-machine multi-failure mode production environment regarding machine deterioration for joint optimization of production sequences and repair strategies. Similar to using health indices, they consider discrete deterioration states that influence the job's processing time. They aim to optimize job sequence and state-dependent deterioration thresholds.[86]

Ait-El-Cadi et al propose one of few publications focusing on joint optimization of maintenance policy, production policy, and quality policy but neglect the integration of condition monitoring.[87,88] Zhang et al. present a model for minimizing makespan and maintenance costs in assembly permutation flow shop scheduling by considering an age-based preventive maintenance strategy.[89] Therefore, they consider probability-based preventive and corrective maintenance activities and neglect the usage of actual condition data. In their recent literature review, Bousdekis et al. as well identified

[81] cf. acatech 2015, p. 7.
[82] cf. Ansari et al. 2019, p. 482.
[83] cf. Zhai and Reinhart 2018, p. 299.
[84] cf. Karner 2019, p. 40.
[85] cf. Sharifi and Taghipour 2021, p. 1.
[86] cf. Ibid., p. 5.
[87] cf. Ait-El-Cadi et al. 2021, p. 4.
[88] cf. Ibid., p. 19.
[89] cf. Zhang et al. 2021b, p. 552.

research gaps in taking into account the current level of degradation and utilizing real-time data[90].

Yang et al. address a single-machine multi-product production problem. They criticize that the interdependent production scheduling and maintenance problems are primarily approached by assuming fixed preventive maintenance activities according to the plan created in advance. They, therefore, model machine condition as a function of usage time but dispense with integrating a data-driven approach for machine condition. They identified two categories for integrating maintenance and production scheduling (considering deterioration effects) discussed in the literature: Models that represent deterioration effects by usage time and models that use certain probability distributions for classifying the condition within a discrete multi-state deterioration process.[91]

Uit het Broek et al. describe their approach to be the first to combine the isolatedly well-studied policies of condition-based maintenance and condition-based production into condition-based maintenance and production policy.[92] They utilize condition information for both scheduling maintenance and adapting production rate but do not consider production scheduling within their approach. Notably, they also discuss various maintenance strategies and production planning parameters according to the impact on costs/revenue.[93] Different situations and their corresponding effectiveness for condition-based monitoring, condition-based production, and a combination of both are highlighted.

Zhai et al. aim to close the gap between research and industry considering predictive maintenance by proposing a holistic framework that directly aims to integrate PdM-models with production scheduling. They propose a framework for predictive maintenance-integrated production scheduling by operation-specific health prognostics. The framework utilizes sensor data, failure events, historical production data, and future production orders as input. It considers data preparation, a health indicator model, and PdM integrated production scheduling as main modules to create a production and maintenance plan.[94]

[90] cf. Bousdekis et al. 2021, pp. 6–7.
[91] cf. Yang et al. 2021, pp. 1–2.
[92] cf. uit het Broek et al. 2021, p. 9.
[93] cf. Ibid., pp. 7–8.
[94] cf. Zhai et al. 2021, p. 4.

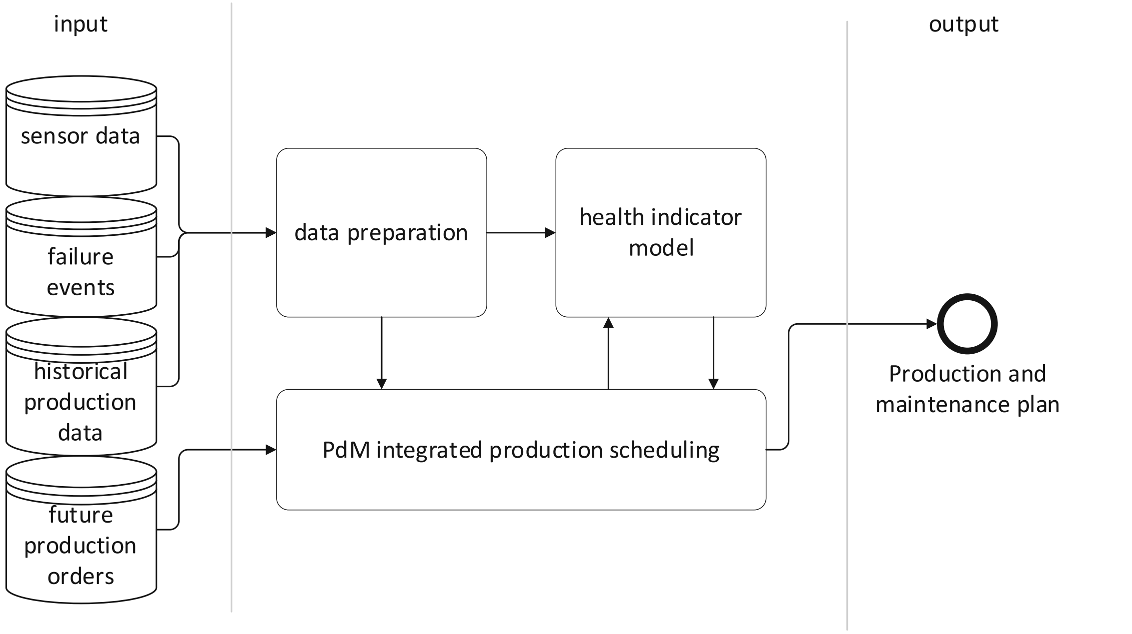


Figure 11: Framework for predictive maintenance-integrated production scheduling[95]

The publication focuses on state prediction and state estimation instead of RUL predictions because a high amount of failure data (required for creating RUL labels for supervised prediction techniques) is often not available in practice.[96]

Moghaddam presents a repairable multi-tasking manufacturing machine problem with multiple components and criticizes that in the literature, the relationship between maintenance and production scheduling is commonly described as a single machine problem with an explicit mathematical model representing machine degradation.[97] Even though, „recent technological complexity of modern manufacturing machines has increased the level of inherent interdependencies between production plans and maintenance operations systems."[98]

Branda et al. use metaheuristics for integrating maintenance activities into a flow shop scheduling problem. They state that researchers assume preventive maintenance without unexpected failures or random machine failures in the literature on this problem. They also refer to the problem of maintenance planning commonly not being integrated with production scheduling activities.[99]

Therefore, the authors Branda et al. provide a new solution to the flow shop scheduling problem by integrating preventive maintenance and machine failure. They thereby do

[95] cf. Zhai et al. 2021, p. 4.
[96] cf. Ibid., p. 2.
[97] cf. Moghaddam 2020, p. 84.
[98] Ibid., p. 83.
[99] cf. Branda et al. 2021, p. 1.

not make use of condition data, as machine failure is modelled stochastically to be subject to a Weibull distribution.[100]

Hajej et al. introduce an approach for the simultaneous integration of production, maintenance, and quality, which they state a minimal number of studies yet deal with. They consider the influences of the production rate on machine condition and quality deterioration but reduce the complexity by assuming i) quality inspections only at the end of manufacturing operations and ii) negligible durations of preventive and corrective maintenance activities.[101]

Kolus et al. propose a mathematical model that integrates production scheduling and predictive maintenance planning or a single-machine problem. They try to minimize tardiness costs by defining an optimal production and PM schedule simultaneously.[102] Like most other publications on integrating production and maintenance scheduling, they assume stochastic machine failure. The failures follow a Weibull distribution with a shape parameter greater one, indicating that the failure rate rises over time.

The operating setting of a machine is sometimes referred to as operating condition (OC) in the literature. Hu et al. propose a two-machine flow shop model taking into account job-dependent OC. They state to be the first to consider OC in the joint optimization of job scheduling and PM planning and demonstrate the necessity of considering OC in a numerical study. Maintenance activities are considered imperfect maintenance (IM), where the state of the machine is restored to a state between good-as-new and bad-as-old, representing the effect of maintenance on a real machine.[103] In many publications on prediction and maintenance scheduling, a simplifying assumption is that maintenance cannot be conducted while a machine operates but only when a job is finished. Hu et al. consider a use case of a milling machine and a grinding machine, where jobs can be continued at the same stage they were interrupted. They, therefore, assume resumable jobs in their model.[104]

One of few publications that consider integrated production and maintenance scheduling utilizing condition data from online condition monitoring is the work of Ghaleb et al. Due to the recent "advent of information technology and industrial informatics in manufacturing (e.g., Industry 4.0), information about the state of the machine and its degradation level have become instantly available."[105] Therefore they consider such a data source, whereby their results show an increase in average savings by 35% if precise information about the state of the machine and its

[100] cf. Branda et al. 2021, p. 10.
[101] cf. Hajej et al. 2021, p. 237.
[102] cf. Kolus et al. 2020, p. 926.
[103] cf. Hu et al. 2020, p. 232.
[104] cf. Ibid., pp. 232–233.
[105] Ghaleb et al. 2020, p. 2.

degradation level is available.[106] They identified studies in the literature that discuss the integration of production and maintenance scheduling and put them into two categories: i) Models that represent the condition of the machine using its age and lifetime information, where failure times follow a particular probability distribution (e.g., Weibull distribution, which is used in several publications cited in this thesis) and ii) models that represent the condition of a machine as a discrete multi-state deterioration process, where transitions between a machine's states follow a certain probability distribution.[107] Ghaleb et al. consider *m* discrete deterioration states, where maintenance activities cause a better state, and a worse state occurs with a rising probability over time. Different types of maintenance are possible, so the state after a maintenance activity can improve by one or several states.[108] The discrete states can be considered similar to methods from prognostics and health management, where machine condition is often categorized into discrete states as well.

Another factor that increases complexity in production scheduling is re-scheduling. Takeda Berger et al., therefore, propose a conceptual model for predictive-reactive production scheduling. While their approach is only data-driven by considering inventory data but no condition data, the work still emphasizes the importance of predictive and reactive schedules in real applications.[109]

Zhai et al. identified that many scheduling approaches exist for the job shop, a widely applied manufacturing process model. However, few have taken into account maintenance activities and current and future machine conditions. Integrating the job shop scheduling problem (JSSP) is vital for the success of predictive maintenance in the industry. They propose a novel conceptual framework for maintenance integrated production scheduling.[110]

3.3 Summary of the literature review

While condition monitoring and remaining useful life (RUL) predictions are well established in the literature and are on the rise for industrial applications, there is a further need for additional research regarding the interpretation and application of machine condition information in production scheduling processes. This research gap, for example, led to the formulation of the maintenance integrated job shop scheduling problem (MIJSSP).[111] However, yet hardly any publications emphasize the MIJSSP or other, similarly derived problems.

[106] cf. Ghaleb et al. 2020, p. 2.
[107] cf. Ibid., p. 3.
[108] cf. Ibid., p. 5.
[109] cf. Takeda Berger et al. 2019, p. 1345.
[110] cf. Zhai et al. 2019, p. 1.
[111] cf. Ibid., p. 3.

Joint consideration of predictive maintenance and production planning is still rarely the case in today's literature. The majority of the publications thus analyzed preventive maintenance. Depending on the main area of the researchers, a clear focus on either i) maintenance or prognostics and health management or ii) production planning and control can also be identified.

Publications that focus on the maintenance or prognostics and health management domain usually emphasize improving condition estimation for predictive maintenance. The technically complex part of such work is often in the area of data mining and the use of machine learning algorithms to make better predictions. If production planning processes are integrated, this usually results in simplifying assumptions, or reference is made in the outlook to further research possibilities.

Publications that focus on the production planning and control domain usually emphasize production optimization problems, which are often solved with heuristics. There are approaches to include condition data of machines and equipment in production planning. However, the majority of them assumes condition information to be available or stochastically determined condition information, which, for example, assume a condition degradation based on probability over time. Some publications, however, also deal with the integration of actual condition data or refer to their necessity. If integration with maintenance strategies is considered, more simplifying assumptions are usually made on the maintenance part. Often only reactive or only preventive maintenance activities are considered, sometimes both. Consideration of predictive maintenance is largely neglected.

The several different ways in which production systems can be implemented pose a particular challenge for generalizing concepts. An example that clearly shows this are the model assumptions made in the analyzed publications. As an example, the assumptions of Zhang et al. (2021) are given here, which imply an adaptation to a particular type of production system:[112]

- All jobs are ready at zero time (typical for group production when demand is fixed)
- Only one job can be processed at one time with no interruption, and PM can only be performed before or after processing one job
- The machine can only process a job or perform PM at one time
- The machine must be re-setup for processing jobs after PM
- setup time for processing identical jobs ignored

[112] cf. Zhang et al. 2021a, p. 7.

Another vital assumption that must be made is about the effect of maintenance activities. The terms “as good as new”, “not as good as new”, and “as bad as old” are therefore commonly used in the literature.

“As good as new” assumes that the machine or equipment condition is fully restored. Therefore, the health indicator of the observed component is set to its maximum again after maintenance is conducted. “Not as good as new” describes improving the machine or equipment condition, but not necessarily restoring the full health by conducting a maintenance activity. “As bad as old” is the assumption of restoring the same condition state of the machine or equipment as it was before a failure and is therefore used for certain corrective maintenance activities. For example, if a machine is in "2" state and a sudden error occurs, the corrective maintenance activity will restore it to "2" state. The majority of the analyzed models and methods utilize the assumption of “as good as new” for preventive (or predictive) maintenance activities.

To our best knowledge, the first publication that integrates predictive maintenance and condition-based production scheduling into one model is the work by Zhai et al.[113] that proposes a predictive maintenance integrated production scheduling (PdM-IPS) model. This model incorporates data of future production order and planned production sequences for an improved health indicator prediction. Their model that utilizes deep learning with three layers is validated on simulated data (NASA’s C-MAPSS turbofan engine datasets) and on CM data from flexible machining centers in a real industrial production environment[114]. Thereby they use clustering methods to be able to work with unlabeled data. This impedes the process of model creation. On the other hand, delivers results that are more likely implementable in real industry use cases because failure data for labeling is often nonexistent.

The output of their proposed framework is a production schedule, which incorporates required maintenance actions. Like other scheduling applications, the plan can be optimized regarding several objectives, such as makespan, tardiness, costs and the predicted machine degradation. However, the paper focuses on the presented health model, which extracts an operation specific health indicator from condition monitoring data. For actual utilization of the proposed degradation model for predictive maintenance integrated production scheduling is referred to as an outlook for future publications.[115]

In conclusion, it can be said that the integration of condition data in production scheduling has not yet been discussed extensively in the literature, although the potential was recognized some time ago. However, especially in the last few years, the topic came in sharper focus. Thus, integrating condition data into production

[113] Zhai et al. 2021.
[114] cf. Ibid., p. 13.
[115] cf. Ibid., p. 4.

scheduling is also developing into a more extensive research area after the paradigm of condition-based maintenance was substantially researched.

4 Applied research design methodology

4.1 Design science

Research in the Information Systems discipline can be categorized into behavioral science and design science. While behavioral science focuses on human or organizational behavior, design science seeks to extend human and organizational capabilities through innovation. Design science is a method to foster knowledge of a problem domain and its solution by building and applying a designed artifact.[116]

The essence of design science is to deliver a process for finding profound solutions for scientifically or economically relevant problems. Therefore, the design science methodology can be structured into the following seven research guidelines:[117]

1. Design an artifact: Building of a construct, model, method, or an instantiation

By definition, the result of design science research is a purposeful artifact addressing organizational problems. Thereby, an artifact can be instances, constructs, models, or methods applied in the practical implementation of information systems. Human behavior and the organizational and social contexts of using the artifact are not considered within the artifact. The behavioral science part is considered interdependent and coequal with artifacts in business needs.[118]

2. Problem relevance: Development of technology-based solutions to important and relevant business problems

The second guideline focuses on developing and defining relevant problems. In the field of information systems, the research's objective is to acquire knowledge for enabling the development and implementation of technology-based solutions. The solutions thereby should be derived from essential yet unsolved business problems. Design science, therefore, focuses on developing innovative artifacts, allowing for a change in the occurring phenomena. On the other hand, behavioral science addresses the same issues by constructing theories explaining or predicting occurring phenomena. An example is technology acceptance, which can be described by behavioral theories. An approach from both the design and the behavioral science side can be required to address such issues.[119]

3. Design evaluation: Evaluation of the design artifact by evaluation methods

[116] cf. Hevner et al. 2004, p. 75.
[117] cf. Ibid., p. 83.
[118] cf. Ibid., p. 82.
[119] cf. Ibid., p. 84.

Evaluation methods assessing the quality and utility of an artifact are emphasized in the third guideline. Evaluating an artifact strongly depends on the business environment and the related problems the artifact is designed for. These problems can define the requirements and, therefore, the foundation for evaluation. Appropriate metrics need to be defined in advance, just like relevant data for measuring predefined attributes need to be gathered. Evaluation of an artifact can emphasize functionality, completeness, consistency, accuracy, performance, reliability, usability, or fit with the organization. Considering an iterative design process, evaluation should also occur throughout the project instead of within one final assessment. Iterative evaluation can deliver valuable feedback already during the construction phase. Hevner et al. summarized the following five groups of evaluation methods:[120]

Observational	Case study: Study artifact in depth in business environment
	Field study: Monitor use of artifact in multiple projects
Analytical	Static analysis: Examine structure of artifact for static qualities (e.g., complexity)
	Architecture analysis: Study fit of artifact into technical IS architecture
	Optimization: Provide optimality bounds on artifact into technical IS architecture
	Dynamic analysis: Study artifact in use for dynamic qualities (e.g., performance
Experimental	Controlled experiment: Study artifact in controlled environment for qualities (e.g., usability)
	Simulation: Execute artifact with artificial data
Testing	Functional (black box) testing: Perform coverage of some metric (e.g., execution parts) in the artifact implementation
	Structural (white box) testing: Perform coverage testing of some metric (e.g., execution paths) in the artificial implementation
Descriptive	Informed argument: Use information from the knowledge base (e.g., relevant research) to build a convincing argument for the artifact's utility
	Scenarios: Construct detailed scenarios around the artifact to demonstrate its utility

Table 8: Evaluation methods and categories

4. Research contributions: Providing clear and verifiable contributions in the areas

Guideline four focuses on answering the question: "What are the new and interesting contributions?" Design science research has to provide contributions in one of the following three areas: The design artifact, the foundations (design construction knowledge), or methodologies (design evaluation knowledge). The design artifact itself is often also the contribution of design science research. Thereby it should either extend the knowledge base or apply existing knowledge in new and innovative ways. The foundations comprehend the development of constructs, models, or instantiations,

[120] cf. Hevner et al. 2004, p.85f.

which are not the artifact itself. A requirement is that they need to extend existing foundations in the design science knowledge base. The third form of research contribution is methodologies, which describe the development of new evaluation methods and metrics for experimental, analytical, and observational testing or descriptive evaluation.

5. Research rigor: Application of rigorous methods in the construction and evaluation of the design artifact

Rigorous research methods are often linked to mathematical formalism describing the specified artifact. Design science requires rigorous methods. Nevertheless, it is worth mentioning that applicability and generalizability have to be considered as well. Over-abstraction and omission of essential parts of the problem should be avoided. Therefore, research rigor in design science aims to use knowledge from theoretical foundations and research methodologies in an effective manner.[121]

6. Design as a search process: The search for an effective artifact requires utilizing available means while satisfying laws in the problem environment

Design science is iterative. It can be described as a cycle of generating design alternatives and testing alternatives against requirements/constraints. The design process is a search process, utilizing available means to discover effective solutions while satisfying restrictions existing in the environment. Thereby, the means comprehend the actions and resources available for artifact construction. All possible means that can satisfy all end conditions specify the set of all possible design solutions. Nevertheless, due to the nature of possible design problems, it may not always be possible to determine the appropriate means, ends, and laws. Therefore, knowledge in both the application domain and the solution domain is required for successful problem-solving.[122]

7. Communication of research: Presentation to technology-oriented as well as management-oriented audiences.

Both, the technology-oriented and the management-oriented communication channel has its importance. Communicating results on a technological level focus on describing the artifact in detail and clarifying construction and application. Researchers and practitioners must be provided with an understandable description of the artifact and its development to enable reproducibility and creating a knowledge base for further extension. Communicating results on a managerial level focus on the benefits and effectiveness of the provided solution for the underlying problem, as well as the required effort for implementing the solution. Therefore, management-oriented

[121] cf. Hevner et al. 2004, pp. 87–88.
[122] cf. Ibid., p. 88.

communication emphasizes the problem relevance and requirements for utilizing a particular solution rather than the artifact's functionality.[123]

4.2 Product development

The starting point for product development is often external or internal product planning, which results in a description of a development request, depending on the project situation. The spectrum can range from clients and customers to development for abstract customer groups or market segments. A development request can thus cover a wide range and include ideas, wishes, visions, goals, etc., as well as already detailed use cases, requirements for functions, features or characteristics, and interfaces of the product. Depending on the complexity of the task, activities can be subdivided into further sub-activities. The activities do not have to run rigidly one after the other. However, they are often iterated through by going back to previous sections in order to achieve better solutions or optimizations step by step. Thus, depending on the development task, activities within the scope of product development can be necessary for various intensities. The following activities are therefore described within product design:[124]

1. Clarifying and itemizing the problem or task

Clarifying the problem or task can deliver new requirements, which have not been obvious from the perspective of given objectives. These activities include gathering all available information on the product context, identifying information gaps, reviewing and adding to the requirements received, adding one's own requirements, or consciously formulating the problem from the developer's point of view. A formulation and itemization of the problem to be solved facilitates the search for a solution. The advantage of a precise formulation of the problem at hand is that it focuses on the core problem and its requirements, without prematurely favoring certain solution approaches. The requirements are not static but build an information base for all subsequent activities and can be further refined. Findings during the development process can lead to existing requirements having to be changed and new requirements having to be added.[125]

2. Determining functions and their structures

In the design process, a function-oriented approach may expand the search space and support the search for alternative or innovative solution principles. Functions define how a product or one of its components operates and what they do. Determining functions and their structures also supports widespread development methods such

[123] cf. Hevner et al. 2004, p. 90.
[124] cf. VDI Society Product and Process Design 2019a, pp. 33–35.
[125] cf. Ibid., pp. 35–36.

as failure mode and effects analysis (FMEA). Undesired disruptive functions should be differentiated from desired purpose functions so that solutions for their avoidance or mitigation can also be identified. Differentiation between primary and secondary functions can help to emphasize the relevance of individual functions. For simple products, a purely verbal description in the form of function lists is often sufficient. For more complex products with more extensive energy, material, and information flows, functional models, such as hierarchically structured function diagrams, are more appropriate.[126]

3. Assessing and selecting the solution concept

A continuous review of the results against the requirements can already limit possible solutions continuously. Nevertheless, often several alternatives that satisfy all previously defined requirements remain. Since it is usually impossible to detail all alternatives for time or financial reasons, there must be planned activities to evaluate and select the most promising solution concepts. Therefore, a vital part is the definition of suitable assessment criteria, which can be done by weighting the existing requirements. The execution of assessments depends on their complexity and objective. Many assessment methods rely on textual or mathematical comparison of solution concepts. Regardless of the assessment method used, it is almost inevitable that they cannot be free of subjective influences, which is why it is permissible to take experience and intuition into account.[127]

4. Subdivision into modules – interface definitions

The selected solution concepts can then be divided into modules for realization. As a result, a systems architecture with its interfaces is developed. Thereby, the intended solution is subdivided into main groups and elements necessary for its implementation. The importance of modularization before starting the design steps is higher for complex products. Possibilities for structuring the modules are discipline-specific or pragmatically work-related. At that point, parallel lines of product development are created that can be considered individually and separately but still must be coordinated with each other.[128]

5. Design of the modules

This activity describes the realization of the modules by specifying them in more detail. It can be performed separately for different modules as well and aims to deliver a preliminary design that allows for identifying and selecting an optimum design.[129]

[126] cf. VDI Society Product and Process Design 2019a, pp. 36–37.
[127] cf. Ibid., pp. 38–39.
[128] cf. Ibid., pp. 39–40.
[129] cf. Ibid., p. 40.

6. Integrating the product as a whole

The previously specified modules are then designed in detail in order to link all groups and elements for merging them to a product. Thereby this phase can be described as the final design. The result of this activity is an overall design necessary for product realization.[130]

7. Elaborating the details of execution and use

This activity interacts with the previous ones because they have already created essential specifications for the technical production realization as well as for the product use. Elaborating on the details of execution and use should deliver the product documentation regarding manufacturing, usage, and certification.[131]

8. Assurance of the fulfillment of the requirements

The assurance covers all activities of analysis that aim for the comparison of results and objectives. One can thereby differentiate between verification and validation. Verification aims to determine whether the product fulfills the requirement of its specification. Validation describes whether the product meets the purpose of its intended usage.[132]

In a practical application, the activities described above, as well as their objectives, are planned in phases. The results of those product design activities, which can be requirements, function models, basic solution concepts, the solution concept, systems architecture, partial design, overall design, and product documentation, are considered iteratively improved artifacts that interact with the objectives and activities.[133]

[130] cf. VDI Society Product and Process Design 2019a, p. 40.
[131] cf. Ibid., pp. 40–41.
[132] cf. Ibid., pp. 41–42.
[133] cf. VDI Society Product and Process Design 2019b, p. 8.

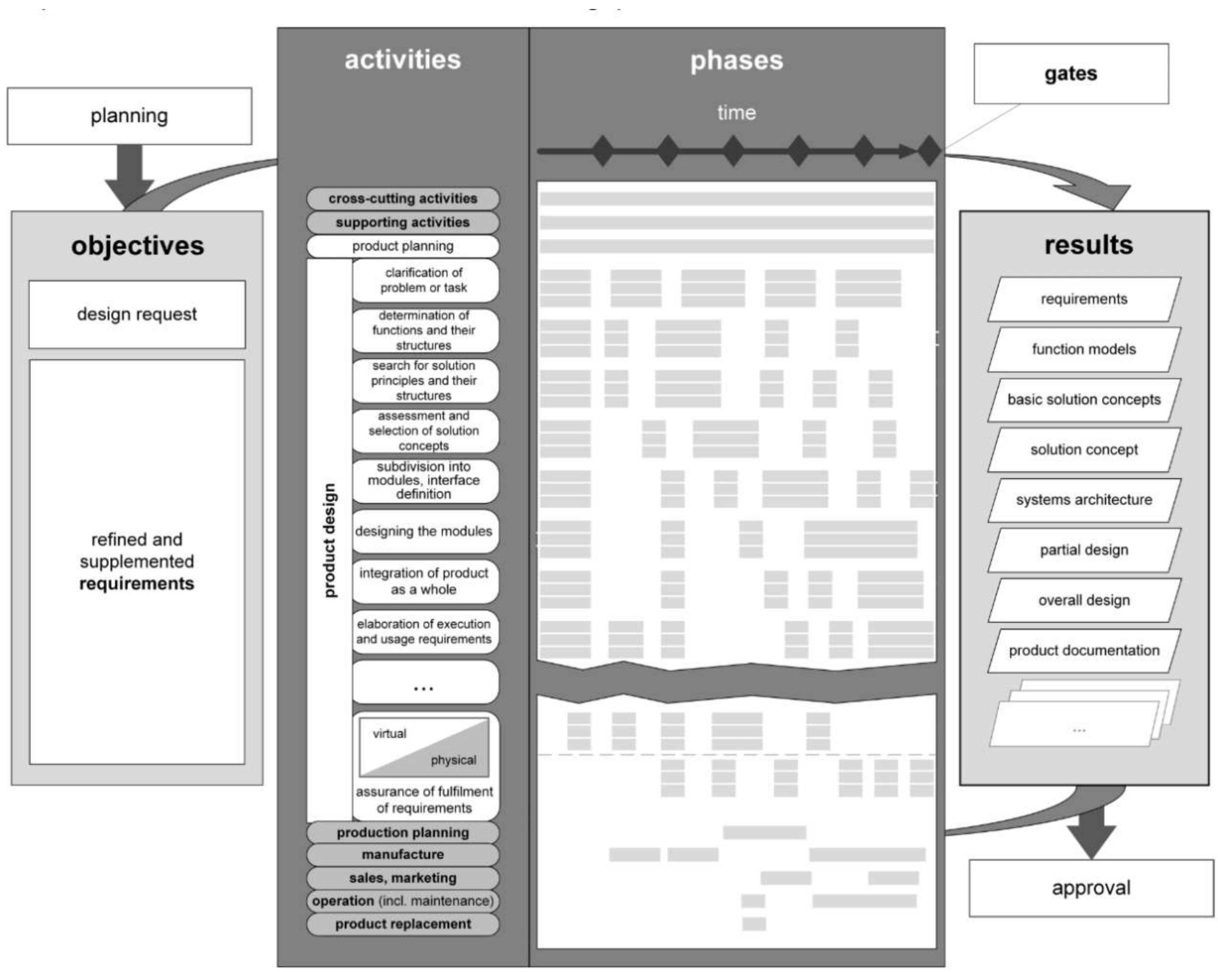


Figure 12: Specific model of a product design process[134]

4.3 Systematic literature review

The research methodology is designed along the lines of Tranfield et al.[135], by depicting a three-step process for conducting literature reviews:[136]

i. Planning the review
   a. Identification for the need for a review
   b. Preparation of a proposal for a review
   c. Development of a review protocol
ii. Conducting a review
   a. Identification of research
   b. Selection of studies
   c. Study quality assessment
   d. Data extraction and monitoring progress
   e. Data synthesis

[134] VDI Society Product and Process Design 2019b, p. 9.
[135] Tranfield et al. 2003.
[136] cf. Ibid., p. 214.

iii. Reporting and dissemination
    a. The report and recommendations
    b. Getting evidence into practice

4.3.1 Planning a review

Tranfield et al. describe the first stage as an iterative process consisting of the definition, classification, and refinement of research objectives. Essential steps are the creation of a review protocol and the formulation of a review question. The review protocol serves to ensure the objectivity of the review by defining and recording all essential steps. Boundary conditions such as time periods, publications, and databases are defined. In addition, a definition of quality criteria is created according to the relevance and quality of the publications to be evaluated, taking into account the context of the review question. Any exclusion of publications can thus be evaluated objectively.[137]

4.3.2 Conducting a review

The fundamental differences between a traditional (narrative) and a systematic literature review are comprehensiveness and objectiveness. The starting point of the review is the selection of keywords from a selective preliminary analysis. Logical combinations of the keywords then form the search terms. The literature review is conducted under consideration of the boundary conditions defined in the review protocol. The result is a list of publications that form the basis of the literature analysis. Next, the publications are evaluated regarding their quality, whereby the quality criteria defined in the review protocol serve as evaluation criteria. If the criteria are not fulfilled, the observed publication is excluded from the list. Once the list of publications has been selected, data and information must be extracted from them. In addition to general information, certain features and specific information are also analyzed. The features that are used to classify the publications are defined initially.

Nevertheless, as the analysis continues, it may be necessary to add additional features. The process of information extraction is, therefore, iterative. The result of information extraction is an aggregated representation of the knowledge contained in the publications that have been considered independently up to this step. In information synthesis, the task is to compare the different publications. In the field of management sciences, comparability between publications is often difficult due to the significant differences in the research questions. Therefore, meta-analyses are suitable for information synthesis. Narrative analyses are also suitable for describing

[137] cf. Tranfield et al. 2003, pp. 214–215.

and comparing the content of different publications, but these often have a notable subjective influence.[138]

4.3.3 Reporting and dissemination

A characteristic of high-quality literature analysis is that they are synthesized from the primary literature and thus provide users with a better insight into the research subject. Specifically for the discipline of management science, results should be analyzed in two stages. The first stage is a descriptive analysis of the research results, including categorizing the literature based on a set of features. The second stage is a thematic analysis of the researched publications (e.g., narrative literature discussion).[139]

[138] cf. Tranfield et al. 2003, pp. 215–218.
[139] cf. Ibid., pp. 218–219.

5 Physical demonstrator for condition-based production scheduling

5.1 Definition of the use-case

At the beginning of the project, the concrete task and the available resources were not explicitly given. Therefore, defining those was an essential part of the work. With regards to the VDI2221, the product development process was thus started with the product planning. Therefore, the first steps are clarifying the problem or task and determining functions and their structures.

5.1.1 Requirements

In the initial situation, an application was available that performed condition-based scheduling using an algorithm based on production and condition data. This application was developed in a PHD thesis[140] at TU WIEN and is further referred to as "scheduling application". To illustrate condition-based scheduling and sequencing, we lacked a use case to provide production and condition data and show the connection between machine condition and production planning. So, on the one hand, the project should cover the physical demonstrator to deliver condition data. On the other hand, a use case that allows assumptions for production data should be developed. The environment in which the demonstrator will mainly be used is at fairs. Thus, knowledge transfer through interaction should be possible even with short attention spans or within limited timeframes.

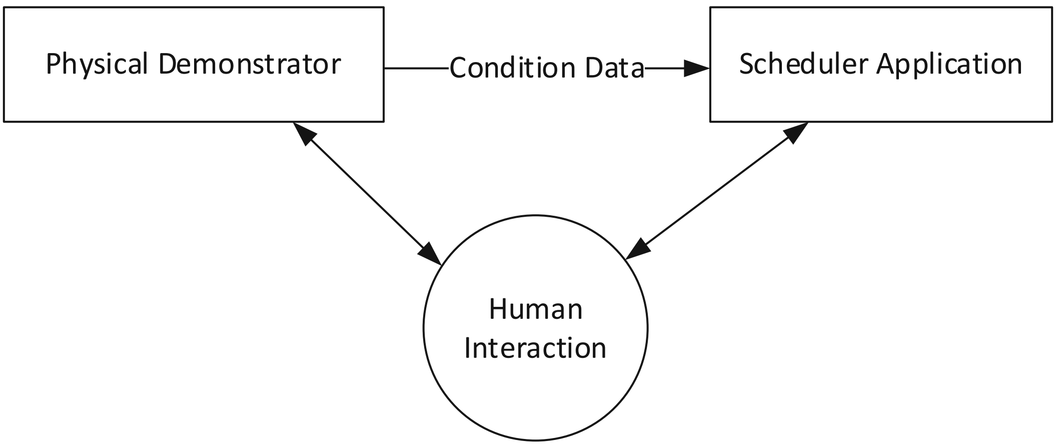


Figure 13: Integration of physical demonstrator

The demonstrator represents a production machine and serves as a data source for condition data acquired by applied sensors. It should be applicable for different use

[140] Karner 2019.

cases, such as a single production machine or as part of a production system with multiple machines.

We could therefore derive the following requirements:

1. Deliver condition data like a real production machine equipped with sensors
2. Emphasize the applicable pillars of industry 4.0: System integration, cloud computing, IoT
3. Utilize condition data for production scheduling
4. Convey knowledge on condition-based scheduling
    - In a limited timeframe
    - Suitable for short attention span
5. Integrate the available scheduling application
6. Transportability

5.1.2 Functions

The scheduler application requires the condition data in the form of a single value that describes the machine's condition with respect to the processing step required for production. The term health points (HP) is widely used in prognostics. In this case, this term describes the value the demonstrator will send to the scheduling application. A higher HP value thereby means a better condition of the demonstrator for the purpose of production planning in the scheduling application.

The initial approach was to develop the physical demonstrator from scratch. To determine the demonstrator’s condition in a data-driven manner for calculating the HP value, sensors need to be installed first. In order to use a data infrastructure that can also be used in real production environments, a gateway should be able to send the sensor values (after optional preprocessing) into a cloud environment, where the HP of all connected machines can be calculated and utilized. For simulating a production process, actuators like motors need to be installed. To allow users to interact with the demonstrator, possibilities to affect sensor values and actuators by hand must be designed as well.

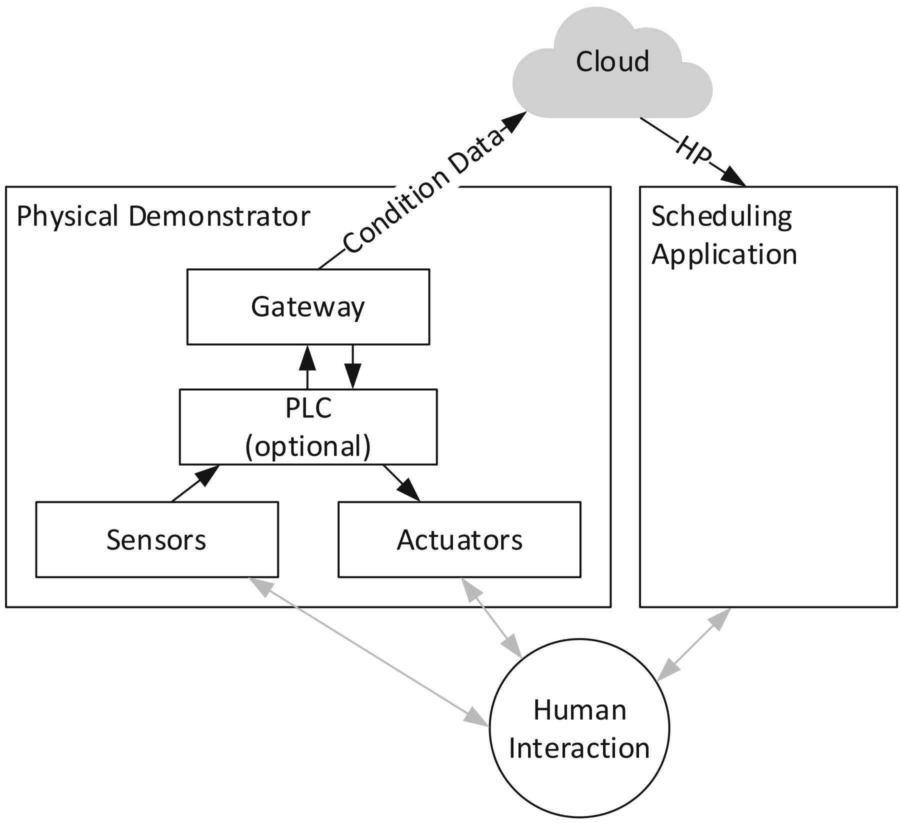


Figure 14: Basic functions of demonstrator

5.1.3 Solution principles

In several brainstorming sessions, we created a variety of solution principles. Those concepts included several features for monitoring and interacting, like oil temperature, leakage detection, hydraulic pressure, bearing condition, and more. However, most concepts were dropped later because an industry partner agreed upon cooperation during the project. This partner provided a demonstrator with already implemented features beyond this project's initial timely and budgetary possibilities. Therefore, we decided to develop additional features for that existing demonstrator in order to implement a suitable use case.

Furthermore, some ideas of those solution principles were later on implemented into the existing demonstrator. Thus, the solution principles can be divided into three main parts:

1. **Hardware and data infrastructure**: What features does the physical demonstrator need? How do we get the sensor data into a cloud environment?
2. **Calculation of health points**: How do we get from sensor data to health points for utilizing them in the scheduler application?
3. **Use Case**: How can we easily communicate the benefits of utilizing this data?

5.1.4 Hardware and data infrastructure

Before discussing further solution principles, we need to describe the demonstrator provided. The hardware contains a drive motor with integrated temperature, angular velocity, voltage, and current monitoring. The driveshaft is connected to a gearbox and a disk brake, with two claw couplings and a rotating torque sensor in between. Users can actuate the disk brake via a rotary knob. The gearbox connects to a clutch that can be switched by pushing a button on the HMI (human-machine interface). The clutch can connect a spindle to the drive. One of the bearings of the spindle is equipped with a vibration sensor. So, users have two ways of interacting with the demonstrator:

1. HMI:
   a. Switch motor on/off
   b. Activate ‘demo mode’ (program that automatically changes mot speed and rotary direction over time)
   c. Control motor speed
   d. Control motor rotary direction
   e. Switch spindle on/off (actuate clutch)
2. Rotary knob
   a. Actuate disc brake

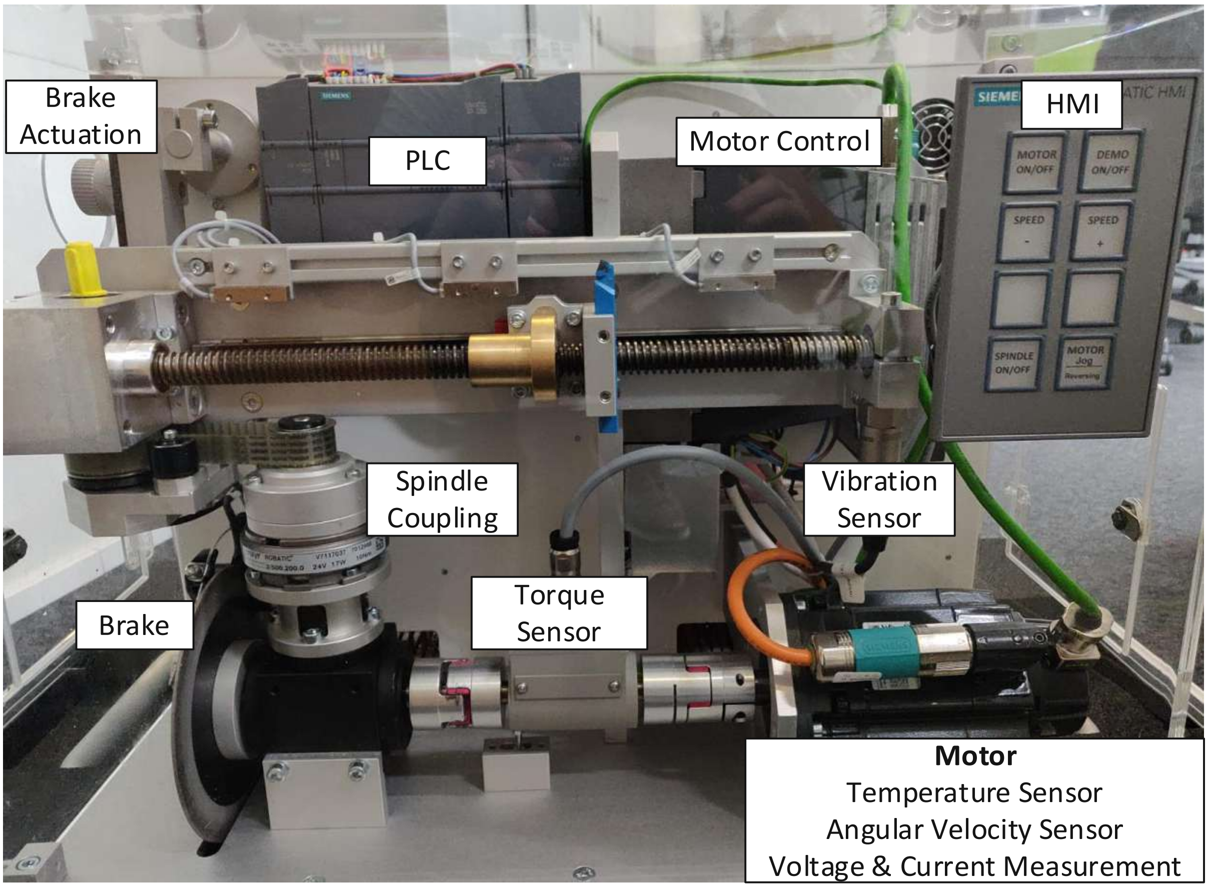


Figure 15: Front of unmodified demonstrator

The PLC gets input data from the HMI, controls the motor and the clutch, and receives sensor data. The demonstrator is also equipped with a CMS (condition monitoring system) that preprocesses data from the vibration sensor. A gateway connected to an LTE module receives data from the PLC and CMS and publishes it to the cloud. This way, a data infrastructure to send sensor data to a cloud environment for further calculation is already available. Figure 16 shows a schematic of the mechanical components and the signal flow:

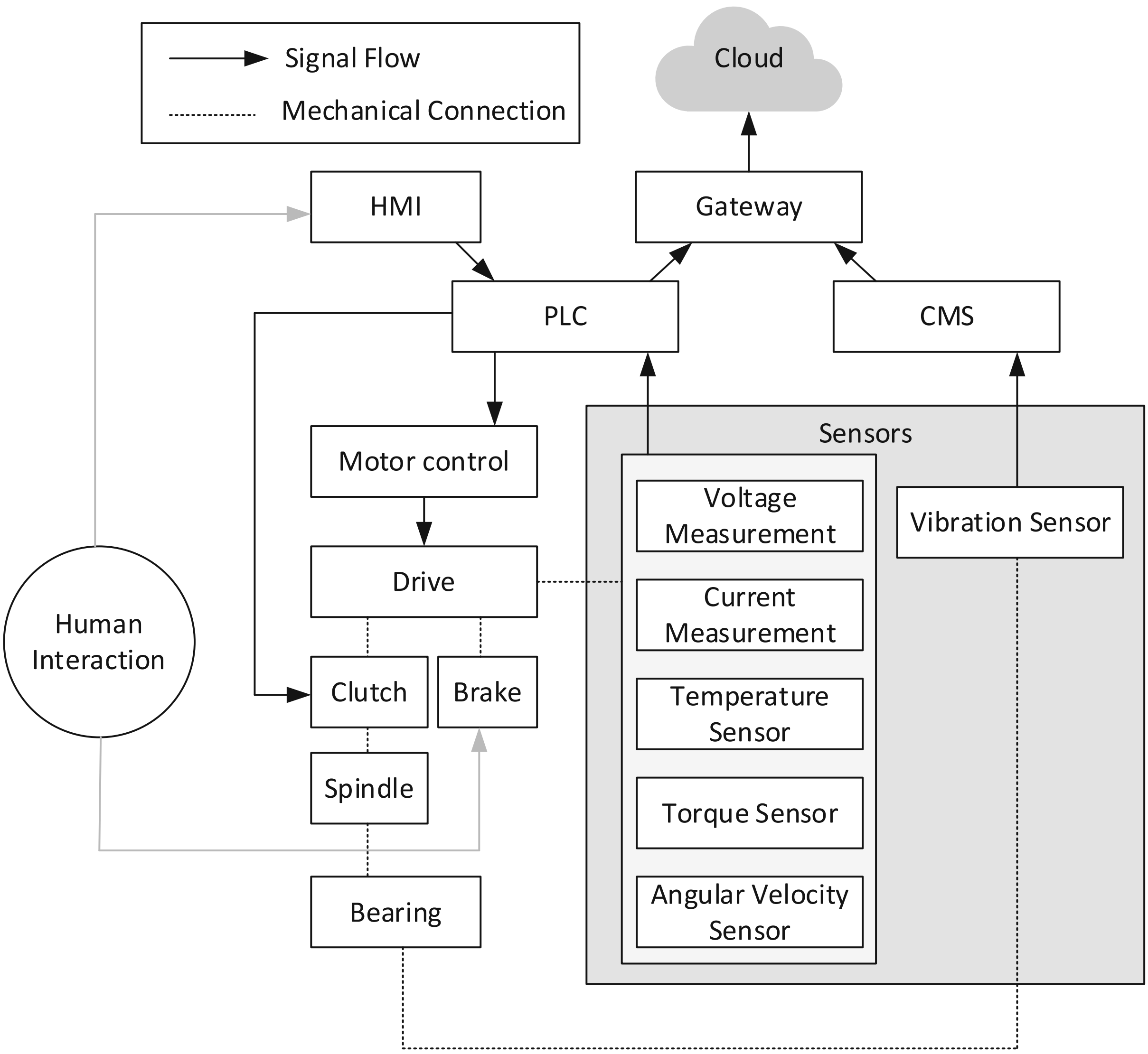


Figure 16: Schematics of unmodified demonstrator

Therefore, the data processing from sensors to the cloud happens according to standards predefined by the industry partner. Therefore, there are some limitations regarding preprocessing and configuration. Configurations can only be changed to some degree and only by a technician of the industry partner. By default, the gateway automatically establishes a connection to the internet on boot. The PLC, condition monitoring system (CMS), and the gateway communicate within one network via OPC

UA (Open Platform Communications Unified Architecture). The gateway establishes a connection to a time-series database within the Mindsphere cloud platform. A snapshot of all sensor values is sent to the cloud each second. There exists a cloud platform to visualize the transmitted sensor data on a timeline view. The data transmission has a delay of about 5 seconds.

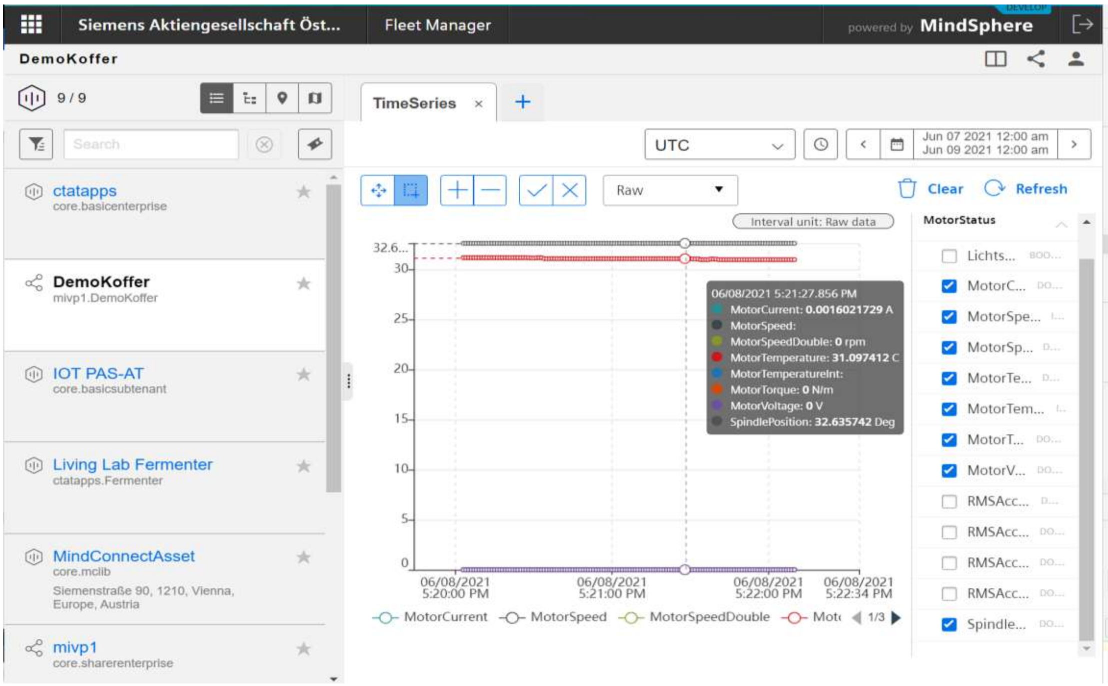


Figure 17: Dashboard of Mindsphere cloud platform

Machine data can be visualized in a chart on the Mindsphere platform. One can browse historical data by utilizing a date- and time-range picker. Also, the chart automatically updates with a delay of about 5 seconds, which helps verify the data empirically when running the demonstrator.

However, no interface allows for receiving that time-series data automatedly at this point. There is only the possibility to export data manually via the graphical user interface. For the purpose of analyzing the data and building prediction models, this is sufficient, but it would not allow for deploying the prediction model.

Figure 18 shows the sensor data's correlation i) motor current and motor torque and ii) motor voltage and motor speed. As they correlate as expected (linear correlation of motor torque and motor current, and linear correlation of motor speed and motor voltage), it can be validated that the sensor measurements of the demonstrator are physically reasonable. We plotted a dataset of 1141 datapoints acquired during test runs and manually exported from the mindsphere platform for this graphic. The second chart shows the correlation between motor speed and motor voltage. We color-mapped the absolute value of the motor torque, showing high torque due to acceleration or deceleration for data points between the predefined motor speed levels (where we see data point clusters).

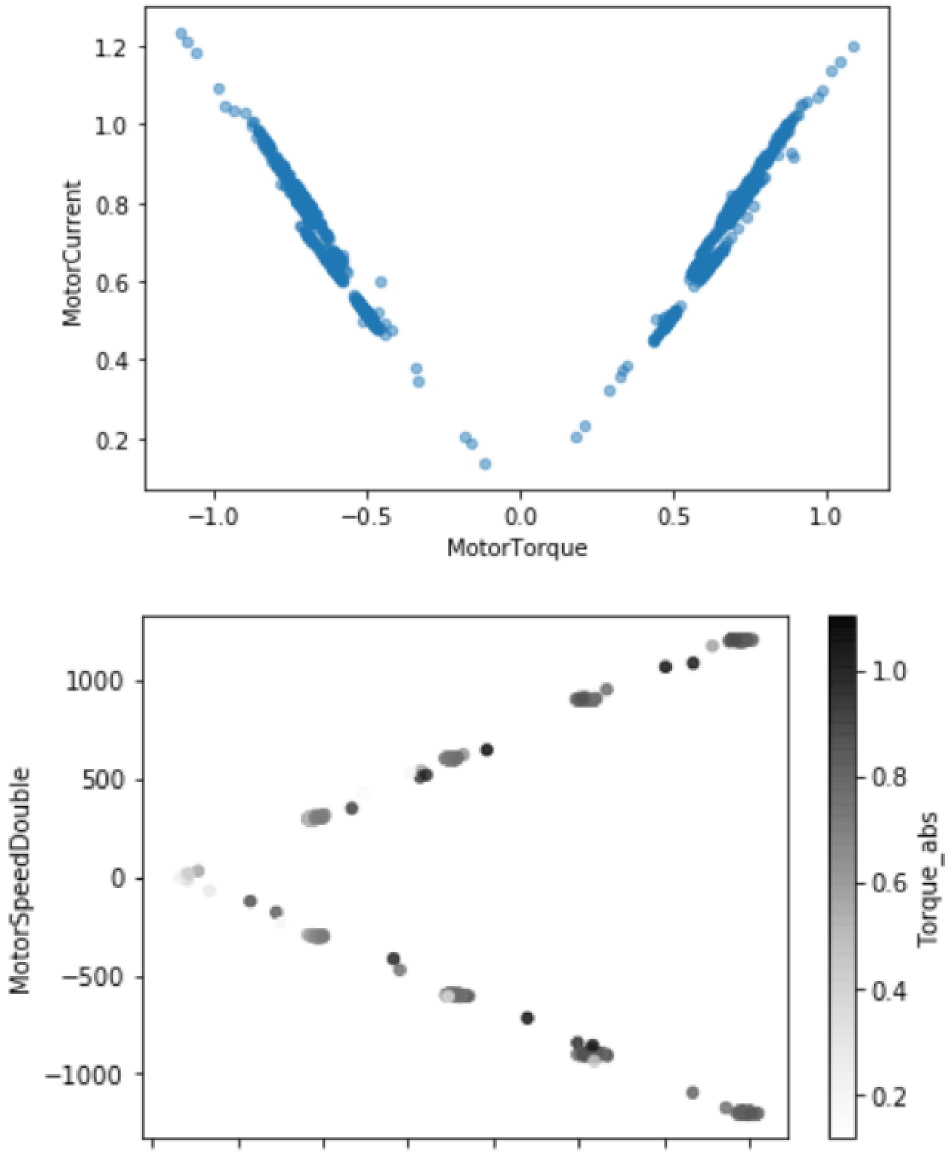


Figure 18: Validation of demonstrator sensor values

As a conclusion of what we talked about in this subchapter so far, we derived two main tasks on modifying the demonstrator at hand:

- Modify hardware of demonstrator to allow for additional user interaction and additional data points
- Modify infrastructure to allow for connecting the demonstrator and the condition-based scheduling application

5.2 Modification of demonstrator

5.2.1 Hardware modifications

Two additional possibilities for interaction were integrated into the physical demonstrator:

- Vibration motor: For simulating a change in environmental conditions, we installed a vibration motor that can be controlled independently and affects the vibration sensor at the spindle bearing.
- Light sensor: We installed a light sensor inside a pipe to simulate the machine's filter contamination. Users can simulate filter contamination by covering the end of the pipe with their hands or objects.

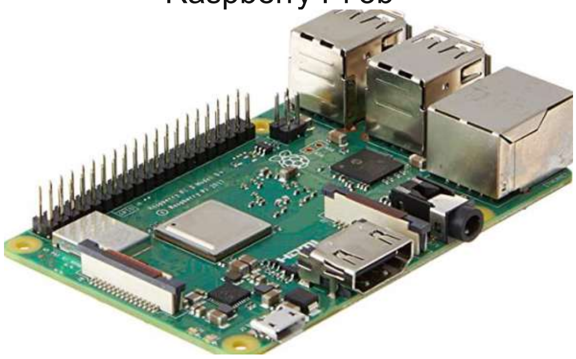
Setup of vibration motor

To operate a vibration motor, we need a motor driver and a human-machine interface to control it. The demonstrator already has an HMI which allows for controlling the demonstrator's motor via colored buttons. However, it was not feasible trying to use this HMI for the vibration motor as well for two reasons:

- All buttons of the existing HMI were already in use
- Controlling different devices within the same frame of buttons might be misleading

We, therefore, decided to develop a web application for controlling the vibration motor. A Raspberry Pi 3b+ brings all features necessary to do so: It has sufficient computation power for hosting a web application, features an integrated wireless LAN module for accessing the application, and brings GPIO (general purpose input/output) pins that provide an I^2C interface for communicating with a motor driver.

The demonstrator features a 24V power supply. Therefore, to avoid using additional power supply units, we designed the solution to use the power from within the demonstrator. Thus the demonstrator will still only need one power cable after the modification.

Voltage transformer	Raspberry Pi 3b+
	

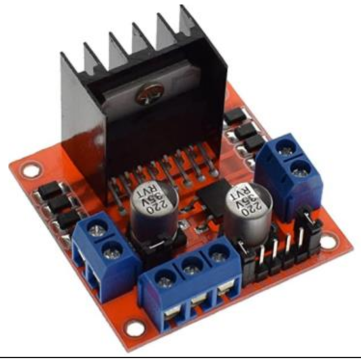
Motor driver L298N	Vibration motor 12V DC
	

Figure 19: Components for vibration motor

For the software part of controlling the vibration motor, all code is running on the Raspberry Pi. It can be divided into four parts:

- Controlling the L298N motor driver using the RPi.GPIO[141] python library:

  The code mainly consists of a python script, providing a function that handles controlling the motor driver via the raspberry's GPIO pins. Depending on one input parameter, one of the modes "stop, low, medium, high" can be executed, as shown in the following schematic:

```
function motorcontrol(input_param):
    if input_param == 'stop':
        →stop motor
    elif input_param  == 'low':
        →run motor on 25%
    elif input_param  == 'medium':
        →run motor on 50%
    elif input_param  == 'high':
        →run motor on 75%
    else:
        →remove voltage from output pins
```

Figure 20: Schematic of motor control function

- Running a Flask[142] application to provide the HMI:

  Flask is a micro-web-framework for python. It is an API of python that enables a simplified way of building web applications. In this case, we use flask to handle user input data from an HTML page to use in our python application to control the vibration motor. The HTML page contains a dropdown menu to select the desired mode and an "apply" button to confirm the selection. It is designed so that clicking the button without opening the dropdown first will always stop the motor. The current state is displayed at the bottom. In the background, when

[141] https://pypi.org/project/RPi.GPIO/.
[142] https://flask.palletsprojects.com/en/2.0.x/.

clicking the apply button, we retrieve the selected option in our main python file (that is running flask) and call the “motorcontrol” function from the previous python file (see Figure 20: Schematic of motor control function). After styling the HTML page with a CSS (cascading style sheet) file, the application looks like this:

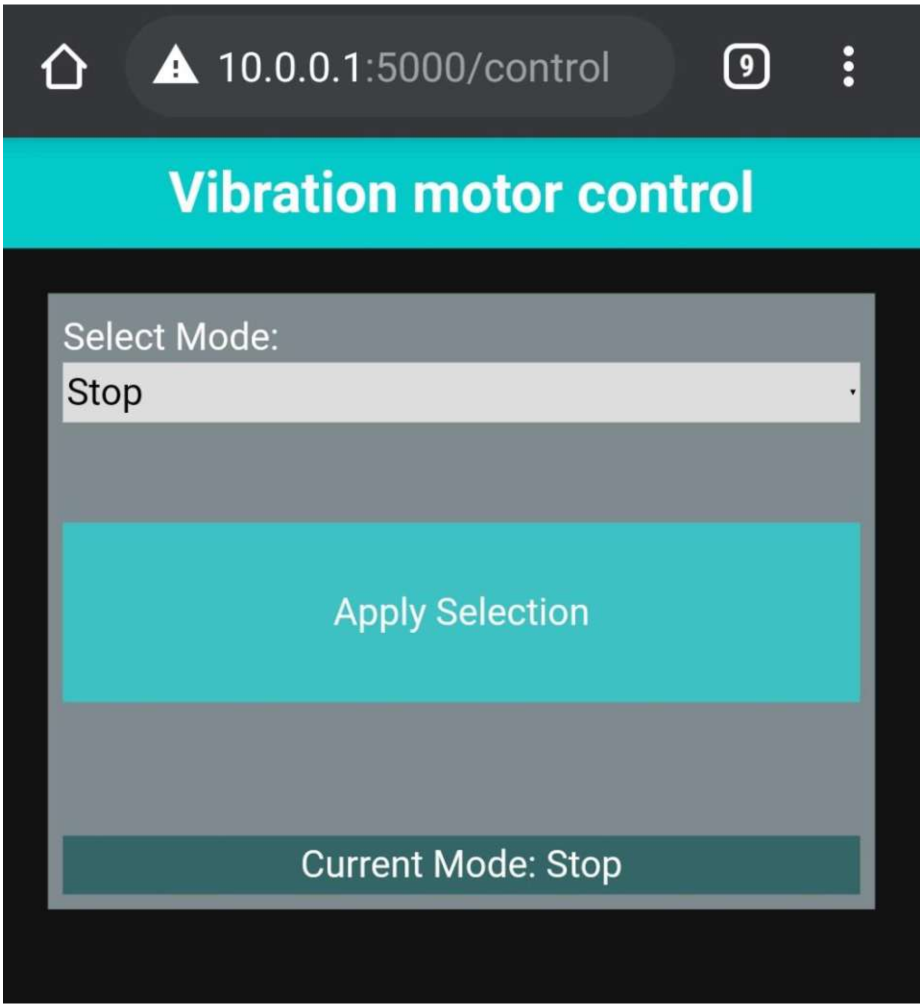


Figure 21: GUI of vibration motor control

- Using RaspAP[143] to make the app accessible directly via WLAN connection to the Raspberry Pi

The application should neither be accessible over the internet nor require a network cable to view it for the use-case at hand. Therefore RaspAP allows for configuring the raspberry to establish a WIFI access point on boot. After configuring the network so that the raspberry can be accessed via a fixed IP address when a device connects to that WIFI hotspot, the flask application can be accessed as well via its specified port. The WIFI hotspot is called

[143] https://raspap.com/.

"Demonstrator-control" and will be visible a couple of seconds after the raspberry is powered.

Figure 22: Wifi access point for vibration motor control

- Using crontab[144] to execute a shell script that properly starts the flask server on boot

  Crontab utilizes the cron-daemon, which is used for the time-based execution of processes. It also features executing processes on boot, which we use in this case. Before running the flask application, environment variables need to be declared, and the desired port to run the application needs to be specified. Also, the flask application is run in a virtual environment. A short shell script takes care of this. This shell script is then executed on booting the raspberry by crontab.

The vibration motor is mounted on the aluminum carrier near the rolling bearing of the spindle, where the vibration sensor is located. Out of two different vibration motors, the smaller one was sufficient for the vibration sensor to detect it properly. Even with the demonstrator's primary motor running, a slight change in the vibration sensor's output is noticeable when turning the vibration motor on and off.

[144] https://www.raspberrypi.org/documentation/linux/usage/cron.md.

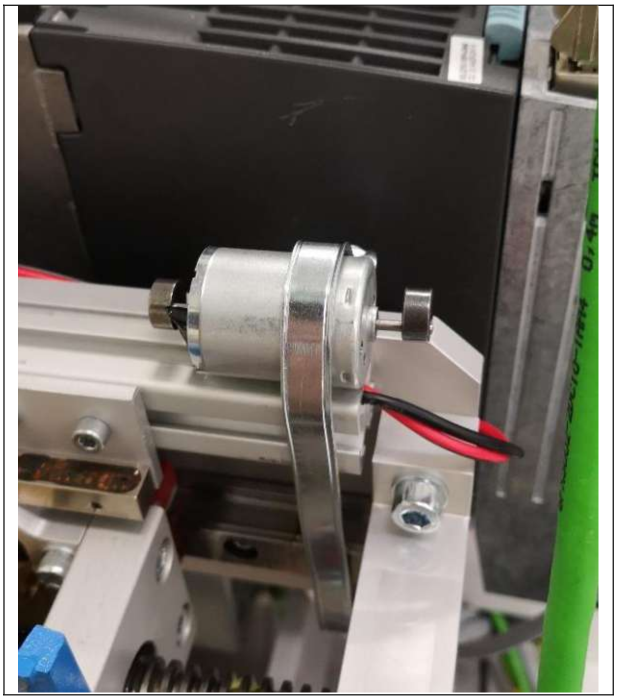


Figure 23: Installed vibration motor

Setup of light sensor

The light sensor's output value needs to be sent to the time-series database in the Mindsphere cloud platform just like the other machine data. Therefore, the light sensor's signal output triggers a relay on which 24 Volts are applied from the demonstrator's power supply. So the light sensor can switch 24V on and off via the relay. The 24V can trigger a free DI (digital input) on the demonstrator's PLC, which allows for processing this value the same way as other machine data from the PLC.

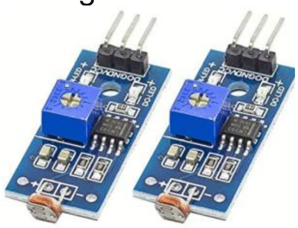
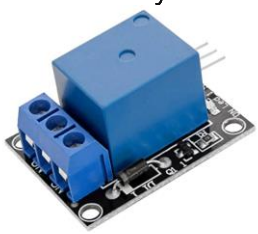
Light sensor	Relay
	

Figure 24: Components for light sensor

The light sensor is installed into a pipe so users can trigger it by covering the pipe. A cover that can be attached to the demonstrator by magnets for triggering the light sensor is also installed.

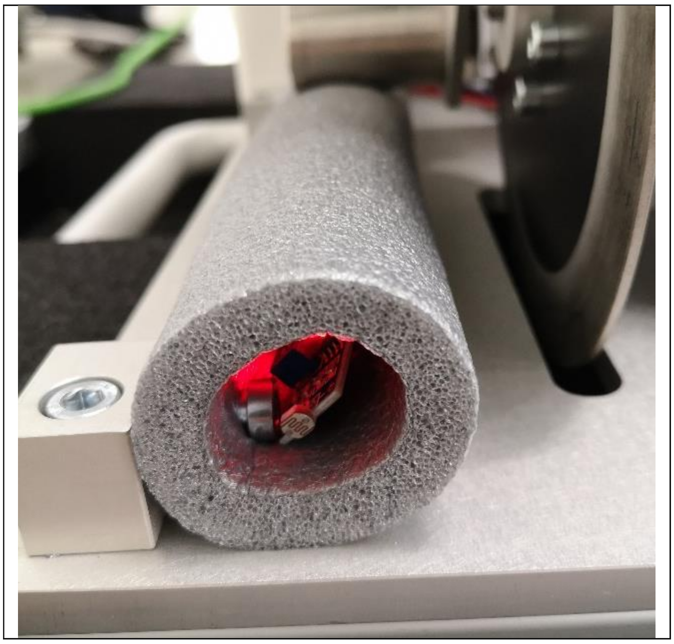


Figure 25: Installed light sensor

Installing modifications on demonstrator

The demonstrator has its own power supply, which has a free 24V output. This power supply is used to power all modifications described above. In addition, the available 24V can be used to switch a digital input at the PLC. The following schematic shows how these components are connected:

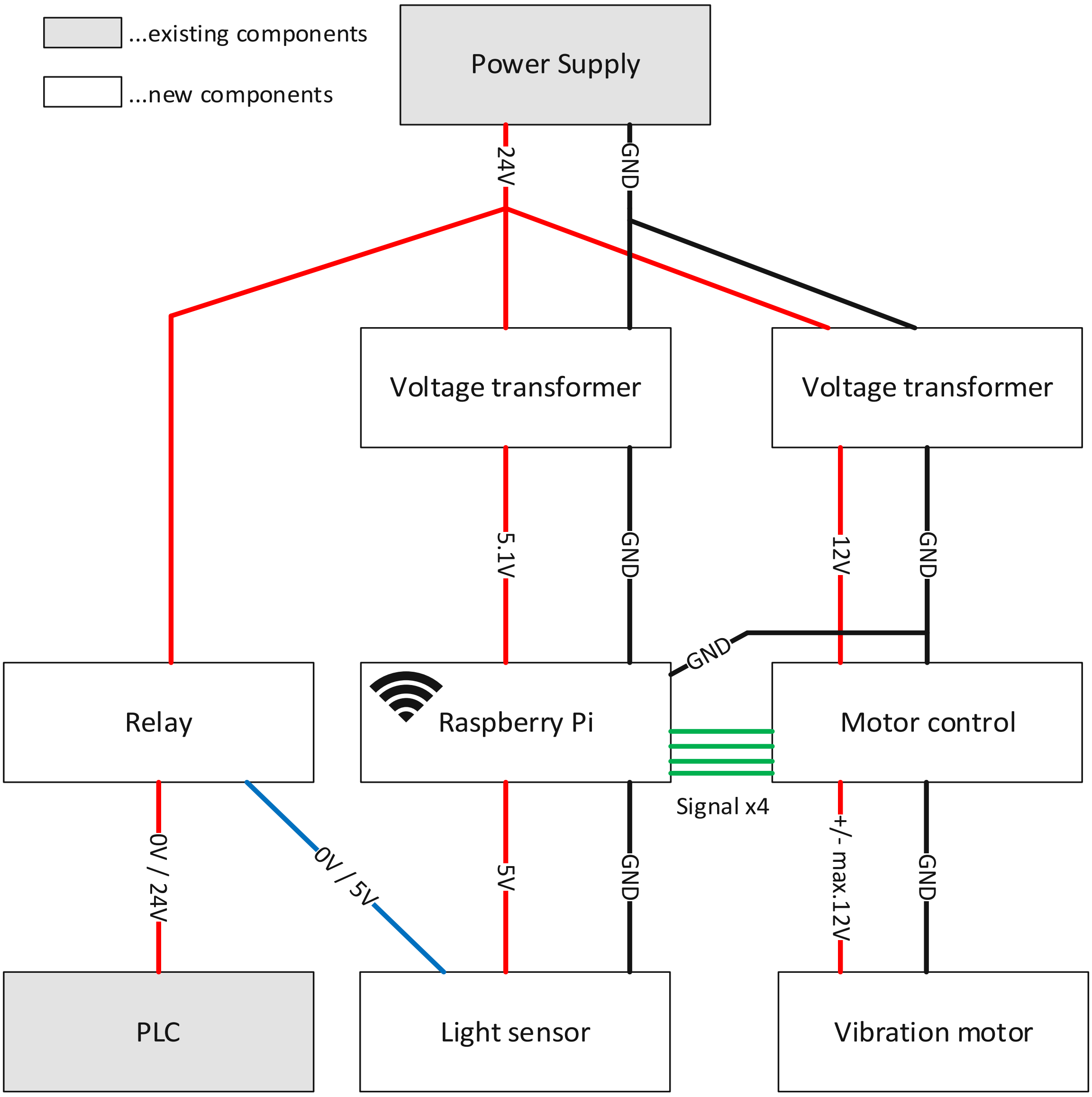


Figure 26: Schematic of demonstrator modifications

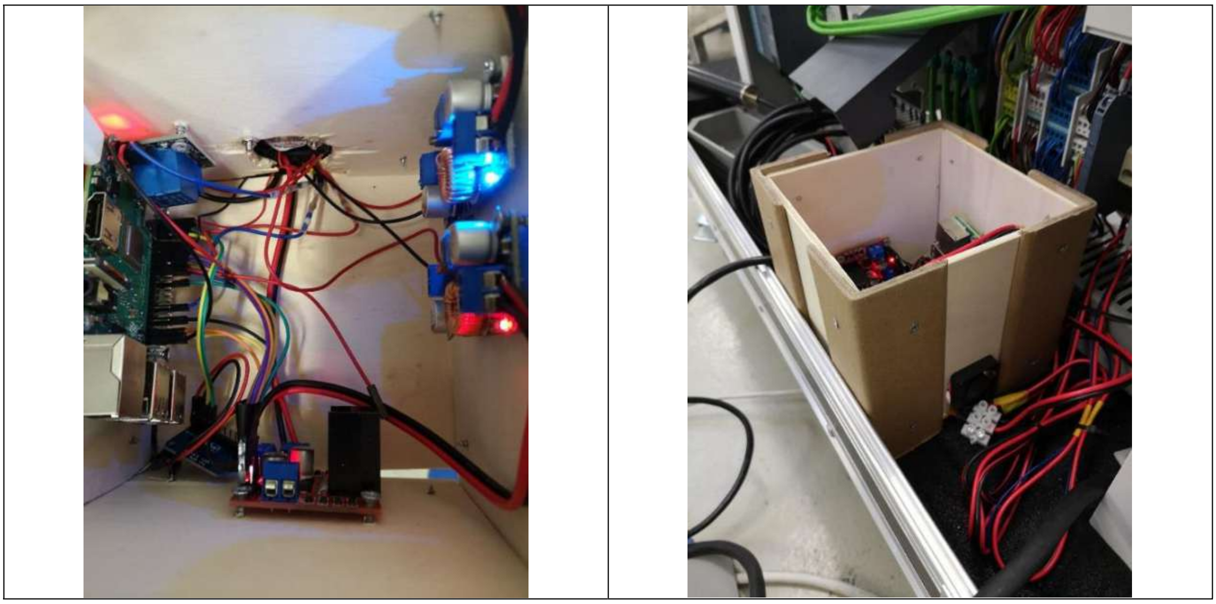


Figure 27: Demonstrator modification unit

5.2.2 Software modifications

To also get the light sensor data into the cloud platform, it is first necessary to forward the signal of the digital input used for this together with the other data from the PLC. For this, we are supported by our industry partner. The next step is to develop a cloud application for calculating the health points.

Cloud application

The goal of the cloud application is to provide a service that allows for providing the scheduling application with the current health points status of the demonstrator. The time-series database containing the demonstrators' raw data can only be accessed from the cloud application within this cloud framework. Also, there is no possibility for a live connection to retrieve the data immediately when it is written into the database. Therefore, we created a REST (REpresentational State Transfer) service within the cloud application, providing specified API endpoints for the scheduling application to call. At the endpoint /hp, the scheduling application receives a JSON message of the following format:

{"value": $healthpoints, "ts": $current_timestamp}[145]

While the demonstrator is running, health points will deteriorate according to user interaction. The scheduling application requires health points in the range of 0 to 100, where 100 means a perfect condition and 0 means machine failure. At another API endpoint /reset, the scheduling application can reset the demonstrator's health points to 100. The calculation of the health points is described in the next chapter.

The cloud application is deployed utilizing Cloudfoundry[146], a tool for easier deployment of applications with Kubernetes[147], which is an open-source system for automating deployment, scaling, and management of containerized applications. Once the application is deployed to the Mindsphere cloud platform using Cloudfoundry, it will run permanently, waiting for requests. To make a get request, specific credentials for receiving a temporary authorization token are necessary. Only the scheduler application has access to such a token, which prevents random access.

5.2.3 Calculation of health points

a) First version of calculating health points

[145] As commonly used in several programming languages the "$" prefix marks a statement as a variable, showing that the statement is a placeholder in this example
[146] https://www.cloudfoundry.org/.
[147] https://kubernetes.io/.

The first version of the cloud application had to function without the light and vibration sensors' data. A connection of these data sources to the cloud platform was not yet possible. Therefore, the brake was the only possible user interaction that could deteriorate the demonstrator's health points. Of course, the actuation of the brake highly correlates to motor torque and motor current. After some test runs and analyzing the data, we discovered that a straightforward model utilizing only data on motor current already delivers good results. Regardless of the setting for the motor speed, the values for motor current would not interfere with the clusters of data points recorded when actuating the brake. Therefore, a simple model classifying instances into three classes based on the motor-current value was preferred over building a sophisticated one, utilizing several input values or machine learning algorithms. The three classes determine i) no deterioration ii) low deterioration iii) high deterioration. Nevertheless, deterioration is not the same as health points. Health points still need to be calculated from deterioration according to the use case at hand.

According to the use case, actuating the brake cannot bring the health points to zero. Also, the same amount of actuating the brake would have a higher impact on the health points when the health points score is still high, compared to when they are already lower. The health points are calculated as a function of deterioration since the last maintenance activity to account for this in the model. A suitable function for this purpose is a first-degree rational function. Choosing the appropriate parameters can return the maximum health points at x = 0 and asymptotically converge towards the minimum health points at x→∞.

$$f(x) = \frac{a}{x+b} + c$$

$$f(0) = \frac{a}{b} + c = healthpoints\_max$$

$$\lim_{x\to\infty} f(x) = c = healthpoints\_min$$

Equation 6: Deterioration to health points

After using those two boundary conditions, there is still one degree of freedom left to parameterize the function's gradient. The degree of freedom is to change a and b along the dimension that $\frac{a}{b}$ stays constant to meet the two boundary conditions. The higher the values for a and b are chosen, the flatter the curve, hence the health points will deteriorate slower.

b) Second version of calculating health points:

As described above, the procedure for calculating health points utilizes severely simplifying assumptions for demonstration purposes due to the lack of necessary sensor data and the proposed function for calculating the health points works well for demonstration purposes. We also developed a data pipeline for preprocessing under the assumption that the acquired data allows for entirely data-driven predictions without an underlying function. Thereby we could receive the following raw data:

- Motor current
- Motor speed
- Motor torque
- Motor voltage
- Motor temperature
- Spindle position

Samples containing those values were labeled during test runs by actuating the brake, where the actuation level was defined as the label. The temperature change could be calculated as a linear interpolated time derivative of the motor temperature and was added as an additional attribute because it can be assumed that it correlates with the brake actuation level. After analyzing the correlations of all attributes, including the label, the attributes were reduced to motor speed, motor torque, and temperature gradient. The neglected attributes either showed insufficient correlation to the label or correlated strongly with another attribute, making it redundant. The next preprocessing steps were to exclude instances with missing and invalid values and normalize the data by scaling values to an interval of [-1,1].

At that stage, the instance can be split into training and test data sets. The dataset splitting was conducted utilizing five-fold cross-validation. This means that the dataset was split into five subsets equal in size where a model is trained on 4 of those subsets and then tested on the remaining one. This can be done five times, so each subset was used for testing once. Cross-validation is a common technique to prevent overfitting and reduce vulnerability to inaccurate data.

The brake actuation level was labeled with the values “0”, “1”, and “2”, indicating best to worst condition respectively. Therefore, the class label can be considered numeric or nominal, allowing for utilizing regression or classification techniques.

The next step is to select a regression or classification algorithm and tweak its parameters. A metric is necessary to evaluate the setting of a parameter. In the case of a linear regression model, this can be the mean absolute error. Then the model can be tested with different settings of the parameter. As we utilize cross-validation, we apply the different settings of the observed parameter five times (to all five combinations of training and test datasets) and calculate the mean of the five split tests of the observed metric for each parameter setting. So, testing n different parameter settings for a dataset of m subsets (for cross-validation), we receive $n * m$ values for the specified metric and n mean values (one for each parameter setting) of the metric to decide for the best setting according to the available data. The model can then be exported (e.g., serialized) for deployment.

The linear regression model described in this section was developed to prepare the procedure of model creation. The goal for utilizing machine learning for the demonstrator's condition was to detect the influences of the vibration motor. In this case, the label of the dataset would be the vibration intensity of the controllable vibration motor. As the vibration sensor of the spindle bearing could not deliver data, the data acquired from the residual sensors was not sufficient to create a working model for that use case. Therefore, for the actual use-case, the label was considered the brake actuation level. For this purpose, the first version of calculating the health points delivered satisfactory results and was therefore preferred over the second one.

5.3 Demonstrator evaluation

For the evaluation of the demonstrator, we present a narrative discussion on the requirements defined at the beginning of this chapter:

1. Deliver condition data like a real production machine equipped with sensors

The demonstrator features measurements of voltage, current, temperature, and angular velocity of a drive motor, a torque measurement sensor on a drive shaft, the (simulated) failure state of a filter, and a vibration sensor linked to a CM system, delivering the root mean square (RMS) for a bearing. These sensors acquire data from real machine elements and therefore behave similarly to real applications.

2. Emphasize the applicable pillars of industry 4.0: System integration, cloud computing, IoT

System integration: The demonstrator integrates the previously available application for condition-based scheduling and is integrable into other systems as well by providing an interface for sharing its condition via a REST API.

Cloud computing: Some preprocessing of sensor values is conducted locally (e.g., a transformation of acceleration to RMS vibration values that are applied to the vibration sensor's raw data). The data is then transmitted to a cloud in a specified format. The database for storing historical data, as well as an application that calculates the machine's condition by utilizing this historical data and the recent data retrieved from the demonstrator, both operate in a cloud environment

IoT: The demonstrator can be considered a connected thing, participating on the internet of things. It is equipped with a gateway to establish its own connection via LTE to communicate with the corresponding cloud environment.

3. Utilize condition data for production scheduling

In the cloud environment, we deployed a model for calculating health points from the received sensor data. This condition data is provided to the scheduling application and therefore closes the gap to combine a production scheduling application and condition data in one use case.

4. Convey knowledge on condition-based scheduling

One use case covering the condition monitoring of the demonstrator and its utilization in the scheduling application was specifically designed to showcase it on fairs. We, therefore, developed possibilities for physical interaction of users that can affect the health points. For example, a filter failure can be simulated interactively by covering a pipe. The vibration motor can be controlled via a mobile web app, delivering additional interaction. The live raw sensor data of the vibration sensor can be displayed on a separate monitor, showing the effects of the vibration motor. Furthermore, we developed an additional view that allows for showing the current health point status of the demonstrator on a separate monitor.

5. Integrate the available scheduling application

All use cases utilize the provided scheduling application for demonstrating condition-based scheduling.

6. Transportability

The modifications of the demonstrator do not extend its size. Therefore, the dimensions remain the same to when the demonstrator was provided by the industry partner and can be transported in its wheeled case.

6 Design and implementation of the procedural model

6.1 Overview of the procedural model

The starting point of the procedural model is defined by considering an existing production process or the planning phase of creating or changing a production process. The objective of the procedural model is to enable the utilization of machine and equipment conditions in PPC and maintenance if there is economic potential for doing so. Therefore, at first, the specific situation needs to be analyzed regarding machine and equipment conditions. The provided model deliberately describes the problems on a high level due to the wide variety of production systems. The model can therefore be seen as a conceptual design applicable for cross-industry use cases. Nevertheless, the description of the model's components covers action statements for specific usage as well.

The first step is "domain understanding" and focuses on investigating the considered production process and currently available data from machines, production processes, and maintenance. Some of the questions to be answered are:

What is the status quo of production scheduling and maintenance? How do the machines or equipment deteriorate? What data is currently utilized for production and maintenance planning? How could condition data improve the overall effectiveness of the production system?

After carrying out the domain understanding process, the gathered knowledge will not yet allow for an economic evaluation, but a rough estimation of the economic potential of the new strategy will be possible. Cases where it is not economically beneficial could be production processes with low setup time and repair costs (in comparison to production rate and product value), or when the deterioration of machines and equipment is not measurable and has no effect on the production process (e.g., makespan or quality) until machine failure occurs (sudden breakdown). In such a case, condition data could be neglected for production planning and maintenance can be scheduled preventively or carried out reactively.

Nevertheless, for the majority of production systems, the economic potential for optimization is indisputable. Therefore, the next step of the procedural model is "condition data exploitation". It emphasizes the procedure of analyzing possible data sources and making that data accessible for gaining information on a machine's condition. The result of this step is a model that predicts the current machine condition from data that can be recorded live.

“Integrative production and maintenance planning” covers the utilization of the acquired condition information for integrative planning of condition-based production scheduling and maintenance. Due to the high complexity of scheduling optimization problems that become more complex when integrating condition data and maintenance planning, the procedural model emphasizes the necessary simplifying assumptions. It delivers a set of valid simplifying assumptions that comply with the objective of integrative and condition-based production scheduling and maintenance planning. As a result, the output is a production scheduling and maintenance plan that depends on the acquired data and future production orders and is updateable on new live data.

As shown in Figure 28, the initially linear process of the three main blocks described above transforms into a circular process when evaluation processes deliver improved knowledge for the previous steps. The evaluation instances of the procedural model’s main blocks, therefore, feature iterative connections to symbolize a feedback loop for continuous improvement:

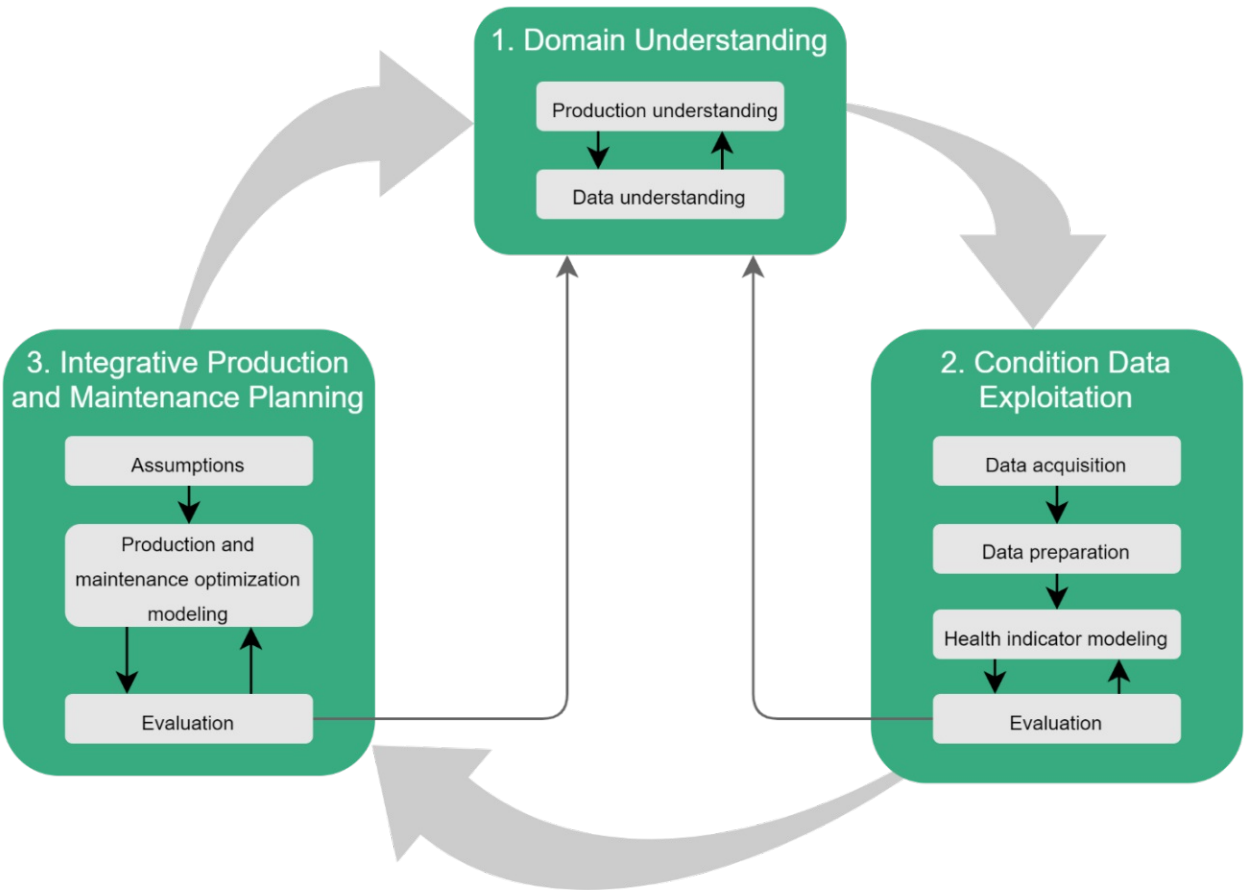


Figure 28: Procedural model for integrative condition-based production scheduling and maintenance planning

6.1.1 Domain understanding

a) production understanding

A solid understanding of the production plant or production system at hand forms the basis for initial assessments. As a guideline in terms of condition-based planning, the production process at hand can be categorized, e.g., into production type, differentiating job-shop and flow-shop systems. The categories are based on the influence that the respective production type has on possible production optimization models. Multi-machine problems have a higher complexity than single-machine problems. The mathematical models and methods used in each case differ in the literature, as they require different degrees of simplifying assumptions to keep the production scheduling problem within manageable complexity. The same is true for other categories. Machines that can produce or process different products may deteriorate differently depending on the product. At the same time, the production or processing of different products may have different levels of the machine's tolerable deterioration (of machine condition). This can be taken into account in production scheduling as well. Products also may be produced or processed in groups, so group scheduling needs to be considered. In many machines, the rate of condition deterioration depends on the production rate. This allows for integrating production rate into condition-based production scheduling. Depending on the production system, jobs may be resumable or not. A resumable job can be continued where it was stopped in case of interruption (e.g., unexpected machine failure). In contrast, non-resumable jobs need to be redone entirely if not finished as planned.

Table 9 shows an overview of the categorization of production systems regarding condition-based production scheduling.

Categories	Options	
Production type	Job-shop	Flow-shop
Number of machines	Single-machine	Multi-machine
Different jobs on the same machine	Yes	No
Group scheduling	Yes	No
Machine degradation is dependent on the production rate	Yes	No
Different jobs cause different machine degradation	Yes	No
Different jobs require different machine condition	Yes	No
Jobs are resumable	Yes	No

Table 9: Categorization of production systems

b) data understanding

Data understanding comprehends the assessment of the production system's available data sources. Therefore, a solid production understanding is necessary to assess the possible impact information from specific data sources could deliver.

The question to be answered by utilizing data is: In what condition state is a particular machine now, and how will this state behave in the future?

Whether and how well this question can be answered depends on the use case. At first, it is crucial to identify all data sources that can allow conclusions to be drawn about machine condition states. These can include:

- Machine data
  - Sensors
  - Dedicated condition monitoring systems
  - The machine's system or PLC
- Production data
  - Production rates
  - History on production activities
  - Production plan (planned utilization, future orders)
- Maintenance data
  - maintenance reports (inspection, repair, service)
  - History on maintenance activities

Machine data requires an infrastructure to make it accessible. Relevant data points to be transmitted need to be selected according to their influence on the machine or equipment condition. Domain experts can support the selection process for suitable sensors, condition monitoring systems, and the selection of data points from a machine's system. The effects of degradation of mechanical components can be fracture, wear, geometry changes, vibration, and force changes. These changes can be detected with sensors for acceleration, force, electricity, imaging, wear volume, roughness, angle measurement, hardness, gyroscope measurements, temperature, torque, or magnetism. If the sensors are manually selected and attached, a transformation of the raw data may be necessary to derive meaningful information from it (e.g., Fourier transform of an accelerometer to assess vibration). For common use cases, such as vibration monitoring of rolling bearings, ready-made condition monitoring systems that can perform this kind of edge computing can also be used. In any case, the data must be made accessible via a gateway at a specific sampling rate. After pre-processing the data, simple correlations such as a wear index calculated from measurements of the wear volume can be established directly. More complex correlations such as machine conditions, which can have multiple sensor values and other data as influencing variables, can be handled using prognostics and health management methods. Most commonly, after a dimensional reduction[148], machine learning algorithms are used to obtain the desired model. The goal is to calculate the RUL from the data, which corresponds to a failure prediction. Nevertheless, depending on the use case at hand, a simpler, rule-based approach perhaps also yields sufficient results.

Production data can be recorded and merged with machine data to enhance the quality of information within the dataset. If the machine can operate at different production rates, which affects the machine deterioration differently, historical data on production rates can be exploited. Also, the information on which production activity was performed when on which machine can yield additional improvement. In many production systems, machine degradation is estimated by the jobs it has processed. Those estimations can be improved by analyzing historical production data and evaluate the assumptions using data points with a known condition state. Data on the planned utilization of a machine can, at a later stage, improve maintenance and production planning by improving the timely prediction of necessary maintenance or rescheduling events.

Maintenance data comprehend information that can be acquired during maintenance activities. For example, when inspection or repair is carried out, the machine condition before and after can be assessed, allowing more precise estimations of the machine condition for certain data points. Also, historical data on when which maintenance activity was conducted can be utilized in the modeling process.

6.1.2 Condition data exploitation

a) data acquisition

This subitem aims to define the relevant data sources for determining the state of a machine. After the existing data sources have been determined in the point "data understanding," these existing data sources can now be used, improved, or neglected. Furthermore, new data sources can be created.

Machines with a comprehensive control unit usually also offer the possibility of querying a wide range of data from the control system. Here, domain experts must evaluate which data could correlate with the machine condition to be determined. Much of that data will not be related to the machine condition and should therefore not be included in a corresponding model.

[148] Reducing the dimension of a prognostics problem is a commonly used method, where the number of features is reduced while losing little (or no) information, because the excluded features contribute little (or not at all) to correlations with the label to predict. The most common method for this is called principal component analysis (PCA).

Improving an existing data source can make sense if a correlation is already known or suspected. For example, replacing a vibration sensor for bearing monitoring with a more sensitive sensor could significantly increase the quality of condition monitoring. However, not only the data quality but also the provision of the data can be improved. If, for example, data from maintenance reports is to be used, it usually needs to be made processable manually. The use of predefined error codes or automated evaluation with methods from text mining can simplify processes here and make data available more quickly.

b) data preparation

Machine data, production data, and maintenance data can occur in various forms and need to be transformed in order to apply health indicator modeling methods.

The data preparation process can be executed similarly to its description in the CRISP-DM model:

Figure 29: data preparation[149]

Data selection is already covered in the previous step when analyzing data sources.

Clean data: Remove invalid instances or replace missing and invalid values with default values or modeled values (e.g., interpolation of neighbor instances). It is also possible to select a clean subset of a dataset.

Construct data: Constructing new data out of the given dataset. For example, calculating the time derivative of the temperature values to obtain a column of temperature gradients in the dataset.

Integrate data: Combining information from multiple tables or records to create new records or values. For example, merge data of operational settings and maintenance reports into the dataset of sensor values.

Format data: Prepare the dataset for health indicator modeling without changing the information content of the dataset.

c) health indicator modeling

The goal is to create a model that calculates health points from the prepared dataset. Therefore, techniques from the research area of prognostics and health management (PHM) can be utilized. The options are regression, classification, and clustering. Regression and clustering both require a particular amount of failure data in order to

[149] cf. Chapman 2000, p. 23.

train a model according to labeled failure states. If this data is available, PHM literature delivers comprehensively researched methods for model creation and evaluation based on labeled condition data and regression and classification algorithms. Nevertheless, in industrial production systems, this data is often absent or rarely available.[150] Clustering and anomaly detection methods usually cannot deliver as precise results as regression or regression but enable health indicator modeling without labeled data.

Regardless of the method, operational settings need to be considered when modeling. Operational settings can heavily influence sensor values, so if this is the case, models need to be trained independently according to operational settings. Therefore, new instances must be evaluated according to the model with the corresponding operational settings when the model is deployed.

d) evaluation

The evaluation of a condition predicting model can be conducted according to PHM literature. The quality of the model can be mathematically described by metrics such as weighed classification accuracy. It is important to remember that evaluating the model quality must only be done on dedicated test data, which was not used in the model creation process.

The evaluation and modeling processes are iterative because the evaluation metrics deliver feedback for model optimization. This feedback can be utilized for parameter optimization or even changing the underlying algorithm.

6.1.3 Integrative production and maintenance planning

A solid domain understanding and the exploitation of condition data are prerequisites for proper strategic planning. In previous literature, the planning phases of production planning and maintenance were described mostly as separate processes. The procedural model presented here deliberately combines these tasks in one process.

One common assumption to be avoided is that the reliability degradation of machines is time-dependent when in real production most machine failures are operation dependent. The benefit of that assumption is that modeling time-based failures drastically reduces the complexity compared to operation-based failures.[151]

a) assumptions

Simplifying assumptions are inevitable for the integrative optimization of production and maintenance of modern production systems. An overview of the assumptions

[150] cf. Zhai et al. 2021, p. 7.
[151] cf. Ait-El-Cadi et al. 2021, p. 3.

made in the relevant literature can provide orientation and at the same time help to become aware of previously ignored influencing variables. Some of the assumptions listed here may only be relevant for certain production systems, but at the same time, they provide an overview of usable information.

Setup time	
All jobs are ready at zero time	
Setup time for processing identical jobs ignored	
The machine must be re-setup for processing jobs after PM	
Processing	
Only one job can be processed at one time with no interruption	
The machine can only process a job or perform PM at one time	
Each job-processing duration depends on the machine's deterioration state at the beginning of the job processing	
Maintenance activities	
Inspection	Inspection has negligible duration and cost
	Inspection always identifies defective components or delivers the current condition state
Repair (corrective maintenance)	The repair strategy can be one-state repair, multi-state repair (i.e., more than one state), full repair, or no repair.
	The repair time is variable and depends on the type of repair and the machine's deterioration state.
	Defective jobs are reproduced after the machine is fully repaired. (non-resumable)
Service (preventive maintenance)	PM can be executed instantly.
	PM can only be performed before or after processing one job
	after each maintenance activity – "good as new" / "bad as old
Deterioration	
Machine deterioration states are known and finite (m). A set of n jobs is available at the beginning of a working day.	
The expected value of the condition deterioration is known for the occurring jobs	
Other	
The energy consumption for processing each job depends on the machine's deterioration state at the start of the job processing.	

Table 10: Assumptions for maintenance and condition-based scheduling optimization

For clarity, variations and the logical opposites of the assumption presented in Table 10 are not displayed but can also be considered possible assumptions.

b) production and maintenance optimization modeling

The next step is the development of the mathematical formulation of the described system under an integrated production-maintenance policy.

At first, a definition of the optimization goals is required. These, for example, can be:

- Utilization
- Inventory levels
- Makespan
- Tardiness

The formulation of a target function depends on the use case at hand. However, a rough formulation of the target function can support the analysis of influencing factors for the optimization problem.[152] The observed production system then needs to be transformed into a mathematical representation model, utilizing the assumptions from the previous step. The goal thereby is to establish the mathematical relations of the target function and the input values.

Emphasis is placed on linking the scheduling of jobs and maintenance activities according to the underlying assumptions and depending on operation-based condition degradation.

As those optimization problems usually have a high degree of complexity in real production systems, the research area of operations research delivers methods for solving those optimization problems.

The result is a model to calculate a production and maintenance plan for the considered jobs to be scheduled.

c) evaluation

To evaluate the effectiveness of the obtained production and maintenance optimization model, it can be tested against the current state of production planning.

If historical production data is available, the orders, inventory levels and production schedules can be reconstructed. Therefore, the new model can be used to create production and maintenance plans for historical situations, so the output can be compared with the actual course of production from the past.

If there is already a model for production optimization in use, another possibility is simulation. The models can be tested against each other by defining several initial conditions that enable the models to calculate their results from the same input values.

[152] cf. Karner 2019, pp. 72–73.

6.2 Model evaluation

6.2.1 Definition of case study

According to design science methodology, artifacts or models can be evaluated observationally, analytically, experimentally, by testing, or descriptive. One way for observational model evaluation is its utilization in a case study, which is a commonly used method if mathematically derived evaluation metrics are not possible or reasonable.[153]

For conducting the case study, the physical demonstrator and the corresponding use case described in chapter 5 are utilized. For the case study, one deteriorating machine component of the demonstrator is defined as decisive for production planning and therefore represents the whole machine condition of the demonstrator. The demonstrator is one part of a production system of multiple equal machines. In the initial situation, production planning for this production system neglects the utilization of condition data, and preventive maintenance is scheduled periodically, according to stochastic estimations of probable machine failures.

The objective of the case study is to utilize the proposed procedural model to integrate condition data and maintenance planning into the production planning process and to evaluate the results of doing so.

Therefore, the following three subchapters represent the three main blocks of the proposed procedural model, applied on the physical demonstrator and defined case study.

6.2.2 Domain understanding

a) production understanding

The first step of the presented procedural model comprehends the description of the current state. The use case consists of the physical demonstrator and the scheduling application. The underlying conditions represent the initial situation of a production system. The demonstrator is one of several machines to which the jobs can be distributed. Other machines of the production system are only represented virtually.

The initial situation is a production planning, where no condition data is used. Maintenance activities are planned according to stochastically expected machine failures. Most maintenance activities can be performed preventively before a machine failure occurs. Since the actual machine condition is not known, it is assumed that corrective maintenance activities are necessary with a certain probability. These

[153] cf. Hevner et al. 2004, pp. 85–86.

unintentional machine failures are scheduled as buffers in production planning based on probability.

As described in the procedural model, the production system can be categorized as follows:

- The production system consists of multiple machines
- Different jobs can be processed on the same machine
- Different jobs cause different machine degradation
- Different jobs require different machine condition
- Production rate is independent of machine condition
- There is no group scheduling
- Jobs are non-resumable

b) data understanding

The next step is to evaluate existing data sources according to their potential production and maintenance planning improvement.

- Machine data
  The demonstrator initially records data for motor current, motor voltage, motor temperature, motor speed, shaft torque, spindle position, and bearing vibration. Two different failure types can be distinguished: Bad condition of the ball bearing at the spindle and bad condition of the drive shaft. Bearing vibration and spindle position may indicate a condition state of the ball bearing, whereas the other values may indicate a condition state of the drive shaft. In this case study, however, the relevant failure for production planning is only the one failure case of the drive shaft.[154] Therefore, there is one failure mode of the production system to be observed.

- Production data
  The production system consists of multiple equal production machines. The production rates are independent of the machine condition, but certain jobs can only be carried out when the machine's condition is above a particular threshold. There is no historical data on production activities, and the jobs to be processed are randomly generated for the planning horizon. A production scheduling algorithm creates a production plan according to the randomly generated production orders.

[154] On the one hand, considering the physical demonstrator it is legitime to define it as a production machine that operates without the spindle, making the potential ball bearing failure obsolete. On the other hand, this is also the only option for the case study, as the vibration sensor of the bearing could not be put into operation during the term of this work, making it impossible to use it.

- Maintenance data
  Maintenance is conducted according to a simple regime: Each job is assigned a specific value that decreases the machine's health points when processed. If a machine's health points fall below a certain threshold, preventive maintenance is conducted. However, in practice, it is possible that a machine's condition deteriorates faster and therefore fails before the planned preventive maintenance activity. Therefore, the planned maintenance activities are available maintenance data, but there is no historical data on maintenance activities.

6.2.3 Condition data exploitation

a) data sources

The machine data considering the observed machine condition is transmitted to a database via a predefined data pipeline that does not allow editing. The machine data is therefore utilized as it is available in the database. We had the possibility to simulate failure states and therefore create labeled data. In several sessions such data was created in test runs in order to produce a dataset of sufficient size. Condition data of test runs, therefore, was added as an additional data source.

Historical production data is unavailable in this use case. The previous assumption that a particular job causes a certain decrease in the machine's health points after processing the job deliberately remains unused for health indicator modeling because there is no link to the failure state in this use case. In a real industry application, such data could be used to create a usage indicator that can be used as an additional feature in the condition prediction model. Maintenance data is also not applicable in this use case because there is already labeled data available, and maintenance is assumed to restore the full machine health. In real industrial applications, however, maintenance data may be utilized to create or improve the condition label in the dataset.

b) data preparation

The data from the test runs was cleaned by removing instances with empty or invalid values and excluding redundant features and features with little (or no) correlation to the label. The motor temperature gradient was created as a new feature by calculating the time derivative of the motor temperature, utilizing the timestamps within the dataset. The remaining features were then normalized in order to have an equal impact on the modeling process.

c) health indicator modeling

The metric used for evaluating the model was the overall accuracy. As in this use case the one motor torque feature highly correlated with the label, state-of-the-art machine learning algorithms could not significantly improve the accuracy compared to a simple rule-based model obtained utilizing the OneR[155] algorithm.

d) evaluation

The model was evaluated using dedicated sub-datasets for testing from the initial dataset and later on as well utilizing new data recorded, delivering similar results.

6.2.4 Integrative production and maintenance planning

a) assumptions

The following assumptions that also describe the observed production system were made in the case study:

- All jobs are ready at zero time
- Setup time for processing identical jobs is neglected
- There is no setup time after corrective or preventive maintenance activities
- Only one job can be processed at one time with no interruption
- Maintenance activities cannot be performed while a job s processed
- Job-processing duration is independent of machine degradation
- There are no inspection activities
- Corrective maintenance and preventive maintenance both restore the full health of the machine ("good as new")
- Jobs are non-resumable (after machine failure, the job at which the failure occurred needs to be restarted)
- There are three known machine deterioration states
- The expected condition deterioration for processing each job is known.

b) production and maintenance optimization modeling

For production scheduling optimization in this case study, the scheduling application of the physical demonstrator was utilized (as described in chapter 5), as a new optimization algorithm is not within the scope of this thesis. The utilized scheduling optimization aligns with the assumptions described in the previous steps and delivers production plans optimized for machine utilization, inventory levels, makespan, and tardiness. Nevertheless, we could incorporate the information from the condition data

[155] The OneR („one rule") algorithm utilizes only one feature and creates simple, human-readable rules for that feature to predict the label. For example: If motor torque < 1 → condition = "green", if motor torque < 2 → condition = "yellow", else → condition = "red"

exploitation step into the existing optimization to create an integrated maintenance and production optimization.

The provision of the live calculated condition information could thus create the possibility to identify machine conditions deviating from the expected value and to optimize rescheduling measures utilizing this knowledge.

c) evaluation

The use case of the physical demonstrator does not feature historical production data. Nevertheless, the previous production optimization strategy featured a model that allows comparing results in simulations.

Since the demonstrator is not a real production machine, a few points have to be taken into account during evaluation. The overall performance depends on the following parameters that need to be determined in real production systems but can be defined in the use case of the physical demonstrator:

- The accuracy of condition prediction
- Condition thresholds for being able to process a particular job
- The time it takes to conduct preventive maintenance
- The time (and other consequences) it takes to conduct corrective maintenance

With an educated estimation of the initial settings, we could determine an improvement of utilization, inventory level, makespan, and tardiness between 2% and 6% each in several simulations. As an example, the influence of those parameters can be shown by setting the duration (and other consequences) of corrective maintenance the same as for preventive maintenance activities. Of course, that probably will never be the case in a real production system, but the model shows that in that case, a condition-based maintenance strategy causes no improvement over a run-to-failure strategy.

Therefore, those parameters can be seen as characteristics of a production system that allow a conclusion on the potential economic benefit of an integrated condition-based scheduling and maintenance strategy.

7 Summary and consolidation of key findings

7.1 Results of applied methods

a) systematic literature review

A systematic literature research on the topic of condition-based scheduling was conducted, the methodology and objectives of which are linked to a previous literature research within the scope of a doctoral thesis at the Vienna University of Technology. The methodology for planning and conducting the review is thereby based on the work of Tranfield et al.[156] It was found that the number of relevant publications has increased disproportionately in recent years (and thus in the interim period since the literature search referred above). This indicates growing research interest in the integration of condition data into production planning.

Overall, the integration of condition data in production scheduling has not yet been discussed extensively in the literature, although its potential is acknowledged in numerous (also older) publications. Nevertheless, especially in the last few years, the topic came in sharper focus. Thus, integrating condition data into production scheduling is also developing into a more extensive research area after the paradigm of condition-based maintenance was substantially researched.

The results are a systematic comparison of recent publications listed in Table 7: Classification of publications, and the discussion and summary of relevant literature in chapter 3.2.3 and chapter 3.3.

b) Product development

A physical demonstrator on the topic of condition-based production scheduling was developed, utilizing an existing production scheduling algorithm. A condition-based scheduling application based on that algorithm was modified in order to integrate the physical demonstrator's condition data into that application via a cloud platform. The physical demonstrator's development methodology was based on the latest VDI product and process design guidelines[157,158].

The result is a cloud-connected physical demonstrator that represents one machine of a production system and allows user interaction for carrying out a dedicatedly designed use case for demonstration purposes. The development, implementation, and evaluation of this demonstrator are addressed in chapter 5. A summary of the

[156] Tranfield et al. 2003.
[157] VDI Society Product and Process Design 2019a.
[158] VDI Society Product and Process Design 2019b.

demonstrator development can also be found in chapter 7.2 by answering research question Q2.

c) Procedural model development

A procedural model on integrating machine conditions into production scheduling and maintenance planning was developed, utilizing the physical demonstrator for conducting a case study. The methodology of model development is based on design science, more specifically on the artifact construction described by Hevner et al.[159].

The result is a procedural model that can be seen as a conceptual framework for establishing condition-based production scheduling and maintenance optimization on existing production systems. The construction of the procedural model and the execution of the case study are described in chapter 6. A summary of the procedural model can also be found in chapter 7.2 by answering the respective research question Q3.

7.2 Results with respect to research questions

Q1: How can machine and equipment condition be determined and utilized for condition-based production scheduling?

A prerequisite for condition-based scheduling is the data-driven acquisition of machine conditions. In the field of maintenance, the term "predictive maintenance" has created a use case that has been discussed in detail in the literature and has already made the leap into industry with numerous practical applications. Thereby, machines are equipped with sensors to monitor their condition. This data is then utilized to predict machine failure and to form a better knowledge base for maintenance planning. We could identify the research area of prognostics and health management (PHM) that focuses exactly on the topic of predicting machine conditions and failure occurrences by utilizing certain input data. The machine condition is expressed by a health indicator (HI), which can, e.g., be remaining useful life (RUL). As it is a prediction to when the machine will fail, the RUL is a suitable indicator for maintenance purposes.

PHM methods for health indicator modeling emphasize data mining, data analytics, and developing models (mostly utilizing machine learning methods). Those methods are also appropriate for health indicator modeling regarding production planning. One difference that should be noted is the formulation of the health indicator. For condition-based scheduling, the indicator RUL would not be as appropriate since it refers to the time to machine failure. In production scheduling, however, machines may require a certain condition for processing a particular job, which is why the machine condition is expressed as health points (HP) in this work. The health indicator class can be

[159] Hevner et al. 2004.

numerical or nominal, whereby we identified a finite number of nominal classes to be the most common method used in the literature considering condition-based scheduling.

The exploitation of the condition data in relation to production planning depends strongly on the production system at hand, which is why a procedural model was created that exploits the assumptions of concrete examples available in the literature in a generalized form.

Q2: How can knowledge on condition-based scheduling be effectively conveyed?

Considering real production systems, the complexity of the scheduling optimization problem increases disproportionally fast when increasing the number of involved machines or different types of jobs to be processed. Moreover, since the integration of condition data into those optimization problems just started to be researched more in-depth in the last years, practical applications utilizing condition-based production scheduling optimization are almost nonexistent in the industry yet.

Aiming at the lack of practical examples, in this work, a physical demonstrator for condition-based scheduling was developed, showcasing the core components of utilizing condition data for production scheduling and maintenance. The demonstrator was designed to represent a deteriorating production machine as one part of a production system consisting of several equal machines.

The development of the demonstrator was conducted according to the latest VDI process and product development guidelines. Since it is an iterative development and evaluation process, some of the discarded concepts can be found in the appendix of this work. The physical demonstrator presented embodies the best possible solution within the scope of this work and according to the predefined evaluation criteria. It features an HMI to control the demonstrator's motor and clutch and is equipped with several sensors (e.g., current, voltage, torque, temperature, vibration) to allow health indicator modeling. The machine data is periodically sent to a cloud environment, where it is utilized as the input for condition determination. For demonstration purposes, several possibilities for interaction are incorporated into the demonstrator. For example, a remote-controlled vibration motor for simulating deteriorated bearing conditions. An application in the cloud environment was developed to enable the integration of the demonstrator to a condition-based scheduling application. This application is the result of a former doctoral thesis at the Vienna University of Technology and features a condition-based production scheduling optimization algorithm. The scheduling application was altered to meet the requirements for the demonstration use case.

To date, the recently finished demonstrator was yet put to action on fairs twice to showcase the dedicated use case and raise awareness on condition-based production scheduling.

Figure 30: Physical demonstrator set up for showcasing

Q3: How can machine and equipment condition be utilized for integrated PPC and maintenance?

In the course of the literature review, it was identified that practice-oriented publications have a strong focus on either maintenance or production planning optimization. Researchers from the field of maintenance or PHM emphasize algorithms for determining and predicting the machines' condition, while researchers from the field of production planning tend to focus on scheduling algorithms.

Therefore, in this work, a procedural model was presented that merges the PPC and maintenance layers. The result is a high-level model based on the more general CRISP-DM[160] model. The model consists of the three main categories:

- Domain understanding
- Condition data exploitation
- Integrative production and maintenance planning

[160] see Chapman 2000.

"Domain understanding" addresses the examination of the production system at hand, as well as the available data. The production system is categorized, and existing data sources such as machine, production, or maintenance data are analyzed.

"Condition data exploitation" includes the analysis of possible new data sources, as well as the improvement of existing data sources and the processing of the data. The main focus is modeling a health indicator that can be constructed utilizing methods from prognostics and health management. It must subsequently be available in a usable form, such as a finite number of nominal classes. The thereby developed model allows the determination and prediction of machine conditions.

"Integrative production and maintenance planning" describes the process of production planning optimization, taking into account condition data and maintenance activities. Since the scheduling optimization problem can reach a high degree of complexity, an essential step is determining suitable simplifying assumptions. The result is an algorithm to compute optimized production and maintenance plans. When the deviation of actual machine conditions to the condition predicted when creating the production and maintenance plan exceeds a certain threshold, the algorithm can suggest rescheduling actions for re-optimization to the current state.

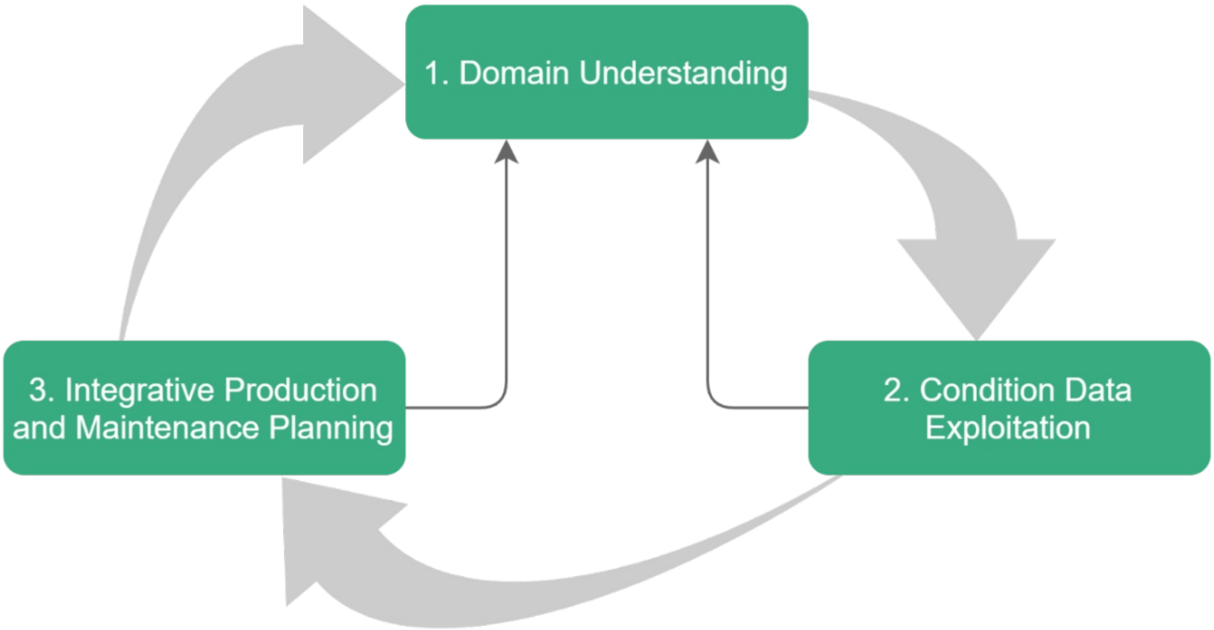


Figure 31: Main categories of the procedural model

The procedural model was evaluated by conducting a case study utilizing the physical demonstrator described in chapter 5. It showed that utilizing condition data for integrative production and maintenance planning has the potential to improve the overall efficiency of production systems significantly. Nevertheless, it must be considered that certain characteristics of a production system (such as the impact on cost and time of conducting an unplanned maintenance activity versus conducting a planned maintenance activity) have a substantial impact on the economic potential of integrative condition-based production scheduling and maintenance planning.

8 Outlook and limitations

The industry is starting to recognize the importance of integrating production scheduling and maintenance planning. Consequently, one can identify an increasing research effort to provide different methodologies for achieving this integration in recent years.[161] As the contributed research grows, different mathematical models for joint optimization of production scheduling and maintenance planning emerge. Nevertheless, actual industrial applications incorporating such models are barely existing yet.

The physical demonstrator presented in this work utilizes a previously developed mathematical model for scheduling optimization. Thereby, a significant limitation is that jobs cannot be fixed in their current schedule when computing a rescheduled production plan. Nevertheless, in an actual production facility, jobs soon to be executed on a machine would be subject to restrictions as to when they can no longer (meaningfully) be redirected to another machine. So, to conduct rescheduling in a real production system, such jobs would have to be fixed at the respective machine in order to consider only the remaining jobs for the optimization by the algorithm.

There is also improvement potential for the demonstrator itself. The existing cloud infrastructure provides a realistic system for processing and providing condition data, but it also causes considerable latencies in the data pipeline, which can be suboptimal for the demonstration use case. As the research methodology of this thesis is based on design science, which excludes behavioral science, another outlook would be to analyze human behavior interacting with the demonstrator and quantify learning effects.

The proposed procedural model for integrative condition-based production scheduling and maintenance planning utilizes knowledge and assumptions of recent literature and can be improved and adopted by considering later publications that present optimization problems for particular production systems. Also, the procedural model was evaluated by conducting a case study that utilizes the physical demonstrator developed within the scope of this work. Compared to purely simulated evaluation, the conducted procedure has the advantage of utilizing actual machine data from sensors and the machine control system. On the other hand, the physical demonstrator only embodies a replica of a real production system. Therefore, an evaluation that utilizes a case study or field study on actual production systems represents an outlook for improvement.

[161] cf. Kolus et al. 2020, p. 935.

9 Appendix

9.1 Discarded concepts for physical demonstrator

The product development process is an iterative one. The following illustrations show concepts that have reached a certain degree of maturity but were subsequently discarded. As the German language was used in the development process, the text in the following figures is German.

In the beginning, the goal was to develop the physical demonstrator from scratch. The following three figures show the drafts of the furthest developed concept at that stage:

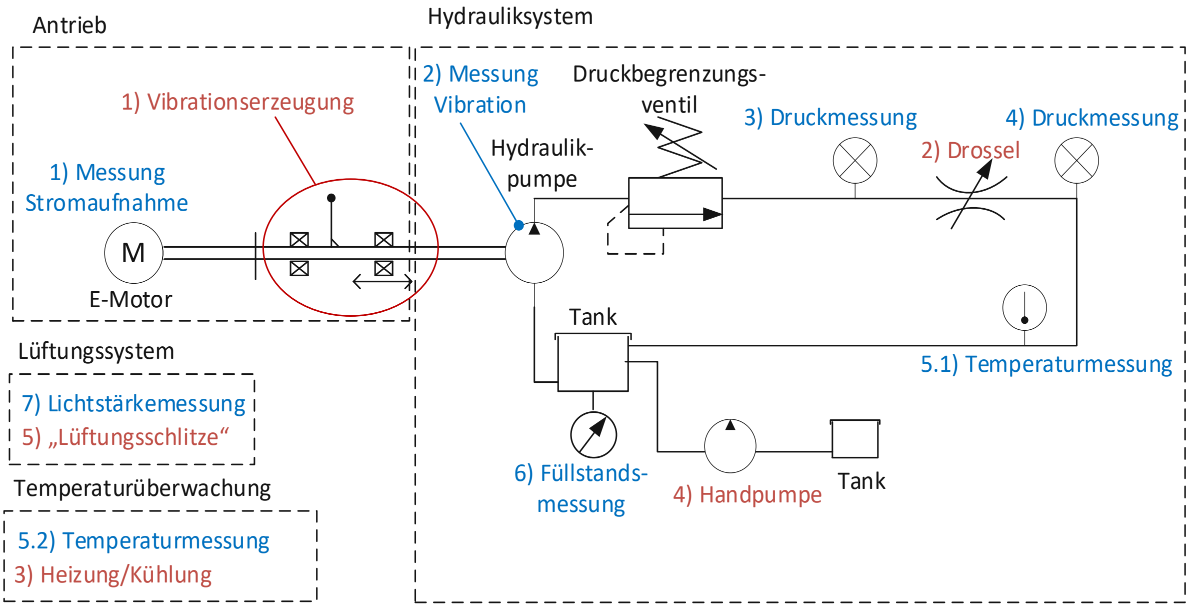


Figure 32: Schematic of discarded demonstrator concept

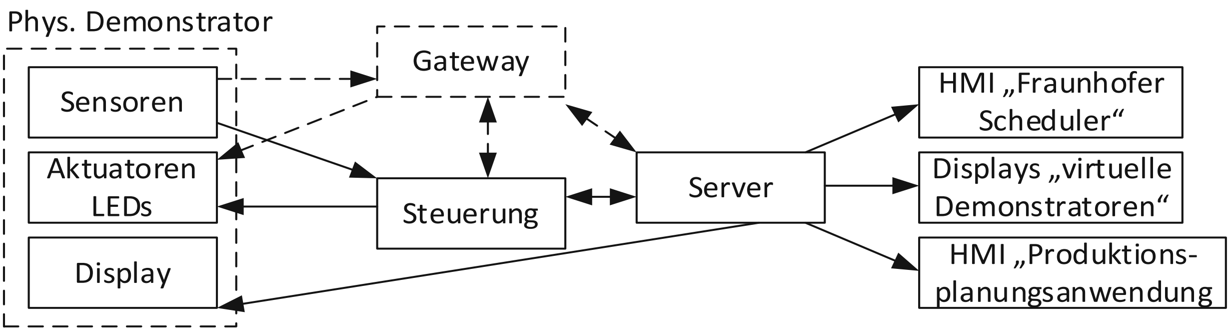


Figure 33: Data infrastructure of discarded demonstrator concept

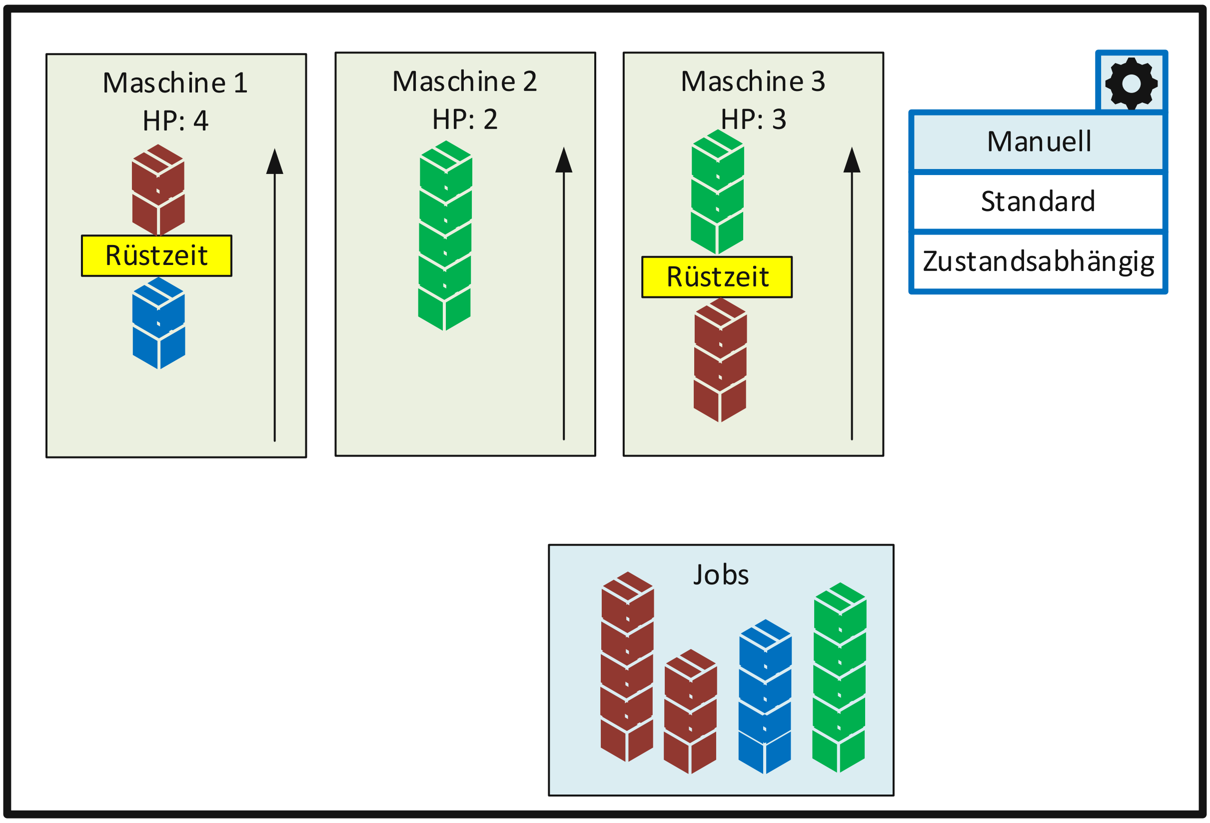


Figure 34: Draft for application of discarded demonstrator concept

For integrating the vibration motor into the provided physical demonstrator, two options were developed. The discarded version featured a bigger vibrations motor, mounted on the ground plate of the physical demonstrator with a 3D-printed mount, as shown in Figure 35:

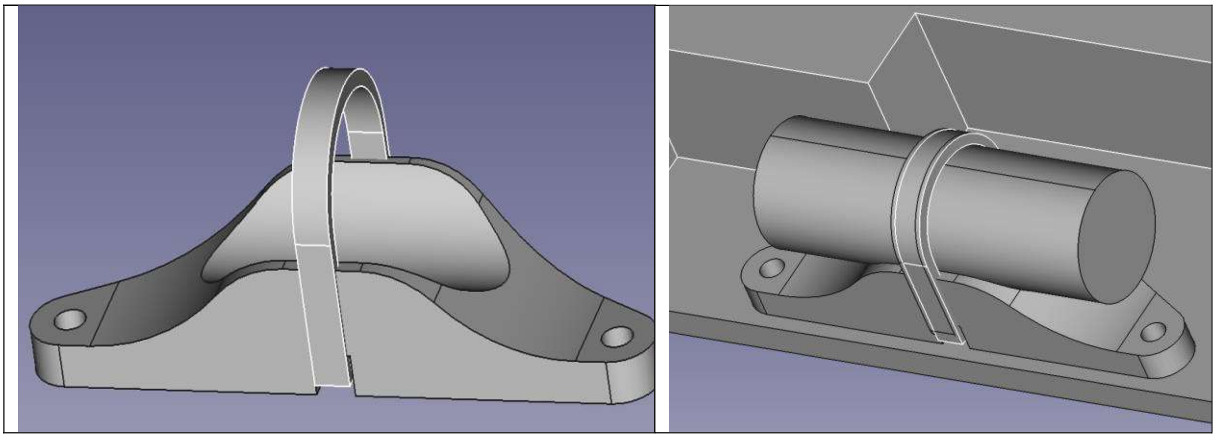


Figure 35: 3D-printed mount for vibration motor

9.2 LOG

Date of version	Remarks
26.09.2021	• Chapters 7-9 finished • Whole thesis and formatting reviewed
16.09.2021	• Chapter 6 finished
22.08.2021	• Abstract finished • Chapters 1-5 reworked and finished • Chapter 6 started
18.07.2021	• Chapter 1 finished • Chapter 2 finished until 2.2.3 • Chapter 3 started • Chapter 4.1 finished • Chapter 5 started
10.01.2021	• First version of chapter 1 and chapter 2.1 • Initial formulation of research questions
10.03.2020	• Project Kick-Off for demonstrator development

10 List of figures

11 List of formulas

12 List of tables

13 List of abbreviations

PM	preventive maintenance
RUL	remaining useful life
PdM	predictive maintenance
CM	condition monitoring
PPC	productin planning and control
CM	corrective maintenance
CBP	condition-based production
ML	machine learning
HI	health indicator
HP	health points
PHM	prognostics and health management
PvM	preventive maintenance
R2F	run-to-failure
CMS	condition monitoring system
PLC	programmable logic controller
LTE	long term evolution
HMI	human-machine interface
OPCUA	open platform communications unified architecture
GPIO	general purpose input/output
LAN	local area network
API	application programming interface
CSS	cascading style sheet
HTML	hyper text markup language
REST	representational state transfer
JSON	javascript object notation
RTF	run to failure
CBM	condition-based maintenance
CI	condition indicator
OC	operating condition
IM	imperfect maintenance
JSSP	job shop scheduling problem
CRISP-DM	cross-industry standard for data mining
KDD	knowledge discovery in databases
RMS	root mean square
MIJSSP	maintenance integrated job shop scheduling problem

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