1 Introduction

1.1 Motivation and Problem Statement

Globalization and the intensified competition have fundamentally transformed the business environment (Pawellek 2016, p. 1). As a result, cost and quality pressure and customer orientation have increased. This situation has stimulated the introduction of new technologies and the continuous improvement of required workflows and operations in companies to remain competitive (Guillén et al. 2016a, p. 992). This drives today's highly optimized production environments, in which success strongly depends on machine reliability. Unexpected machine failures not only lead to high maintenance costs and downtime but can even cause production targets to be missed. This has given rise to a fundamental change in perspective with regard to maintenance. In the past, maintenance was recognized as a "necessary evil" lacking its own contribution, whereas today, it is an integral part for businesses with high potential for improvements (Levrat et al. 2008, p. 409). The maintenance costs of a complex machine can, in most cases, consume up to half of the initial investment costs by the time it is replaced (Saunders 2007, p. 2; Zaidan 2014, p. 1). Acquisition costs can even be exceeded for well-designed and durable machines (Saunders 2007, p. 2). Conversely, one-third to one-half of the expenses are wasted due to ineffective maintenance (Zaidan 2014, p. 1; Heng et al. 2009, p. 724). As a result, there is potential for cost-saving that leads to financial benefits, which cannot be addressed adequately by traditional maintenance types, namely corrective and predetermined maintenance. While corrective maintenance is characterized by low machine reliability, predetermined maintenance is characterized by high maintenance costs (Haddad et al. 2012, p. 874). This has induced a shift towards more sophisticated maintenance approaches (Bousdekis et al. 2015a, pp. 1226 f.; Jardine et al. 2006, p. 1484).

In the age of digitalization and the fourth industrial revolution, the importance of *predictive maintenance* as a proactive maintenance type that anticipates and reduces severe and costly failures has grown significantly in recent years. The availability of machine sensor data incites the realization of predictive maintenance, in which data is used to monitor and analyze the machine's current condition and to predict its future condition. For this purpose, the implementation of predictive maintenance represents a logical step towards maintenance optimization in the industry. Predictive maintenance increases the transparency of the production plant and can, therefore, be used to provide decision-makers with accurate information at the right time (Lee and Bagheri 2015, pp. 299 f.). Using this information, maintenance can be scheduled with minimal interruption of the regular operation (Xue et al. 2008, p. 200).

Predictive maintenance is currently receiving much attention in practice. It is the most frequently requested application in the realm of the fourth industrial revolution (Schlick and Negele

2019, p. 32). Thus, it is a topic worth investigating for companies that want to improve themselves and strive for future success. The implementation of predictive maintenance has created substantial economic benefits for companies that have already successfully incorporated it within their maintenance department (Haarman et al. 2018, p. 19). Several surveys among practitioners indicated that the majority are actively engaging with the topic (different surveys report between 60-81% of the addressed participants) (Feldmann et al. 2017, p. 6; Haarman et al. 2018, p. 14). The most frequently mentioned drivers for realizing predictive maintenance are maximizing machine uptime and minimizing maintenance costs (Haarman et al. 2018, p. 16). For these two aspects, an optimization potential of 30-50% in machine downtime, as well as 10-40% for after-sales maintenance costs, can be attributed to predictive maintenance (Lucks 2017, p. 781).

Despite these promising facts, predictive maintenance for practical applications is still in its infancy, and the majority of companies are only in the early stages of their implementation (Haarman et al. 2018, p. 5; Schlick and Negele 2019, p. 34). In fact, very few companies have currently integrated and deployed solutions (Feldmann et al. 2017, p. 6). Beyond that, only about 20% of predictive maintenance projects achieve the desired goals (Hart 2017, p. 1). This is due to two prevailing practical challenges in particular. On the one hand, there is a deficiency of knowledge about predictive maintenance and its concrete realization. Up to now, several realizations have failed to take a sufficiently systematic approach (Feldmann et al. 2017, p. 13). On the other hand, the lack of high quality and rich data of historical machine failures frequently denotes a limiting factor for the successful implementation of predictive maintenance (Schleichert et al. 2017, p. 11; Blume et al. 2017, p. 6). This may lead to unreliable predictions (Schleichert et al. 2017, p. 11) and thus jeopardizes attaining the desired goal. These two described current challenges within predictive maintenance have also been stressed several times by the different experts through interviews conducted as part of this thesis. In particular, referring to the first challenge, it was mentioned that lack of knowledge in the area of predictive maintenance and its implementation has often led to misconceptions and resulted in additional effort or even hindered the realization. It was emphasized that the development of a structured process was critical to the company's success. The process enabled a means of communicating the project concept and required steps as well as guidance through the project.

Regarding the research field of predictive maintenance and its related field of prognostics and health management (PHM), it can be generally stated that it features a solid and well-established knowledge base. A considerable amount of the existing literature covers prognostics, which constitutes the critical element in predictive maintenance and focuses on identifying and estimating upcoming machine failures (Lee et al. 2017, pp. 9 f.). However, existing research is most times only explanatory, application-dependent, and targets particular problems of the complete implementation process (Elattar et al. 2016, p. 126; Voisin et al. 2010, p. 178; Saxena et al. 2010a, p. 2; Lee et al. 2014b, p. 319). Even though most solutions require a high effort of adaptation and are application-dependent, both the general procedure and the key concepts are universally applicable (IEEE Std 1856-2017, p. 8). Nevertheless, a shortage of and demand for a coherent approach and supportive guidance for the implementation of predictive maintenance has been highlighted by several authors (e.g., Lee et al. 2014b, p. 319; Elattar et al. 2016, p. 126; Tsui et al. 2015, p. 13).

Furthermore, due to the aforementioned data scarcity of real machine data, prognostic models in research are frequently developed on the basis of experimentally generated data, e.g., through simulations or accelerated life testings (Lee et al. 2014a, p. 5; Sutharssan et al. 2015, p. 216). These models, however, over-simplify the actual degradation behavior and are thus often not able to adequately reflect the complexity of real-world systems (Dragomir et al. 2007, p. 435). In particular, this leads to a deficiency of information on the actual degradation behavior of machines and consequently to low robustness under different working conditions and environmental influences (Lee et al. 2014a, p. 5). For this reason, data must be collected over a long time period before accurate predictions can be achieved. Hence, this option is difficult to apply in most industrial implementations. However, since data is often gathered from multiple similar machines, i.e., a fleet of machines, this information could be exploited to expand the available database and increase the data representativeness (Lee et al. 2014a, p. 5; Michau and Fink 2019, p. 1). Nevertheless, this machine fleet data should be evaluated with regard to the individual characteristics and distinct behavior of a single machine. The analysis of fleet data for prognostics is addressed by the field of fleet prognostics. Fleet prognostics is credited with several potential benefits, including reduced uncertainty (Medina-Oliva et al. 2012, p. 2), increased long-term accuracy (Liu et al. 2007, p. 558), as well as robustness (Lee et al. 2014a, p. 5). Nevertheless, to date, the exploitation of fleet data for prognostics remains immature in the research community (Jia et al. 2018, p. 7; Palau et al. 2020, p. 330).

From the above paragraphs, it can be concluded that both identified practical challenges have not yet been comprehensively addressed and studied in the research field of predictive maintenance. In light of these findings, the thesis targets a process-centric view of application-independent predictive maintenance implementations, with a particular emphasis on fleet prognostics. The process-centric view aims to enable systematic design guidance for practitioners and researchers to help overcome the challenges above.

1.2 Research Objective

The previous chapter underlines the importance of supporting companies and researchers in carrying out predictive maintenance, as well as in handling fleet data. In particular, it shows that an existing gap between practice and research must be bridged. This gap can be broken down into two parts. First, it depicts missing systematic guidance for predictive maintenance projects. Second, it addresses the data scarcity problem of real data. For this purpose, it is necessary to exploit the existing knowledge within research, extend it, and make it more accessible for both researchers and practitioners.

With these considerations in mind, the scope of this thesis includes supporting the effective implementation of predictive maintenance, with a particular emphasis on fleet prognostics. It establishes a link between science and industry by preparing and devising theoretical knowledge to overcome practical challenges in predictive maintenance. Consequently, the main research question of this thesis is stated as follows:

> **Main Research Question:** How can the implementation of predictive maintenance projects and fleet prognostics be guided?

From this main research question arises the need for comprehensive and application-independent support for predictive maintenance as well as accompanying assistance for fleet prognostics. In order to derive the envisaged support from the existing knowledge, the theoretical knowledge must be compiled, augmented, and appropriately structured. As the process of a predictive maintenance solution is highly application-specific, support in terms of standardization involves guidelines rather than strict procedures (ISO 13381, p. V). Due to their guiding character, processes are used as a means of structuring. They describe a logical sequence of activities that must be accomplished in order to reach the desired target (Becker et al. 2011, p. 4). Processes are therefore well suited to support the implementation of predictive maintenance and the processing of fleet data for prognostics. The developed processes serve as general guidelines to assist both the structuring of the overall predictive maintenance project as well as the development of prognostic algorithms considering fleet data. Furthermore, these guiding processes can serve all project participants as a basis for discussion and thus, also facilitate the transfer of knowledge and expertise (Wirth and Hipp 2000, p. 2). Consequently, the development of processes with varying abstraction levels is essential to answer the main research question. This leads to the main research goal:

> **Main Research Goal:** Provide a process-centric view of predictive maintenance and fleet prognostics to guide its effective realization.

Three interrelated research questions and goals are formulated in order to address the main research question accordingly. The first part primarily targets the challenge of systematically supporting the implementation of predictive maintenance. This lays the foundation to address the challenge of analyzing fleet data and developing appropriate fleet prognostic algorithms. This is subsequently covered in the second and third part of this thesis. The derived research questions are presented and discussed in the following.

> **Research Question 1:** How can the process of implementing a predictive maintenance project be designed?

Developing a predictive maintenance solution requires a number of steps that are essential for its successful implementation. However, the detailed design of the complete process largely depends on the specific application. Predictive maintenance implementations are targeted by projects due to the limited time duration and unique results (Project Management Institute 2017, p. 4). Thus, in order to support researchers and practitioners during the planning and execution of a predictive maintenance project, the generic implementation process has to be derived. For this purpose, it is necessary to identify the relevant steps and integrate them into an applicable process structure. Due to the strong practical orientation of this thesis, the process development should be driven by real-world requirements. In particular, a comprehensive view of the complete predictive maintenance process is to be devised. It should provide supporting detailed prescriptions for the design of an application-specific process while remaining application-independent. The creation of a generic process model can be effectively approached by means of a process reference model. A process reference model describes recommended practices for a specific area by outlining a set of applicable processes (Rosemann and van der Aalst 2007, p. 2). It is, therefore, driven by the concept of reusability and aims to facilitate the design of application-specific models (Rosemann and van der Aalst 2007, p. 2). Their key desired characteristics are generality, flexibility, completeness, usability, and understandability (Matook and Indulska 2009, pp. 62 f.). As a result, a process reference model for the realization of predictive maintenance enables systematic guidance for researchers and practitioners to define key steps and conceive their unique process tailored to the specific application. For this purpose, the first research question is addressed by the following research goal:

> **Research Goal 1**: Develop a process reference model for the realization of predictive maintenance projects.

Consequently, the result of the first research question constitutes a process reference model for the design of an application-specific process, which covers all relevant phases during the realization of a predictive maintenance project. Besides generic phases, potential detailed processes are elaborated, which can be adapted to specific applications. Above all, the process reference model offers information regarding which processes a predictive maintenance project should cover and therefore describes the highest level of the overall research result. The process reference model aims at high generality and can therefore be applied independently of the consideration of fleet data. The challenge of processing fleet data for prognostics is thus targeted in-depth by the second and third research questions. To this end, a development method for fleet prognostics is derived. Given that the handling of fleet data exclusively affects the algorithm development phase within a predictive maintenance project, this phase of the process reference model is subsequently supplemented by the algorithm development method for fleet prognostics.

However, in order to consider fleet data in the development of a prognostic algorithm, two aspects need to be examined and researched in more depth. First, the characteristics of fleets, and second, the available data must be thoroughly understood. This is addressed by the second research question:

Research Question 2: How can fleet data be characterized with regard to its use for prognostics?

The exploitation of fleet data is a comparably novel and, therefore, rather unexplored field of research (Jia et al. 2018, p. 7). The little research that exists is exploratory and targets specific applications. Thus, in order to gain a more general view of fleets and the available data for prognostics, the concept of a fleet must be explored both conceptually and from a data-driven perspective. Here, in particular, the extent of heterogeneity between machines within a fleet is a decisive factor for further data processing. This heterogeneity can be due, among other things, to different technical machine characteristics as well as deviating operating and environmental conditions (Voisin et al. 2013, p. 2). The manifestation of fleet heterogeneity has a major impact on the design of the prognostic algorithm and, thus, needs to be adequately reflected during its development. For this purpose, it is required to gain a better understanding of fleets and the available data by first researching general fleet characteristics and second determining means to define and measure machine heterogeneity. In light of these research findings, a method is developed to guide users towards characterizing their fleets and the fleet data and identifying the key features to be accounted for when developing prognostic algorithms. A method, in this context, comprises systematic procedures that serve as a basis to solve the targeted problem (Becker et al. 2007, p. 1). Furthermore, methods have a recommendation character with regard to the completion of activities (Winter et al. 2009, pp. 7 f.). In this thesis, the method should support the characterization of the fleet and its data with regard to its use for prognostics. The second research goal is, hence, stated as follows:

Research Goal 2: Provide a characterization method for fleets and the available data to identify crucial characteristics to be addressed within fleet prognostics.

As a final outcome, the research result of the second question provides a method to characterize fleets and the corresponding data for their usage within prognostics. As a preliminary step, the characterization method establishes the prerequisites for the development of an appropriate prognostic algorithm. It enables the structured description of the analyzed fleet and provides a means to assess the fleet heterogeneity from a data-driven perspective. On the basis of this knowledge, an appropriate prognostic algorithm can be developed. To this end, it is necessary to investigate approaches that accommodate the identified fleet characteristics as well as assist prospective researchers and practitioners with their implementation. This constitutes the subject of the third research question:

Research Question 3: How can the development of algorithms for fleet prognostics be guided?

The majority of approaches that leverage fleet data apply general prognostic methods that do not capture the machine's specific characteristics or build individual models for each machine overlooking the great potential of learning from other machines. Only recently, some methods have been proposed to address the problem of fleet data within prognostics taking into account individual machine degradation behavior (Tsui et al. 2015, p. 7; Palau et al. 2020, p. 330). Nevertheless, algorithms that are tailored to a specific application can hardly be transferred to another application without loss of quality. Thus, for each application, the most appropriate method must be selected, taking into account the identified fleet characteristics as well as general requirements of both the data and the organization (Sikorska et al. 2011, pp. 1807–1809). To support the development of a prediction algorithm for fleet prognostics, it is necessary to provide guidance both in the selection of a suitable method and in the design of the corresponding algorithm. Here, an algorithm defines the entire set of activities, which are required to develop an application-specific solution (from data preparation to performance evaluation), whereas a method represents a general principle and procedure to solve a mathematical task (e.g., artificial neural networks). Analogously to the second research goal, a method is targeted to support the development of a fleet prognostic algorithm. This method should facilitate, on the one hand, the selection of suitable prognostic approaches, taking the identified fleet characteristics provided by the characterization method, as well as general data and application requirements. On the other hand, it provides design support for an application-specific fleet prognostic algorithm for each of the identified fleet prognostic approaches. The third research goal can be framed as follows:

Research Goal 3: Design an algorithm development method for fleet prognostics.

The algorithm development method complements the characterization method. Taken together, they form the fleet prognostic development method, which provides structured support for the implementation of a fleet prognostic algorithm.

In summary, this thesis aims to answer the main research question through the provision of a process reference model for predictive maintenance, a characterization method, and a fleet prognostic development method. The three research results require the definition of several processes that target the design of a predictive maintenance solution. The process reference model provides generic processes to be performed in predictive maintenance projects. The process reference model is supplemented by the fleet prognostic development method as part of the second and third research goals. For this reason, the generic algorithm development phase is used as a basis, which is adapted and elaborated for the specific requirements of fleet prognostics. The resulting method facilitates the development of a fleet prognostic algorithm by providing step-by-step guidance for researchers and practitioners. Figure 1 summarizes the three research goals as well as their relations.

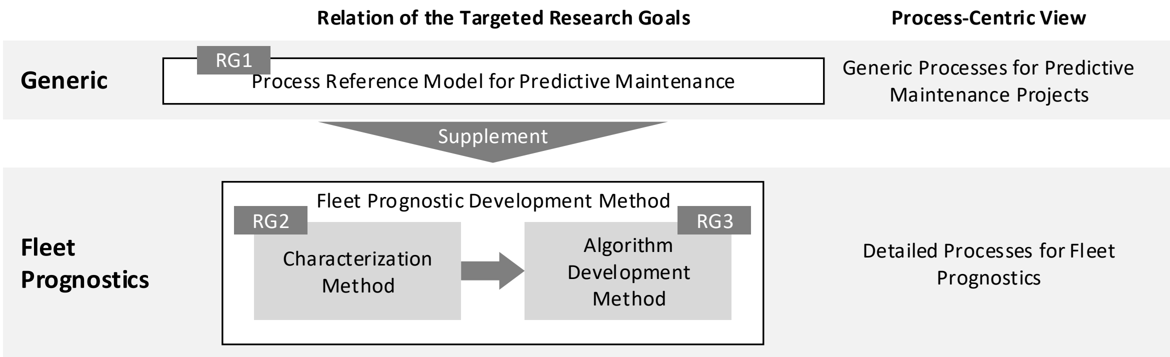
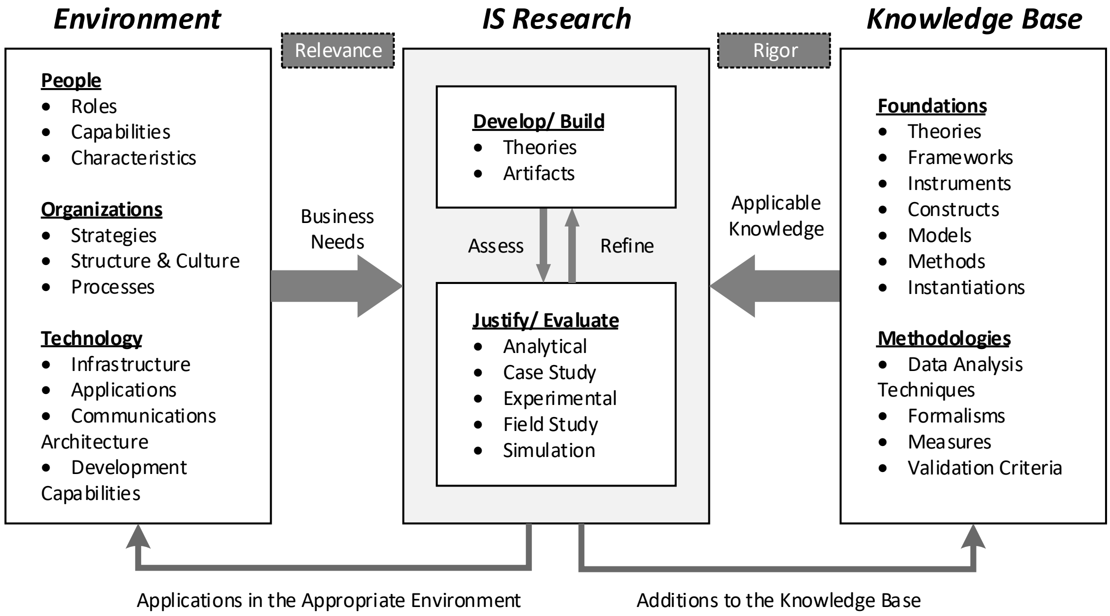


Figure 1 | Summary and Relation of the Research Goals

1.3 Research Design

The stated research objective targets the effective and efficient realization of predictive maintenance and fleet prognostics. Therefore, it is adequately addressed by the design-science research methodology. Unlike natural science, which is a descriptive knowledge-producing activity, design science is prescriptive and knowledge-using (March and Smith 1995, p. 252). It is based on existing theories that are applied, tested, modified, and extended for the specific research objective (Hevner et al. 2004, p. 76). Its purpose is to create, deploy, evaluate and improve a purposeful artifact that can be exploited to effectively and efficiently analyze, design, implement, manage, and use information systems (Hevner et al. 2004). Design science research is embedded between the two pillars, environment and knowledge base, and thus seeks both relevance and rigor. For this purpose, this research methodology lays great importance on the practical significance of the research. In particular, a relevant organizational problem should be focused on, and research should be aligned with the respective business needs (Hevner et al. 2004, p. 79). Furthermore, research rigor is achieved by applying the theoretical foundations during the building of the artifact (Hevner et al. 2004, p. 80). The development process of the artifact comprises an iterative development and evaluation loop (March and Smith 1995, pp. 258–260; Markus et al. 2002, pp. 193–196). The resulting information systems research framework by Hevner et al. (2004) is shown in Figure 2.



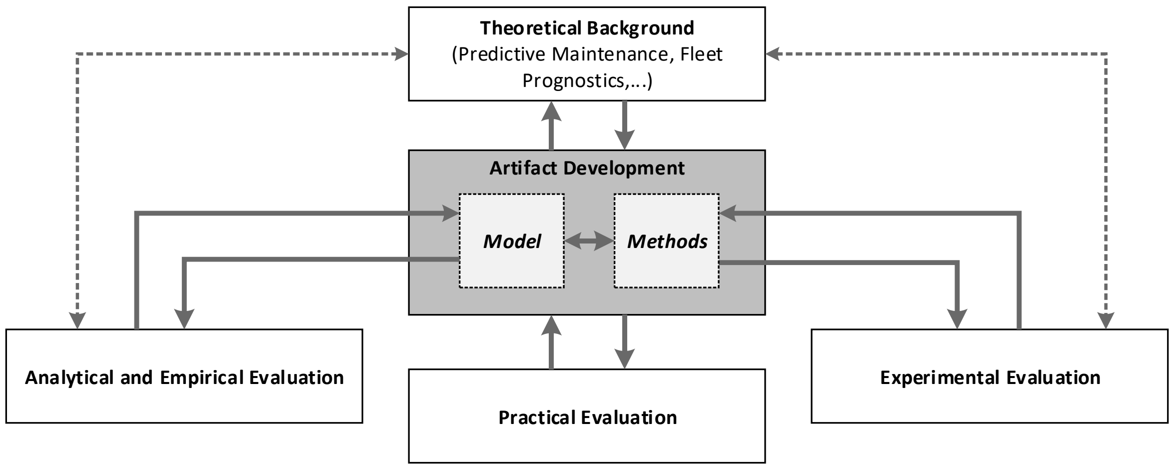
(Hevner et al. 2004, p. 80)

Figure 2 | Integration into the Information Systems Research Framework

Artifacts in design science research can be constructs, models, methods, or instantiations (March and Smith 1995, p. 253). This research contributes to the knowledge base with three artifacts. As the name implies, the first artifact, the process reference model, depicts a *model*. A model in design science research is a representation of the real world with the purpose of understanding the problem and its solution (March and Smith 1995, pp. 256–258; Hevner et al. 2004, pp. 78 f.). It, therefore, provides recommendations for design results (Winter et al. 2009, pp. 7 f.). The developed process reference model illustrates the generic predictive maintenance implementation process. By this, it assists practitioners and researchers in designing their application-specific process. The second and third artifact, the characterization method and the algorithm development method for fleet prognostics, denote *methods*. As already defined in the previous subchapter, methods define processes that prescribe recommendations for activities and provide systematic guidance and instructions for solving the addressed problem (Becker et al. 2007, p. 1; Winter et al. 2009, pp. 7 f.). In this thesis, two multi-step methods are proposed which provide assistance to solve the problem of developing a prognostic algorithm considering fleet data. The two methods together form the fleet prognostic development method.

Design science research must adhere to seven guidelines (Hevner et al. 2004, pp. 82–90). The first guideline, *design as an artifact*, states that the research must address an important organizational problem by means of an artifact. This thesis aims to improve the realization of predictive maintenance and fleet prognostics by means of one model and two methods, as described before. The second guideline, *problem relevance*, calls for the practical orientation of research in the form that a relevant problem for practitioners is solved. Predictive maintenance denotes a currently highly discussed topic in companies. The three artifacts provide guidance for both academics and practitioners. *Design evaluation* is the third guideline. This guideline prescribes the execution of evaluations to verify the utility, quality, and efficacy of the artifacts. The evaluation loop should provide feedback to further enhance the artifact. For this purpose, the thesis applies different types of evaluations. Analytical and empirical evaluation is carried out for the process reference model. The former comprises the descriptive feature-based approach adapted from Fettke and Loos (2003, p. 83), while the latter involves semi-structured expert interviews, which are collected under consideration of the seven stages of interview investigation as defined by Kvale and Brinkmann (2009, p. 102) as well the four interview phases identified by Misoch (2019, p. 68). For the second and third artifact, the characterization method and the algorithm development method, experimental evaluations are performed on the established Commercial Modular Aero-Propulsion System Simulation (C-MAPPS) data set. This data set comprises four data sets of a fleet of turbofan engines generated under different conditions and settings. This allows different fleet characteristics to be covered within the evaluation. To conclude, three application cases are carried out in terms of practical evaluations of the overall research result of the main objective of this thesis. To achieve this, three predictive maintenance projects were realized in close cooperation with various companies. *Research contribution* denotes the fourth guideline, which states that research must enrich the knowledge base either by solving an open problem or by finding a more effective and efficient solution. As described above, the research targets the assistance of predictive maintenance and fleet prognostics, thus providing a more efficient approach to solving this problem. *Research rigor* (fifth guideline) examines the manner in which research is pursued. Rigor in this thesis follows from the exploitation of the relevant knowledge base. It is based on past research, in particular, originating from the fields of process models in predictive maintenance as well as fleet prognostics. This knowledge base is established through systematic literature reviews following the methodology of vom Brocke et al. (2009) and Webster and Watson (2002). In addition, the development and evaluation of the artifacts were accomplished, taking into account existing research development and evaluation methodologies. Subsequently, the *design as a search process* guideline (sixth) claims that the search process is inherently iterative. For the construction of the process reference model, the guideline was implemented by first creating the level of highest abstraction on the basis of the literature. Then, additional levels of detail were added iteratively. Higher abstraction levels are adjusted in case of deviations. For the two methods, the problem is decomposed into simpler and manageable sub-problems. The achieved results are then taken as a starting point, and the overall objective is solved by iteratively combining, adjusting, and extending the component solutions, resulting in a comprehensive characterization process and algorithm development process for fleet prognostics. The design for the three artifacts follows a heuristic search process, which aims at finding a solution which "satisfices" (Simon 1996, p. 27). Lastly, *communication of research* denotes the seventh guideline. Research results should be prepared in a form that is appropriate for the target audience. For this reason, results are structured in a hierarchical manner adressing different audiences. While management at the top level is mainly concerned with the key processes (highest level) for deriving decisions, details are provided at the lower levels for technology-oriented audiences to ease implementation.

The previous paragraph illustrated the grounding of the overall research in design science, particularly in relation to the seven guidelines. Further information about the methodology that was used to develop the respective research results is explained in detail at the beginning of the corresponding chapters. Figure 3 summarizes the key components of the artifact development. Artifacts are designed, taking into account the knowledge base. All three artifacts are evaluated individually by analytical, empirical, and experimental evaluations as part of the build-evaluate loop. The overall thesis result is conclusively validated within three practical projects. The detailed methodological approach for each artifact is presented at the beginning of the corresponding chapters (see Chapters 3.2, 4.2, and 5.2).



Adapted from Moody and Shanks 2003, p. 647

Figure 3 | Composition of Artifact Development

1.4 Thesis Structure

The structure of the thesis is designed to reflect the presented research objective. The resulting structure is visualized in Figure 4. Up to this point, the current chapter motivates this research and presented the research objective. In addition, the underlying research design is provided. The following chapters pursue the research objective.

Chapter 2 lays the foundation for an informed discussion of the thesis's research objective. To ground the thesis, maintenance management is introduced first, and existing maintenance types are analyzed. Subsequently, predictive maintenance and its related components are addressed in detail, and established data-driven methods are outlined. The chapter concludes with current research gaps in predictive maintenance, which are covered by this thesis.

Chapter 3 targets the development of the process reference model for predictive maintenance. For this purpose, the requirements guiding the development are derived, and the applied methodological approach is presented. This is followed by the discussion of existing process models and related influencing fields. In light of this information, the process reference model is depicted. Lastly, the process reference model is evaluated analytically and empirically.

The process reference model is supplemented by the fleet prognostics method in Chapters 4 and 5. For this purpose, initially, in Chapter 4, the fleet characterization method is inferred. To do so, the research guiding target and the resulting requirements are specified for the fleet characterization method, and the related methodological approach is described. Subsequently, the basis of the method construction is laid by presenting a consolidated view of the current literature. Thereafter, the characterization method is developed, which focuses on an improved conceptualization of the fleet as well as the data-driven classification of fleet prognostic types for the purpose of prognostics. The resulting method is evaluated on the turbofan engine degradation data set. As the last step, current limitations are presented.

Building on these results, the fleet prognostic development method is developed in Chapter 5. Similar to the fleet characterization method, primarily derived requirements, the resulting methodological approach, as well as the targeted knowledge base, are described. This is followed by the presentation of the method, including the fleet approach selection and the generic fleet prognostics implementation processes. To demonstrate the applicability, the method is considered for an exemplary fleet prognostics application, and existing limitations are discussed.

In Chapter 6, the application of the developed artifacts is demonstrated in different industrial projects. Therefore, the three realized predictive maintenance projects are briefly described, analyzed, and discussed in view of the scientific results.

The thesis concludes with a consolidated discussion of the overall result. It summarizes the obtained findings and critically reflects the overarching research. Furthermore, future research opportunities are proposed.

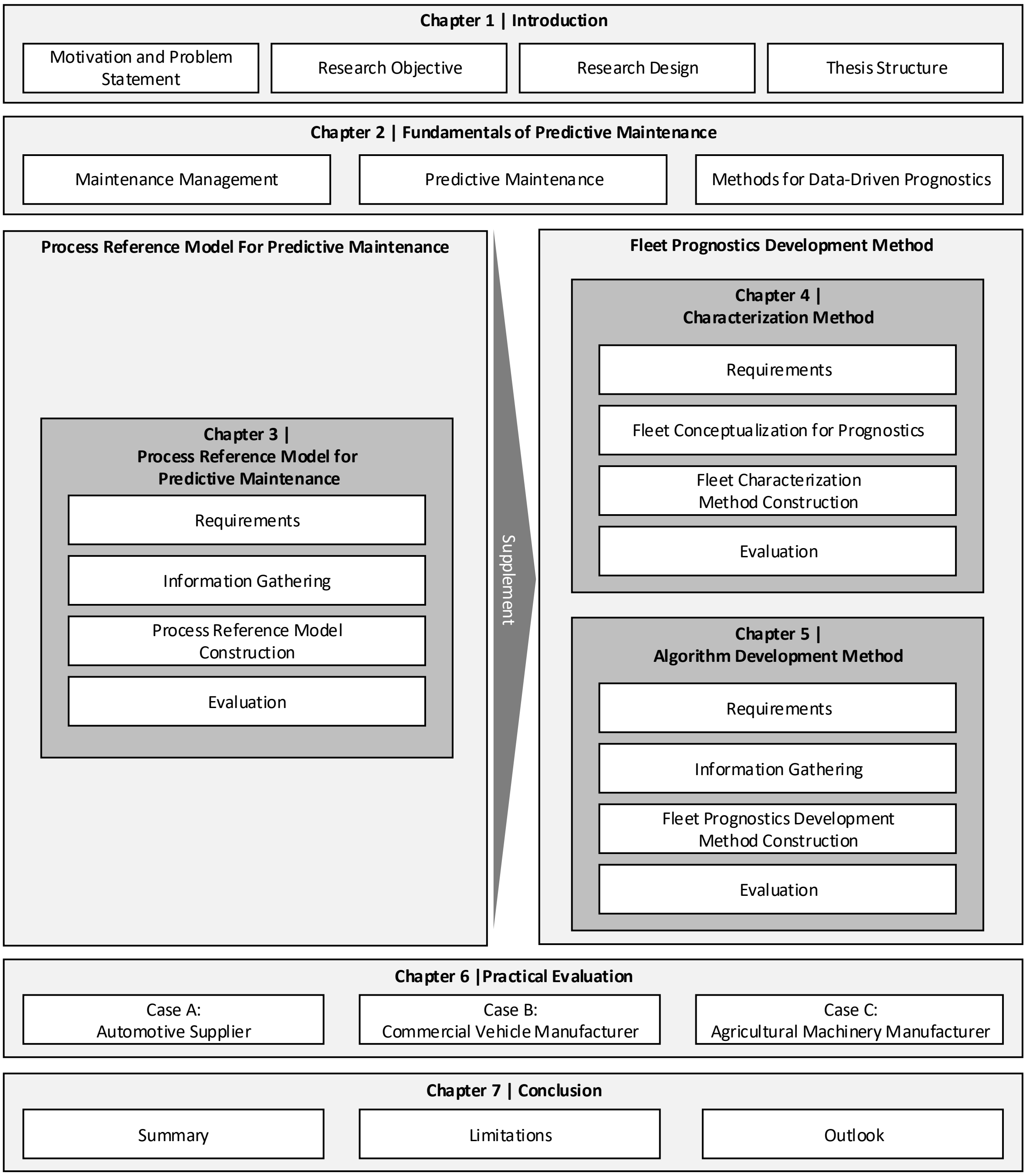


Figure 4 | Structure of the Thesis

2 Fundamentals of Predictive Maintenance

The following chapter introduces the foundations for this thesis's research. It addresses the main concepts in predictive maintenance which are essential for answering the targeted objectives. First, the positioning of maintenance management within spare parts management as well as the different maintenance types, including their key distinctions and application possibilities, are addressed (Chapter 2.1). This is followed by the presentation of predictive maintenance and its key components. Here, the predictive maintenance data analysis process is introduced, and its key steps are subsequently examined (Chapter 2.2). Thereafter, established prognostic methods are investigated. Besides different approach types, data-driven methods are investigated in more depth (Chapter 2.3). In the last chapter (Chapter 2.4), identified research gaps are briefly depicted, and their elaboration in the thesis is outlined.

Since fleet data is still a largely unexplored area that is to be examined in more detail in this thesis, this chapter refrains from introducing fleet data for predictive maintenance in depth. Instead, the foundation for the following research is to be laid here. A detailed discussion of the topic of fleet data for predictive maintenance follows in Chapters 4 and 5.

2.1 Maintenance Management

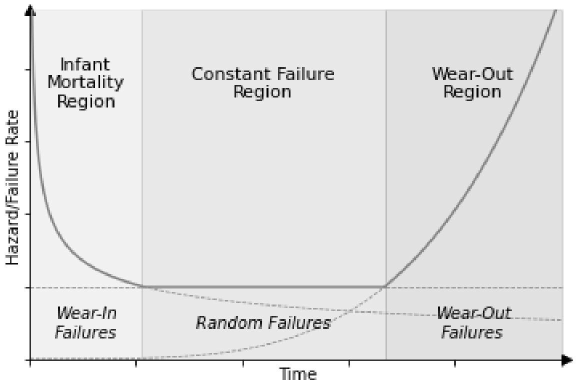
Predictive maintenance belongs to the field of maintenance management. This chapter, therefore, lays the foundation for maintenance management. For this purpose, initially, the concepts of spare parts management, maintenance management, and maintenance (including the general lifetime failure pattern) are shortly presented (Chapter 2.1.1). Thereafter, the different maintenance types are described and comparatively analyzed (Chapter 2.1.2)

2.1.1 Maintenance Context and Definition

Today, companies face a highly competitive environment and are thus operating under constant cost and efficiency pressure (Pawellek 2016, p. 1). In production, this challenge is often countered by, e.g., automation, inventory reduction, efficient production scheduling, and improved machine design. However, as a result, unexpected disruptions of the production process can hardly be compensated and become thus increasingly expensive. To ensure reliability and continuity of production, improved maintenance management has become essential (Jardine et al. 2006, p. 1484; Pawellek 2016, pp. 1 f.). For this purpose, a shift can be observed in companies that no longer regard maintenance as a necessary expense but instead as a reasonable measure to reduce costs (Khazraei and Deuse 2011, p. 96). This has led to growing attention for maintenance in recent years.

The tasks related to the preservation of the machine's functioning are addressed by spare parts management (Biedermann 2008, p. 6). Spare parts management comprises the ordering and provision of spare parts as well as maintenance control (Strunz 2012, pp. 570 f.). Spare parts logistics and maintenance management are, therefore, integral parts of spare parts management. *Spare parts logistics* support spare parts management by supplying the right spare parts to the right place at the right time with minimal costs (Pawellek 2016, p. 27). In contrast to material logistics, spare parts logistics has to cope with additional challenges, such as higher service requirements, lumpy demand patterns, and a high number of different spare parts (Huiskonen 2001, p. 125; Bacchetti and Saccani 2012, p. 723). *Maintenance management*, on the other side, comprises all activities which specify maintenance objectives, strategies, and responsibilities as well as their implementations (DIN EN 13306, p. 6). For this purpose, all technical, administrative, and managerial measures to preserve the function of a machine are addressed by maintenance (DIN EN 13306, p. 6). Maintenance activities can be grouped into maintenance, inspection, repair, and overhaul (DIN 31051, p. 4). Maintenance denotes the actions to delay the degradation, which is covered by regular maintenance intervals (Khazraei and Deuse 2011, p. 97). Inspection includes activities to identify the current state of the machine, along with the causes of degradation and the definition of possible consequences for future use (DIN 31051, p. 5). In addition, repair covers the physical actions performed to restore the functional state of a faulty machine (DIN 31051, p. 54). Finally, overhaul refers to the combination of measures to increase the properties of a machine (such as reliability, ease of maintenance, and safety) without changing its intended purpose (DIN 31051, p. 6). These maintenance services can be performed either directly by the manufacturer or through maintenance service providers (Bacchetti and Saccani 2012, p. 728).

Maintenance addresses the degradation and failure of machines in order to prevent or counter breakdowns in an appropriate manner. For this purpose, it is important to consider the typical failure patterns over the lifetime with respect to the failure rate, respectively, the hazard rate. This is usually depicted by the Bathtub curve, as shown in Figure 5. Instead of assuming constant failure rates over time, the lifetime is characterized by three stages. In the early stage, the infant mortality region, the failure rate is decreasing. In this stage, failures are usually related to material and manufacturing flaws (Goodman et al. 2019, p. 342). These failures can be eliminated through burn-in testing. This is followed by a stage with constant low random failure. These failures are often caused by fatigue damages (Goodman et al. 2019, p. 343). In the wear-out region, the failure rate is increasing significantly (Vachtsevanos 2006, p. 267). Even though the bathtub curve depicts an often over-simplified representation of the failure rate over time and disrespects usage and environmental conditions (Vachtsevanos 2006, pp. 267 f.), it can be used to gain deeper insights into machine failure rates.

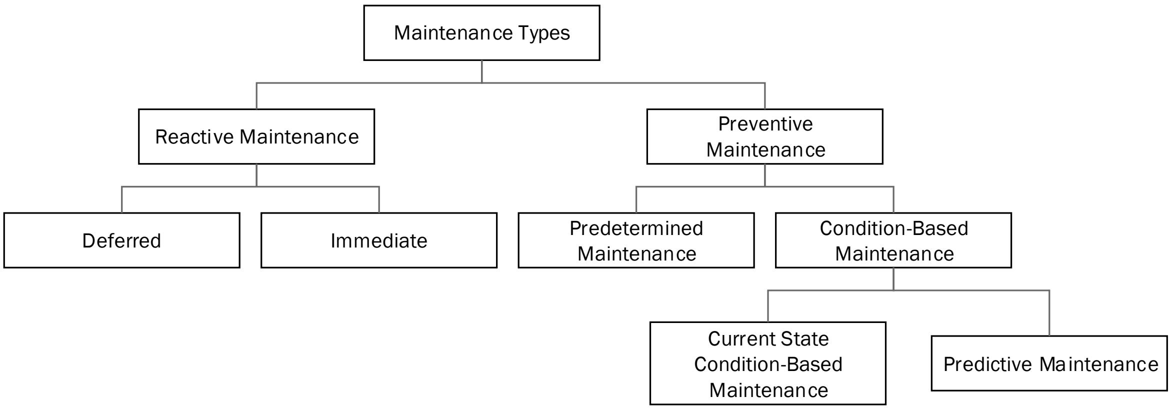


Based on Sikorska et al. 2011, p. 1817; Goodman et al. 2019, p. 343

Figure 5 | Bathtub Curve

2.1.2 Maintenance Types

The increasing importance of maintenance had an essential impact on the determination of the maintenance time from post-failure maintenance to the anticipation of future failures (Gouriveau et al. 2016, p. 3). This paradigm shift has given rise to various types of maintenance. Figure 6 presents a classification of the most commonly described maintenance types.



Based on DIN EN 13306, p. 39; Gupta et al. 2012, pp. 2 f.

Figure 6 | Maintenance Types – Overview

On the highest level, maintenance types are categorized into reactive and preventive maintenance. *Reactive maintenance*, also referred to as corrective, unplanned, or run-to-failure maintenance, depicts the oldest maintenance type (Jardine et al. 2006, p. 1484). In this case, machines are operated until failure, and maintenance is only carried out thereafter (Khazraei and Deuse 2011, p. 100). This type can be further divided into deferred (maintenance is delayed according to rules) and immediate (maintenance is carried out without delay) (DIN EN 13306, p. 23). Corrective maintenance allows to utilize the total machine lifetime; however, it is also usually accompanied by longer downtimes due to, e.g., missing spare parts, which can disrupt the production schedule and thus lead to high costs (Lee et al. 2009a, p. 3; Haddad et al. 2012, p. 873).