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PriMa: a prescriptive maintenance model for cyber-physical production systems

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ABSTRACT

Cyber-physical production systems (CPPS), as an emerging Industry 4.0's technology, trigger a paradigm shift from descriptive to prescriptive maintenance. In particular, maintenance management approaches nowadays are more and more transformed to (semi-) automated knowledge-based decision support systems. This paper is intended to examine existing approaches and challenges towards rethinking maintenance in the context of Industry 4.0 and thus contributes to the literature of production management and planning, by introducing a novel prescriptive maintenance model (PriMa). PriMa is comprising of four layers (i.e. data management, predictive data analytic toolbox, recommender and decision support dashboard as well as an overarching layer for semantic-based learning and reasoning). The integrated approach of PriMa enhances two functional capabilities, namely i) efficiently processing large amount of multi-modal and heterogeneous data collected from multidimensional data sources and ii) effectively generating decision support measures and recommendations for improving and optimising forthcoming maintenance plans correlated with production planning and control (PPC) systems. An industry-oriented proof-of-concept study has been conducted to explore the feasibility of applying PriMa in real production systems by implementing a decision support solution and achieving a significant reduction of downtime. Finally, future research directions in this area are outlined.

1. Introduction

1.1. Rethinking maintenance in the CPPS environment: context and objectives

The emergence of Cyber-Physical Production Systems (CPPS) (Monostori et al. 2016) and evolution of sensing and computational technologies in smart factories (Zühlke 2008), (Kagermann, Wahlster, and Helbig 2013), (Wagner, Herrmann, and Thiede 2017) influences maintenance approaches to incorporate certain functional capabilities for implementing smart and knowledge-based solutions. A recent market report forecasts a Compound Annual Growth Rate (CAGR) of 39% for predictive maintenance investments within the period 2016–2022 (IoT Analytics 2017). This corresponds with the key findings of an in-depth industry survey including 151 analytics professionals and decision-makers from industrial companies, in particular, Original Equipment Manufacturers (OEMs), product manufacturers and service providers (Lueth et al. 2016). It reveals that predictive and prescriptive maintenance of production systems including equipment, machineries and physical assets will be the most important application area of Industrial Analytics within the upcoming three years (79%) (Lueth et al. 2016). In line with this fact, approximately 60% of the respondents emphasise on developing knowledge-based decision-support systems to improve efficiency and effectiveness of industrial processes (i.e. using data from operation to automate maintenance planning decisions) (Lueth et al. 2016). Furthermore, it is also well-known from production management theories and empirical studies that efficient and effective

maintenance is an integral part of the production strategy and is a critical factor for overall production system stability (Wireman 2014).

In spite of all the excitement about technological enhancements with respect to automation, digitalisation and intelligentisation of manufacturing industry; predictive maintenance approaches implemented in real production systems have been limited to the application of condition monitoring systems for detecting the outliers (anomalies) and forecasting the moment of failure. In fact, prediction of a failure is the most important aspect to prevent and resolve persistent dilemmas in maintenance management (i.e. lack of availability, process instability and resource inefficiency). However, the aforementioned dilemmas, which have been understood as fundamental deficiencies of maintenance in production systems over several decades, are rooted in inappropriate maintenance strategies, models and measures for planning, monitoring and controlling. In other words, the lack of adequate, up-to-date, comprehensive and mature knowledge is the foundation for all failures. The missing link is a data-driven and knowledge-based recommender and decision-support system for maintenance management, including planning, monitoring and controlling, which enables answering not only the question 'What will happen when?' (i.e. Prediction) but also the significant question 'How should a specific event happen?' (i.e. Prescription). While no prediction techniques independent of planning strategies yields to significant results, making an informed decision based on a reliable prognosis of failure

events may achieve considerable system performance improvements and continuously improves decision quality and timeliness. This aspect has been largely neglected in the recent literature and real-life use-cases demonstrating smart and predictive maintenance applications (cf. Section 2).

In CPPS environment employing sensing and computational technologies and existing data-driven processes turn on the light into the dark side of maintenance and trigger rethinking maintenance approaches through continuing exploration of new knowledge and enriching as well as preserving existing knowledge. Hence, this paper investigates establishing the missing link between predictive approaches and maintenance planning strategies and decision-making. In the view of the authors, 'Prescriptive Maintenance Model' (PriMa) bridges the missing link in the maintenance literature and in fact, in industrial maintenance in order to achieve an acceptance by the planner/operator using data-driven approaches. PriMa completes the dynamic and iterative process of exploiting and exploring maintenance knowledge (cf. Section 3). While knowledge exploitation aims at searching, retrieving, providing and using existing knowledge elements located in databases, knowledge exploration seeks opportunities to discover new knowledge for deepening the insights into the state of maintenance activities and to provide recommendations for improving existing strategies and measures. The above discussion emerges the following key questions:

- From a conceptual and theoretical perspective, how to discover and preserve maintenance knowledge in CPPS environment to enhance decision-making processes? This research question investigates the lack of conceptual approaches in the literature of maintenance and CPPS, focusing on integration and adaptation of existing data analytic and semantic technology approaches for continuing knowledge discovery and -preservation from heterogeneous and multimodal data sources collected from various dimensions of maintenance (i.e. operational, tactical and strategic level).
- From a practical perspective, how to apply such a conceptual model in industrial use-cases where several technological and non-technological barriers exist? Notably, in order to tailor theoretical and conceptual models to real use-cases, several factors across industries should be considered such as technology readiness levels (e.g. with respect to ICT infrastructure, data accessibility, availability and quality as well as staff qualifications) (cf. (Ansari and Glawar 2018)).

1.2. The search for common ground for rethinking maintenance and related challenges

In order to rethink maintenance approaches in CPPS environment, it is worth underscoring the diversity of terminologies for this theme. While there are many similarities between novel maintenance approaches enhanced by sensing and computational technologies, there is a lack of consensus among researchers regarding what qualifies a maintenance approach in the era of Industry 4.0. This situation often leads to a lack of standardised definitions and common terminology for categorising maintenance approaches. Therefore, the frequently used keywords (such as smart maintenance, maintenance 4.0, intelligent maintenance, data-driven maintenance and predictive or prescriptive maintenance) remain vague or ambiguous. To arrive at a common ground of understanding, the authors propose to identify five functional capabilities for characterising maintenance in the context of smart factories, namely i) Prediction capability to monitor, analyze and anticipate hidden patterns and anomalies and accordingly predict critical and unexpected events (i.e. moment of failure), ii) Optimisation capability to achieve an optimal point in maintenance planning through economically efficient use of human and physical resources as well as knowledge assets, iii) Adaptation capability to conform to (unexpected) changes and reconfigurations in work-orders and production plans, iv) Learnability to continuously learn from former experiences (i.e. failure events and former decision-making instances), and finally v) Capability of intelligent actions and self-direction to (completely) automatise maintenance workflow and decision-support systems (i.e. autonomous maintenance management).

Realisation and consolidation of the aforementioned functional capabilities confront fundamental technological and non-technological challenges in the CPPS environment. According to the former investigations the main technological and non-technological challenges for design and realisation of CPPS, which directly or indirectly affect maintenance management (cf. Section 1.3), are summarised in Table 1.

Taking the above discussion into account, the two key aspects for (re-)defining maintenance in the context of smart factories are proper identification of the functional capabilities and optimal selection of the features in accordance with technological readiness level of a factory and its capacity to overcome non-technological challenges. The main focus of this paper is on the challenge V (cf. Table 1). In particular, the authors extend the scope of the challenge V towards extracting knowledge from heterogeneous, multimodal, multidimensional data sources. The authors propose that the term 'Knowledge-Based Maintenance' (KBM) should be used to denote the entire range of functional capabilities and features. KBM overarches multiple maintenance concepts and approaches including descriptive, diagnostic, predictive and prescriptive maintenance (cf. Section 2.1). Hence, the specific contribution of this research is to conceptualise a knowledge-based model (aka PriMa) for prescribing (high quality) maintenance measures and recommendations, based on multimodal data represented in heterogeneous structures, which are acquired from multi-dimensional sources such as maintenance (business) processes, machines and products. In addition, the paper investigates realisation of the PriMa in an industrial use-case and provides a proof-of-concept study. Accomplishing this task, this paper paves the way towards establishing the missing link between predictive approaches and prescriptive maintenance planning strategies and decision-making in industrial maintenance.

The rest of the paper is structured as follows. Aiming at identifying research gaps in the identified literature and also the competition in the field, Section 2 examines the

Table 1. Challenges for design and realization of CPPS (Adapted from (CPS Summit 2008), (Lee and Seshia 2015), (Seidenberg and Ansari 2017)).

	Challenges	Description	Type	
			Technological	Non-Technological
I	Compositionality	Compositionality problems may cause due to the integration of heterogeneous cyber and physical elements of CPPS, i.e. in system integration of both subsystems and Cyber-Physical Systems-of-Systems (CPSoS).	✓	
II	Distributed sensing, computation and control	Key problems include (semi-)real-time collection of adequate information, processing and asserting control in a distributed environment.	✓	
III	Physical interfaces and integration	An essential feature of CPPS is to be able to contact with the physical world using various sensor technologies.	✓	
IV	Human interfaces and integration	Another essential feature of CPPS is the ability to effectively communicate with various types of end-users in diverse qualification and competence levels through use of human-machine interfaces.	✓	✓
V	Extracting knowledge from heterogeneous data sources	Processing raw-data collected in structured, semi-structured and non-structured format as well as various quality and veracity levels, and extracting knowledge for supporting decision-making and learning from each decision instance, require deploying smart data analytics and Artificial Intelligence (AI) techniques, in particular predictive data analytics and deep learning.	✓	
VI	Modeling and analysis of physical and cyber components	A massive complexity is exhibited through modeling and analysis of heterogeneous physical and cyber components with different notions of time, across different scales, and integration of the feedback collected from them.	✓	
VII	Privacy, trust, security	Application of CPPS in diverse sectors raises new issues in privacy, trust and security, inter alia, revealing information from cyber-physical-socio space may require new rules on accessibility and transparency of information, i.e. what information can be hidden. In addition, new kinds of physical and cyber-physical attacks are possible e.g. in the context of smart and connected factories, i.e. there is a demand to new concepts and tools for cyber-security.	✓	✓
VIII	Robustness, adaptation, reconfiguration	CPPS operates in dynamic (production) environments and thus needs to handle uncertain situations and disturbances without affecting the outcome quality. In addition, CPPS should be reconfigurable and adaptive to deal with (unexpected) faults in both physical and cyber levels.	✓	
IX	Software technology	Development and deployment of CPPS require new programming languages, which could deal with complexity of cyber-physical spaces. In addition, CPPS requires integrated software solutions to support performance planning, monitoring and controlling of CPPS and dealing with high volume of (real-time) data fellow among sub-systems, systems-of-systems and environment.	✓	
X	Verification, testing, (safety) certification and guidelines	CPPS requires new approaches for verification and testing to check and regulate potential events such as physical or cyber related faults by comparing with certain standards derived from historical patterns, physical correlations and characteristics of a CPPS. For this purpose, a detection, learning and reasoning module should be developed to assure correctness of decisions and promote learning from former ones. Application of CPPS in diverse industrial sectors also requires handling safety certifications, e.g. to identify hazard sources and the way to deal with them in accordance with health and safety legal requirements in the workplace.	✓	✓
XI	Societal impact	Social aspects of CPPS may also affect the design, verifiability, validation, operation, privacy, trust, and fault tolerance. Especially, developing human-centered CPPS confronts several societal, cultural and ethical resistance to technological change e.g. due to the risks that robots or intelligent systems may take over human jobs and authorities in the workplace.		✓

state-of-the-art in KBM. In Section 2.1, the authors have critically reviewed the KBM concepts and models appeared in the literature and accordingly they have reflected their own views on KBM. Section 2.2 provides an extended discussion focusing on four aspects in the identified literature, namely prognostic-based and condition-based decision support, big data as an enabler to enhance maintenance management, prescriptive maintenance approaches, and finally integration of maintenance and Planning and Control (PPC) systems. Section 2.3 summarises the literature findings and indicates the most notable theoretical and practical challenges for bridging the existing gaps and establishing a missing link between predictive and prescriptive approaches (cf. Section 1). Section 3 introduces PriMa, as a knowledge-based approach for prescriptive maintenance in CPPS. It elaborates on the four-layer architecture of PriMa and related methods to be employed for realisation of each layer. Section 4 explores the feasibility for the realisation of PriMa and provides a proof-of-concept study including a step-wise methodology for industrial applications. Finally, Section 5 summarises the key findings and identifies future research directions.

2. State-of-the-art in knowledge-based maintenance

2.1. Review and synthesis of KBM terminologies and views

The term Knowledge-Based Maintenance (KBM) has been discussed in the literature of maintenance and assets management, where the main assumption is that competitive advantages for reducing maintenance cost are achieved through holistic

consideration, rather than atomistic, of all influential components and gaining knowledge of maintenance (Sturm 2001), (Reiner et al. 2005), (Pawellek 2013), (Biedermann 2014). According to the model presented by (Pawellek 2013) illustrated in Figure 1, KBM takes into account long-term effects of maintenance policies and decisions on economic terms, as a non-isolated sub-domain of production systems, which influences on organisational value creation. From this point of view, maintenance should be considered as a learnable organisation (Biedermann 2014). In the learnable organisation, knowledge is created in different organisational levels (strategic, tactical and operational levels) through comprehensive consideration of maintenance consequences, system conditions, and processes (Pawellek 2013).

KBM collects machine (systems), process, and products data, which are then transmitted to three areas that provide overall strategies of maintenance, namely i) risk-based maintenance, ii) condition- or time-based maintenance, and iii) Total Productive Maintenance (TPM) and lean maintenance (Pawellek 2013). KBM is responsible for unified consideration of outcomes collected from the three areas (Pawellek 2013).

In the former studies, the authors have examined the above-mentioned views on KBM and argued 'although the proposed approach to KBM is comprehensive, it only reveals the relation between several management approaches without indicating the logics of the relation, and the extent of deploying or producing knowledge. Moreover, no mechanism for acquisition, modelling and representation of the knowledge is proposed. The types and homogeneities of knowledge assets have not been discussed' (Ansari 2014). In fact, the concept of KBM in the context of CPPS should necessarily hold or comply with principles of Artificial Intelligence (AI), in particular, Knowledge-Based Systems (KBS) and pertained approaches (Beierle and Kern-Isberner 2008), (Russell and Norvig 2010). Hence, the authors have made efforts persistently to extend the definition of KBM particularly from the perspective of semantic modelling and representation as well as static rule-based or dynamic model-based analytics (e.g. in Ansari 2014, Matyas et al. 2017, Ansari, Glawar, and Sihn 2017, Nemeth et al. 2018, Kovacs et al. 2019, respectively). From the perspective of knowledge management (c.f. (Maier 2009), (North and Maier 2018), (Ansari and Glawar 2018)), KBM can be approached by focusing either on organisational and individual knowledge (human-oriented KBM) or data-driven strategies and approaches, sensing-, computational-, digital technologies, analytical tools and platforms (technology-oriented KBM). The main goal of technology-oriented KBM yet is i) to enrich the aforementioned definition of KBM by introducing and categorising different approaches (i.e. subsets of KBM) in relation to their complexity and maturity levels and ultimately ii) to achieve both holistic and atomistic consideration of all influential components for gaining and protecting the knowledge of maintenance (cf. Figure 2). Further, the authors describe how to tailor a KBM solution to a real use-case (cf. Section 4). Notably, human-oriented KBM remains open for discussion in the future (cf. Section 5).

In view of the above discussion, the authors define KBM as a functional unit responsible to i) continuously support value generation and ii) facilitate developing and protecting maintenance collective knowledge across smart factories, which is enhanced by need- or opportunity-driven knowledge detection, discovery, modelling and representation approaches. Hence, KBM employs a variety of methods including advanced statistics, stochastics, real-time computing (cf. (Lee 2017)) and analytics, machine learning algorithms, static rule-based or dynamic model-based analytics, and sematic modelling and representations. In the context of CPPS, KBM is demonstrated by its advanced functional capabilities, namely, knowledge discovery, prediction, optimisation, adaptation, (self-)learning and ideally self-direction. As depicted in Figure 2, in the view of the authors, KBM is categorised into four instances depending on the maturity and complexity of its functional capabilities. Each type of KBM can answer a certain competence question as follows:

- **Descriptive maintenance (Type I, Low Complexity, Low Maturity)** answers the question 'What happened?' by providing information about previous maintenance operations. Thus, it supports information collection and analysis and increases the level of information visibility.
- **Diagnostic maintenance (Type II, Medium Complexity, Low Maturity)** answers the question 'Why did it happen?' by analyzing cause-effect relations, reasoning, and providing further technical details about former maintenance operations. Therefore, it supports knowledge generation and increases the level of knowledge transparency.
- **Predictive maintenance (Type III, High Complexity, Medium Maturity)** answers the question 'What will happen when?' by learning from historical maintenance data, possibly in real-time, and predicting future events. Thus, it supports knowledge discovery and enhances the level of (semi-)supervised or unsupervised prognostic capabilities. Notably, this is often referred to as 'Smart Maintenance', 'Data-Driven Maintenance' and 'Maintenance 4.0', not only in scientific but also in commercial contexts.
- **Prescriptive maintenance (Type IV, High Complexity, High Maturity)** answers the question 'How can we control the occurrence of a specific event?' (How should it happen?) by providing actionable recommendations for decision-making and improving and/or optimising forthcoming maintenance processes. It also refers to the recent advances in enhancing self-organisation and self-direction capabilities of CPPS, which ideally aim at machine self-diagnosis and self-scheduled maintenance. Hence, prescriptive maintenance may reach the highest degree of maturity which involves complex methods to produce and reinforce adaptation and optimisation capabilities.

In the context of CPPS, the authors propose to interlink the predictive and prescriptive capabilities by providing a feedback loop, which examines the belief value on former

predictions and aims at improving the quality of maintenance measures and recommendations (cf. Figure 2). The most popular way is to distinguish between predictive and prescriptive maintenance. Instead, the authors stress on combining these two types to achieve synergistic capabilities on both prediction of forthcoming events and improvement of related outcomes (action plans). The combination of predictive and prescriptive maintenance involves i) modelling and representing (domain-specific or expert) knowledge, ii) predictive data analytics and iii) semantic reasoning. It, therefore, enhances and automatises decision-making processes by optimal selection and proposing the right strategies, tactics and action plans for foreseeing and handling problems pertained to the entire maintenance management. From this point of view, prescriptive maintenance, as the highest level of maturity and complexity of KBM, combines descriptive, diagnostic and predictive analytics to not only understand and reason out past events, but also to anticipate the likelihood of future events and potential effects of each decision alternative (associated with maintenance strategies) on the physical (machine) space and associated business processes.

2.2. Review of related KBM approaches

Considering the above discussion on KBM, the literature review presented in this section focuses on four aspects, i) Evolution of prognostic-based decision support solutions for Condition-Based Maintenance (CBM) based on various combinations of mathematical, statistical, stochastic and rule-based models, ii) Big data as an enabler to enhance maturity of maintenance approaches through gaining insights and depths to solve the aforementioned persistent dilemmas in maintenance management, iii) Emergence of prescriptive maintenance approaches, and finally iv) Integration of maintenance and Production Planning and Control (PPC).

In the past decade, several research works have been conducted on knowledge discovery in maintenance with the focus on big data analytics. A large body of literature deals with specific challenges such as predicting the health state of machinery, based on historical and real-time data as well as expert knowledge. In this context, different combinations of methods have been selected for developing prognostic-based decision support solutions for CBM. In this way, Bousdekis et al. (2015) provided insights into the literature and paved the way for the state-of-the-art analysis. They systematically reviewed and synthesised an extensive body of literature on prognostic-based decision support for CBM and provided a practical technique to effectively identify and select appropriate combinations of methods (Bousdekis et al. 2015). In particular, they identified a hierarchical structure for selection of i) prognostic- and ii) decision-support methods using condition monitoring data. The former, prognostic methods, is comparable to 'predictive maintenance' and the latter, decision support methods (equivalent to decision-making and recommendation methods in the literature), with 'prescriptive maintenance', respectively. In the view of their proposed hierarchical structure, they identified a pattern of prognostic and decision support methods reported in the literature. The authors examined and validated

the proposed structure by cross-checking the body of the literature reviewed by (Bousdekis et al. 2015) and recently published articles appear in multiple scientific databases, namely Scopus, Springer-Link, IEEE Xplore and Google Scholar (2015–2017). Likewise, prognostic methods have been categorised into three classes (P-X) as follows:

- P-I) Statistics subdivided into P-I-A) Statistical analysis such as statistical quality control, support vector machine, moving average, and P-I-B) Degradation modelling;
- P-II) Machine Learning (ML) subdivided into P-II-A) (Dynamic) Bayesian Network (DBN), P-II-B) Artificial Neural Network (ANN), and P-II-C) Reinforcement Learning (RL), and finally
- P-III) Markov Chain consisting of P-III-A) Continuous time and P-III-B) Discrete time.

Similarly, decision support methods have been categorised into two classes (D-X), namely:

- D-I) Operation Research (OR) approaches subdivided into D-I-A) Mathematical Programming (MP) including Linear-, Non-linear- and Stochastic Dynamic Programming, and D-I-B) Markov Decision Process (MDP), including Markov Decision Process, Semi-Markov Decision Process, and Partially Observable Markov Decision Process, and
- D-II) Rules subdivided into D-II-A) IF-THEN and D-II-B) Event-Condition-Action (ECA).

As a result, employing various P-X methods or different combinations of P-I, P-II and P-III has been reported for building prognostics models. However, decision support methods reported in the literature shape two clusters, namely, 1) a combination of Mathematical Programming (D-I-A) and optimisation rules (D-II) is typically used when the decision support objective function intends to estimate 'optimal time for a predefined action', and 2) Rules (D-II) are used when the decision support objective function targets 'optimal action AND optimal time for action' (cf. (Bousdekis et al. 2015)).

As mentioned earlier, within the recent literature (beyond the time horizons of the Bousdekis et al. 2015), the same trend on selecting various combinations of statistics and machine learning methods for predictive maintenance is apparent. As an example, one may refer to the following selected studies: for developing a periodic preventive maintenance model (Franciosi, Lambiase, and Miranda 2017), enhancing preventive maintenance through integrating probabilistic and predictive models (Ruschel, Santos, and Loures 2017), establishing a generic simulation-based predictive maintenance (Zarte, Wunder, and Pechmann 2017), developing cloud-based predictive maintenance framework (Schmidt, Wang, and Galar 2017), and introducing a smart maintenance decision support using corporate big data analytics (Bumblauskas et al. 2017) as well as applying various combinations of statistical data-mining and supervised machine learning for condition-based maintenance examined in (Accorsi et al. 2017). Specifically, dynamic-based prognostic models are used for predicting dependability in (Aizpurua et al. 2017), Bayesian modelling is

employed for optimisation of maintenance strategies in (Belyi et al. 2017), and application of various machine learning methods for self-parameterising process monitoring and self-adjusting process strategies for series production has been investigated in (Denkena et al. 2017). In this perspective, Wöstmann, Strauss, and Deuse (2017) examined existing predictive maintenance applications and their transferability to production systems considering a set of prerequisites for a successful implementation (i.e. a catalogue of preconditions and requirements to achieve business understanding, proper collection, exploration and modelling of data as well as dealing with data availability and quality issues) (Wöstmann, Strauss, and Deuse 2017).

Besides, the emergence of CPPS and Industrial Internet of Things (IIoT) as well as data-driven technologies brings the attention of maintenance professionals to 'data', in particular, 'big data'. Apart from the debates over the definition and characteristics of big data in maintenance (cf. (Ansari and Glawar 2018)), maintenance is supposed to gain benefits from big data to enhance its functional capabilities (i.e. ability to predict and react to failure). Hence, KBM may contribute to the enhancement of business values by manufacturing companies, based on decreasing maintenance costs and most importantly retaining and increasing availability of facilities over time. Focusing on big data in the literature of maintenance management, Yan et al. (2017) addressed the challenge for structuring multisource heterogeneous information for predictive maintenance and proposed a framework for characterising structured data with multi-scale analysis (Yan et al. 2017). The proposed multi-scale analysis takes into consideration the spatio-temporal properties (i.e. system-dependent and time-dependent) and modelling invisible factors (i.e. hidden root-causes and cause-effect interrelations) for causality mining (Yan et al. 2017). Zhang et al. (2017) also provided a big data analytics architecture for maintenance processes of complex products, which deals with structuring multi-source heterogeneous data (Zhang et al. 2017).

An emerging trend in the literature of maintenance is on knowledge-based decision support approaches for prescriptive maintenance. However, the authors' investigations reveal that this area is not yet extensively explored. Karim et al. (2016) discussed the maintenance analytics process including discovery, understanding, and communication of maintenance data (Karim et al. 2016). Aligned to the categorisation of KBM approaches in Figure 2, the maintenance analytics process is correlated with four perspectives, namely; descriptive, diagnostic, predictive and prescriptive maintenance (Karim et al. 2016). In order to develop a maintenance analytic-based decision support solution, the need of an overarching approach has been indicated, which should combine modelling of data, knowledge and context (Karim et al. 2016). The solution for information logistics, therefore, should not only answer the key questions such as 'when to deliver' (time management), 'what to deliver' (content management), and 'how to deliver' (communication management), but also should deal with 'where and why to deliver' (context management). Applying this concept, Famurewa, Zhang, and Asplund (2017) developed a decision support framework for the assessments of rail conditions (Famurewa, Zhang, and Asplund 2017). Moreover, Mourtzis, Boli, and Fotia (2017) proposed a reasoning methodology for knowledge-based

estimation of maintenance time, based on monitoring of Key Performance Indicators (KPIs) (Mourtzis, Boli, and Fotia 2017), using a Case-Based Reasoning (CBR) technique. The proposed approach supports knowledge capturing and reuse in maintenance activities within Product Service Systems (PSS) (Mourtzis, Boli, and Fotia 2017). Miebach, Schmidt, and Nyhuis (2017) presented a knowledge-based approach to design a self-learning maintenance library using Artificial Neural Networks (ANN), for selecting the right maintenance measures at the right time.

From a planning and controlling perspective, the weak linkage between maintenance and PPC approaches is evident. In particular, the meta-analysis of 54 job shop models published between 2014 and 2018 conducted by the authors (cf. (Glawar et al. 2018)) reveal that only 10 models consider a kind of linkage mainly to capture and use (feedback) information about maintenance for PPC by focusing either on periodic maintenance (e.g. for flexible job-shop scheduling using heuristic methods cf. (Li, Pan, and Tasgetiren 2014), (Fnaiech et al. 2015) and (El Khoukhi, Boukachour, and Alaoui 2017), minimising makes pan under availability constraints cf. (Benttaleb, Hnaien, and Yalaoui 2016), energy-efficient flexible job-shop scheduling cf. (Mokhtari and Hasani 2017), and production scheduling with different orders (Liao and Wang 2018), or on CBM for solving various job-shop scheduling problems cf. (Shamsaei and Van Vyve 2017), (Zandieh, Khatami, and Rahmati 2017) and (Rahmati, Ahmadi, and Karimi 2018)). A few models address the link between PPC and predictive maintenance (e.g. for job-shop scheduling depending on degradation rates and forecasting failures moments cf. (Mokhtari and Dadgar 2015) and time-varying machine failure rate (Fitouri et al. 2016)).

2.3. Summary of literature findings

The discussion in Section 2.1 and 2.2 reveals two particular issues. First, the advancement of KBM theory requires an integrated analytical framework that systematically and continuously seeks to exploit existing knowledge and explore new knowledge (i.e. comply with the dynamics of knowledge assets (cf. (Schiuma 2009))). Most of the approaches presented in Section 2.2 aim at solving a certain isolated problem under the premise of ensuring accurate estimation of a failure moment. However, they do not consider incompleteness and incomprehensiveness of information in decision situations as well as dynamics of decision-making in maintenance, especially under risky and exceptional choices.

Second, decision-making models in maintenance cannot afford to ignore the multi-dimensionality of maintenance organisation and processes, heterogeneity of IT-landscape and data sources as well as the fundamental demand for establishing a bidirectional communication channel between PPC and maintenance.

Therefore, in order to establish the missing link (cf. Section 1.1), the most notable theoretical and practical gaps and challenges confronting KBM are summarised in the followings.

Multiple maintenance strategies and approaches evolved over several decades increase the complexity in modeling of knowledge and identifying decision-making measures and related processes. Maintenance strategies that should be considered can be classified into three major groups as follows (cf. (Ansari and Glawar 2018), 1). Management strategies like total productive maintenance (TPM), total life cycle cost strategy (TLC) or reliability-centred maintenance

(RCM), which provide certain recommendations and standard measures for goal-setting and proper definition and implementation of maintenance activities including division of tasks, cost monitoring and controlling strategies, quality and performance management, organisational learning, documentation and content management, knowledge transfer, etc., 2) Maintenance strategies and approaches without sensing and computing technologies, which can be categorised into three approaches, namely run-to-failure-strategy, preventive maintenance, and proactive maintenance, and 3) Maintenance strategies and approaches with sensing and computing technologies, which can be categorised into three approaches, namely CBM, predictive maintenance, and prescriptive maintenance.

Multi-dimensionality of maintenance organisation, processes, actors and IT-systems shapes a complex knowledge landscape. In particular, a maintenance organisation consists of operational, tactical and strategic levels, in which different internal/external actors (i.e. knowledge-holder, -producers and -users) ranging from operators, engineers, project managers, top management and suppliers play a certain role. In addition, maintenance IT-landscape consists of several production information systems (PIMs) and (centralised or decentralised) databases, which continuously store and provide (meta-level) knowledge about machines, processes, resources (personnel, material, etc.), plans, quality control, costs as well as operational, tactical and strategic measures and key performance indicators (KPIs), such as overall equipment effectiveness (OEE), availability, productivity, etc.

Multi-modality of data is highly affected by big data or industrial data space (cf. (Otto et al. 2016)) consisting structured and unstructured data sources linked to multiple maintenance strategies and dimensions of maintenance organisation, actors and IT-systems. Hence, invisible semantics and interrelations among data sources may cause inevitable lack of comprehensiveness. This lack makes it difficult to properly solve (scalable) multi-objective optimisation problems and leads to incomplete information in decision-making situations. For example, linking single data elements collected from machine's Programmable Logic Controller (PLC) or maintenance processes may provide independent information about different aspects of maintenance (i.e. while machine failure signal can reflect malfunction of one of its subsystem; it can also indicate inappropriate planning, which causes subsystem degradation and affects its remaining useful lifetime). Furthermore, establishing a bidirectional communication channel for exchanging knowledge between maintenance and PPC may contribute to discover hidden relational patterns across multiple databases and to support learning invisible correlations and cause-effect relations (i.e. exploring new knowledge). In manufacturing companies, one may envisage two possibilities to establish a bidirectional communication channel as follows: i) Integration of condition monitoring and PPC systems to correlate (e.g. equipment's condition data and the production program or tool-wear and product quality (tolerances) data), ii) Integration of maintenance planning, monitoring and controlling and PPC to not only correlate (e.g. equipment condition and production program); but also establish reciprocal relations between maintenance and PPC to correlate strategies, programs, measures, processes and databases. Hence, changes and priority settings (e.g. for critical products or orders) could be communicated to maintenance and vice versa (e.g. to avoid quality loss or increasing unplanned maintenance costs).

3. PriMa: prescriptive maintenance model

Following the above-discussed line of research and the gaps identified in Section 2.3, Section 3 introduces a novel Prescriptive Maintenance Model (PriMa) towards realising KBM in CPPS environment. PriMa deals with i) multidimensionality of maintenance processes and ii) multi-modality and heterogeneity of maintenance records, while establishes iii) a linkage to PPC systems. In particular, Section 3.1 elaborates on the four-layer architecture and building blocks of the model and Section 3.2 discusses the interaction of PriMa with PPC systems.

3.1. Description of the model

Figure 3 reveals the overall architecture and building components of PriMa. PriMa consists of four layers, namely i) data management, ii) predictive data analytic toolbox, iii) recommender and decision-support dashboard, and finally an overarching layer iv) semantic-based learning and reasoning. These layers are described in the followings.

The data management layer employs a scalable data warehousing solution, which continuously collects temporal maintenance records, in particular management and cost data as well as operation-related data from three dimensions, namely, machines (through collecting conditions, diagnoses etc., as well as via direct query from machine's PLC), processes, and products. These three dimensions could be mapped to the horizontal and vertical data flow of CPPS and associated processes, including actors (maintenance managers and engineers, operators, technicians, administrative staff) and production (maintenance) information management systems (i.e. Supervisory Control and Data Acquisition (SCADA), Computerised Maintenance Management System (CMMS), Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP)). The horizontal perspective denotes data flow within either maintenance operation (i.e. machine or shop floor level) or maintenance management (i.e. tactical or strategic level of maintenance organisation). The vertical perspective considers semantic interlinking of operation and management data. Considering both horizontal and vertical perspectives, PriMa deals with multimodality of maintenance records. The multimodality reveals that each signal or single record provides independent information about different aspects of maintenance. For example, a failure signal can reflect the malfunction of a subsystem or component of a machine. At the same time, it may also indicate inappropriate workload planning in correlation with Remaining Useful Lifetime (RUL) of the machine. The latter may cause subsystem degradation and may lead to unscheduled downtime and unplanned maintenance costs. Hence, multiple influential factors should be interlinked to provide a complete picture of maintenance management, system conditions and related/dependent consequences and accordingly gain maintenance knowledge (cf. the foundation of KBM presented in Figure 1).

To this end, PriMa's Database Schema (cf. Figure 4) is developed using Data Vault 2.0 (Linstedt and Olschimke 2015). The Data Vault 2.0 allows modelling, interlinking multimodal data and building a scalable data warehouse (Linstedt and Olschimke 2015). Thus, PriMa's Database Schema deals

with the multiple dimensions of scalability and complexity of big data due to volume, velocity, variety and veracity of data as well as secure accessibility to integrated data (Linstedt and Olschimke 2015). Figure 4 depicts PriMa's Database Schema consisting four main Hubs. Each Hub refers to a key functional area, namely i) maintenance organisation (MO), ii) production planning and controlling (PPC), iii) cost controlling (CC), and iv) event tracking (ET). Hub-MO represents the maintenance activities, including ID number, type, category and timestamp. Hub-PPC establishes the relations between various data sources used for production planning (P) and controlling (C), including material and (human) resources as well as PPC processes. Hub-CC represents hierarchical cost relations, including infrastructure (IC), logistics (LC), personnel (PC), and external/residual service costs (ES) associated with maintenance activities. Finally, Hub-ET presents the event-sensor(-network)-system relations on the shop floor, including the type of event, which is determined through processing sensor (sensor-network) signals in conjoined with analysis of (sub-)system states. The relationships between the Hubs are stored in the Link (L) such as L-MO-CC-ET-PPC, which enables associative tracking of maintenance plan-activity-costs-events relations in both planning and controlling phases.

Furthermore, maintenance records represent heterogeneous data (i.e. structural heterogeneity). In particular, the recorded data can be either directly used by analytical tools, independent of its quality, or may require pre-processing (i.e. structured or semi-/unstructured maintenance records (cf. (Baars and Kemper 2008))). Structured data includes, for instance, conditions or environmental data captured by condition monitoring systems or via direct queries from the machine's PLC. The unstructured or semi-structured maintenance records are, for example, text reports or emails captured via reporting and documentation tools, or audio or images collected by means of microphones and cameras, respectively. The pre-processing time may vary depending on the volume

and quality of unstructured temporal data using text-mining approaches introduced in (Klahold et al. 2013) and (Ansari, Uhr, and Fathi 2014), or signal and/or image processing algorithms discussed in (Perner 2008). Notably, the present version of PriMa deals only with one type of unstructured data (i.e. textual maintenance records).

In the second layer of PriMa, several machine learning and knowledge discovery algorithms are used depending on the purpose of data analysis. In particular, four families of machine learning approaches are foreseen, namely, information-based, similarity-based, probability-based, and error-based learning (cf. Table 2). In addition to the practical technique proposed by (Bousdekis et al. 2015), extensively discussed in Section 2.2, the authors discussed the process for systematic selection of a single algorithm or combination of various algorithms tailored to specific problem characteristics under different data quality conditions in (Nemeth et al. 2018). As an example, the process for application of Dynamic Bayesian Networks (DBN) has been elaborated in (Ansari, Glawar, and Sihn 2017).

Moreover, extracting and learning new concepts and knowledge from textual data is supported by textual-meta analytic algorithms. In particular, word associative measuring and associative gravity force calculation are employed, which has been introduced and evaluated in (Klahold et al. 2013) and (Ansari, Uhr, and Fathi 2014) (cf. Section 4.3.2).

In the third layer, the outcome of various data analytic algorithms should be correlated to exclude processing errors, to identify the interrelations and aggregate the findings (i.e. provision of evidences for causality detection and finding patterns), to improve maintenance measures, and finally to recommend appropriate actions (decision alternatives). In order to accomplish this task, there are two possible and in fact compatible approaches. First, various decision support methods can be used such as (dynamic) rule-based techniques (cf. the discussion in Section 2.2 and (Bousdekis et al. 2015) and (Nemeth et al. 2018)). Second, knowledge modelling,
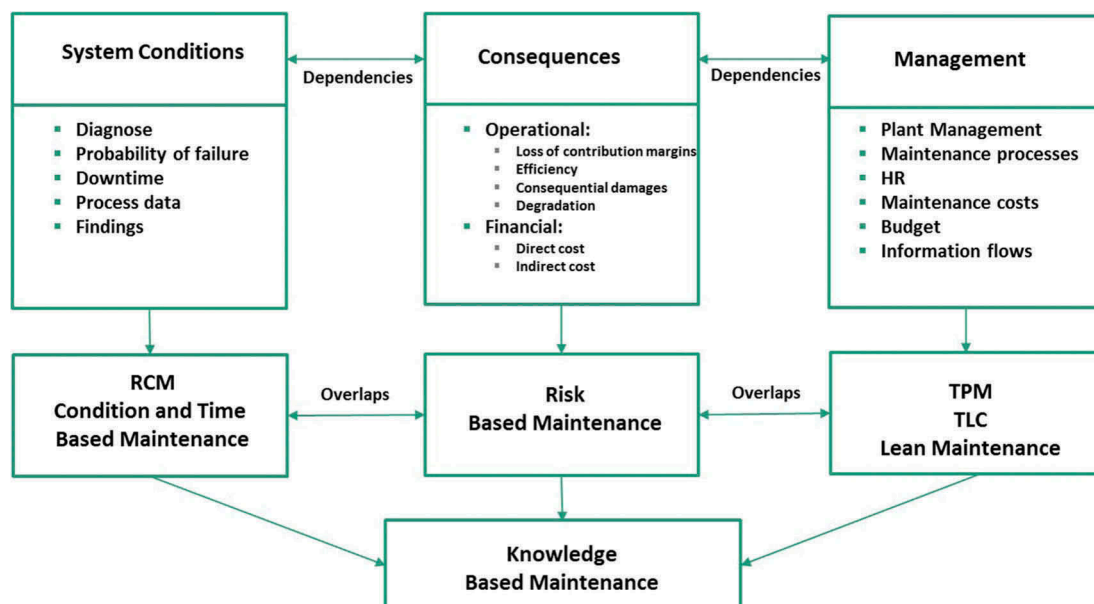

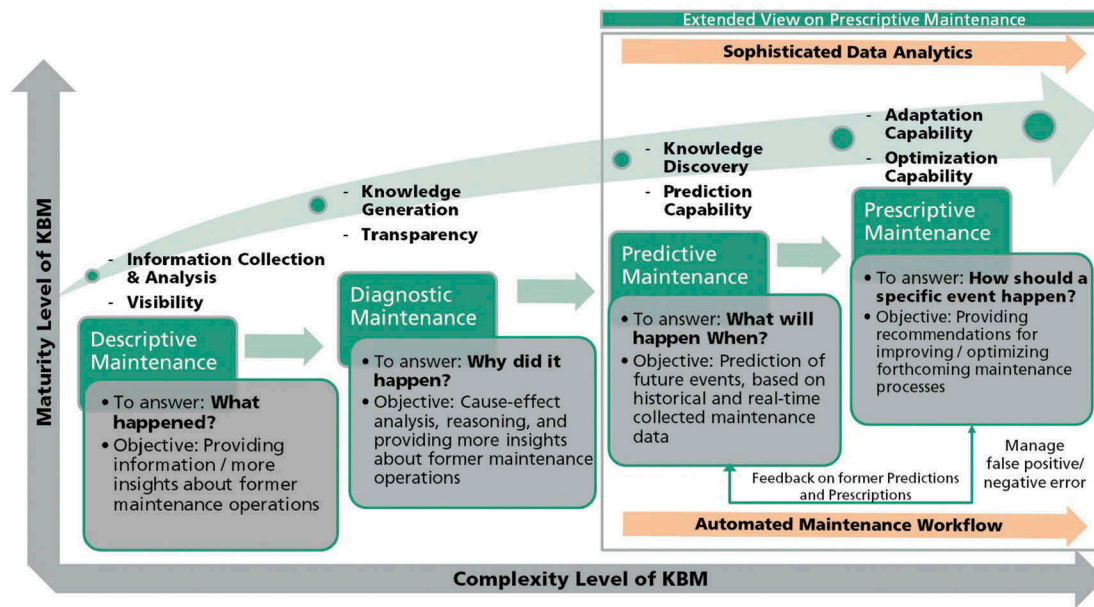**Figure 1.** The basic model of KBM – Adopted from (Pawellek 2013).

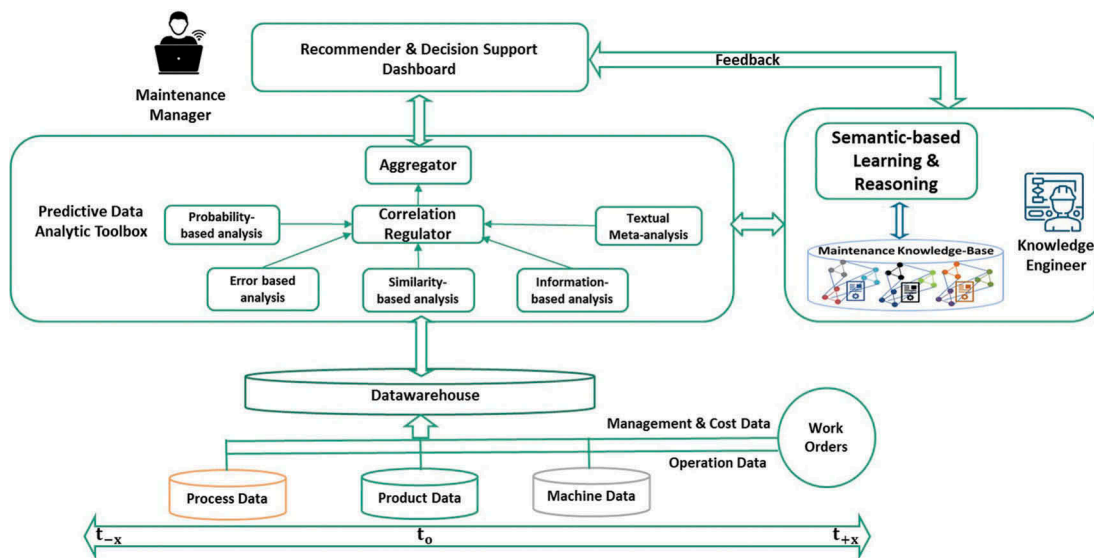**Figure 2.** Evolution of KBM – Maturity and complexity levels.

Figure 3. Overall architecture of PriMa.

representation and reasoning methods can be used to establish maintenance knowledge-base for storing and preserving knowledge created in each decision-making and problem-solving iteration. Furthermore, enriching existing knowledge as well as learning new semantic relations in various iteration of problem-solving (i.e. learning from former experiences as well as meta-learning) should be considered to keep the knowledge-base up-to-date over time. The former approach is part of the third layer and the latter is considered in an overarching layer linking second and third layers.

In particular, the overarching layer is responsible for semantic-based learning and reasoning. To achieve this goal, two types of knowledge-based methods can be employed, ontology and case-based reasoning (CBR). In an earlier publication, one of the authors has extensively discussed the methodology for establishing an ontological knowledge-base in human-centred CPPS (cf. problem-solving ontology discussed in (Ansari et al. 2018)). Ontology is a method to structure and build up a domain-specific knowledge-base (Studer, Benjamins, and Fensel 1998). Ontology conceptualises and structures the domain of the interest (i.e. maintenance) from an abstract to a detail level in a taxonomy form and provides possibilities to incorporate ontological and non-ontological resources as well as editing, discarding, updating and matching stored knowledge (Gruber 1993),
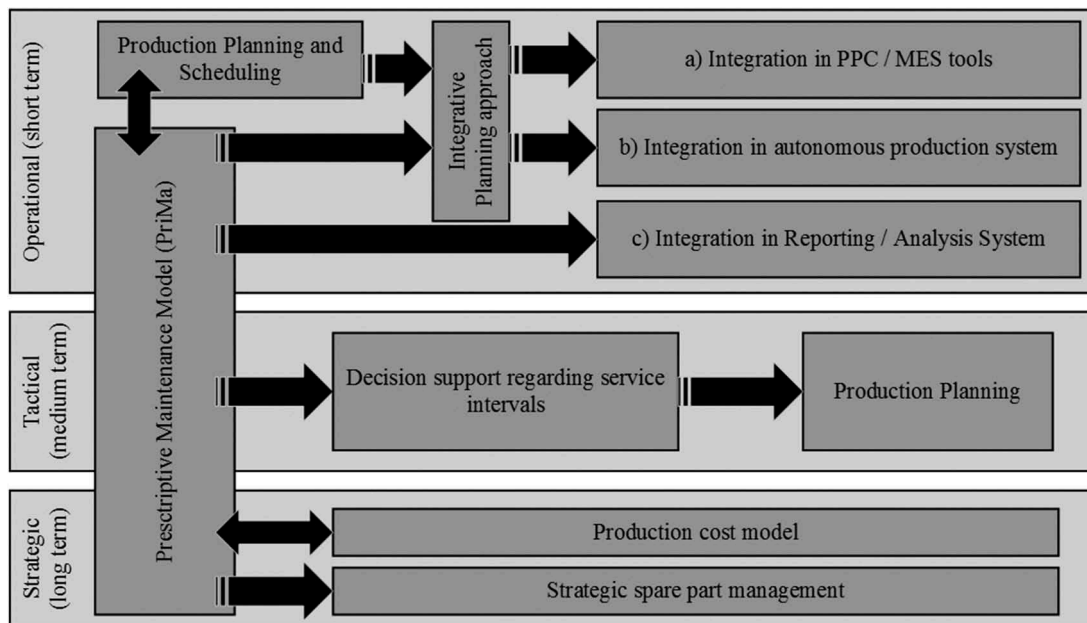
Figure 4. PriMa's database schema – Interlinking multimodal data and building a scalable data warehouse.

Table 2. Four main families of machine learning algorithms (Adopted from (Kelleher, Mac Namee, and D'Arcy, 2015), (Ansari et al. 2018)).

	Learning Approach	Description	Example of algorithm
Machine Learning Families	Information-based Learning	Employing concepts from information theory to build models.	Decision Trees
	Similarity-based Learning	Building a model based on comparing features of known and unknown objects, or measuring similarity between past and forthcoming occurrences.	k nearest neighbor (k-NN), Case-Based Learning
	Probability-based Learning	Building a model based on measuring how likely it is that some event will occur.	Dynamic Bayesian Network
	Error-based Learning	Building a model based on minimizing the total error through a set of training instances.	Multivariable linear regression

(Guarino and Giaretta 1995). Ontology has been used in production management to build up domain-specific knowledge-bases (e.g. in the automation domain (Legat et al. 2014), human-robot collaboration on the shop floor (Ullrich 2016) and CPPS in the field of process technology (Engel, Greiner, and Seifert 2018)). Nevertheless, the problem-solving and learning from experiences (i.e. solution of similar past problems) remains incomplete. The method to accomplish this task is CBR (Aamodt and Plaza 1994). The CBR cycle consists of four steps to solve a problem '1) Retrieve the most similar case or cases, 2) Reuse the information and knowledge in that case to solve the problem, 3) Revise the proposed solution, and 4) Retain the parts of this experience likely to be useful for future problem solving' (Aamodt and Plaza 1994). Various studies in engineering and production management reveal the capability of CBR in comparison with other AI methods (e.g. for managing order-picking operations in warehouses (Poon et al. 2009), estimation of maintenance time for complex engineered-to-order products (Mourtzis, Boli, and Fotia 2017), detection of mechanical faults (Nasiri, Khosravani, and Weinberg 2017), and decision support on diagnosis and maintenance in the aircraft domain (Reuss et al. 2018)). In particular, PriMa gains benefits from the systematic approach for knowledge engineering and implementing the CBR cycle presented in (Reuss et al. 2018).

3.2. Interaction of PriMa with PPC systems

As highlighted in the state-of-the-art analysis (cf. Section 2), far-reaching research has been performed aiming at developing innovative maintenance planning, including predictive or prescriptive maintenance planning. Furthermore, plentiful research has been done in the fields of PPC. However, little

Figure 5. Relation between PriMa and PPC.

literature exists, where those two disciplines are integrated. Existing models are not applied in the operational praxis since they often do not provide realistic results. Moreover, the interaction between innovative maintenance planning, the scheduled production plan and current quality measurements of the produced parts is not considered in most of the available approaches. Since a holistic optimisation of these factors is generally not done, these models are only based on idealised assumptions and therefore lack a validation in real industry environments (Glawar et al. 2018).

In Figure 5 the possible interaction between PriMa and the area of PPC is illustrated. From a strategical long term perspective, the results of PriMa can be used for the optimisation of the strategic spare part management. In particular, availability of spare parts can be planned based on the recommendations provided by PriMa rather than historical knowledge gained through experience. Furthermore, the production cost model may use the results of the analysis for the purpose of adjustment. On the other hand, the model uses the input from the cost model in order to derive prescriptive maintenance measures. From a tactical medium-term perspective, PriMa is used for decision support regarding the adjustments of service intervals and therefore directly influences the production planning. At the operational short term perspective, the interaction between PriMa and production control is quite strong. On the one hand, the derived prescriptive measures are influenced by the current production scheduling. On the other, the maintenance measures, which were carried out, may be again used for the forthcoming production scheduling and production control. Such an integrative planning control can be implemented in either a PPC or MES tool within an industrial IT-landscape, or in an autonomous production system. Of course, the results of PriMa can also be used for the integration in a reporting system on the short term perspective.

4. Application of PriMa within an industrial use-case

Section 3 discusses the theoretical foundations of PriMa and elaborates on four layers including various sets of analytical and knowledge-based methods. Especially, the bidirectional communication channel between PriMa and PPC has been introduced in Section 3.2. In order to discuss the industrial application of PriMa, an industrial use-case is presented in Section 4. The methodology for industrial application of PriMa (cf. Section 4.3) relies on the premise of supervised learning and reasoning, in which a group of data analysts and knowledge engineers collaborate with domain and business experts. Hence, the use-case study contributes to realisation of layer one to three of PriMa. Notably, implementing a (semi-)automatise semantic learning and reasoning using the CBR framework provided by (Reuss et al. 2018) remains for future works (i.e. consolidating and validating key-findings), based on research in progress on developing the CBR component of PriMa. In addition, building an ontological knowledge-base for problem-solving in maintenance has been discussed in an earlier paper (Ansari et al. 2018). The above-mentioned limitation of the proof-of-concept study is due to the time-consuming and step-wise approach to realise layer one to three of PriMa, especially in cooperation with an industry parthner, consisting several verification and validation iterations.

4.1. Description of the use-case

The proof-of-concept study was carried out at an international manufacturer of gearboxes and engines for the automotive sector. The primary objective of the manufacturing company was to explore possibilities to employ data-driven approaches and develop a new knowledge-based maintenance strategy, which predicts critical events on the basis of machine, process
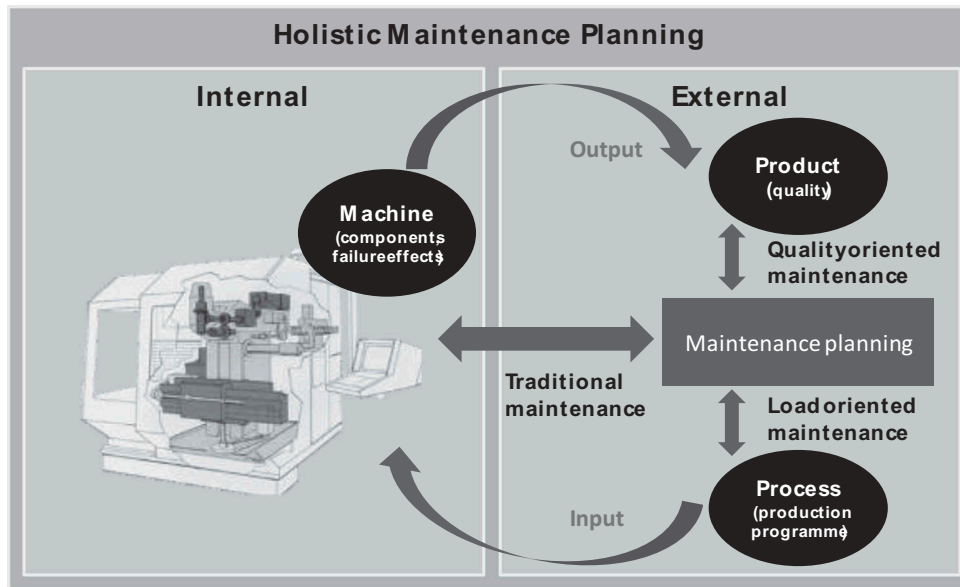
Figure 6. Different data perspectives of the industrial use-case. Reprinted from (Glawar et al. 2016a).
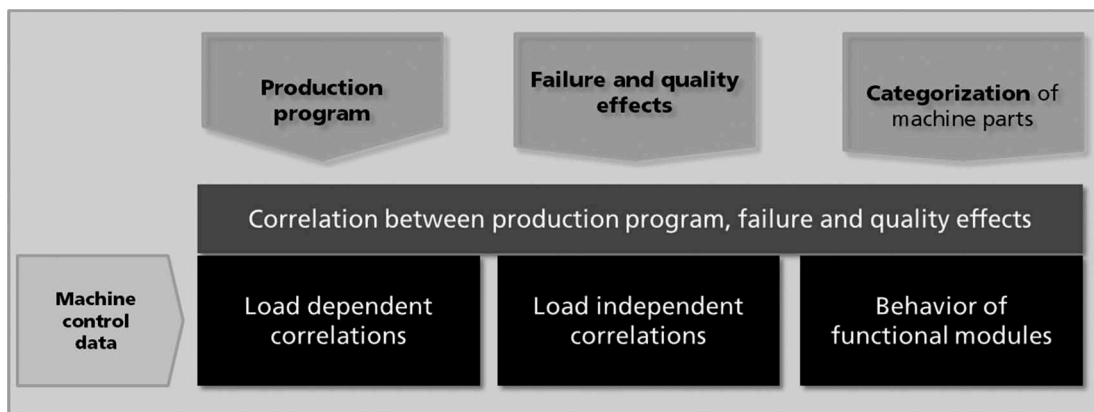

Figure 7. Different types of component behaviour.

and product quality data and (semi-)automatically derives measures for decision support on maintenance (cf. Figure 6). To explore and demonstrate the feasibility of the new concept, a three-axis machining centre for milling, turning and honing has been selected as a pilot machine type. In particular, two different machines are investigated as reference machines (machine instances). Due to the fact that the selected industrial company runs around 60 structurally identical machines from this machine type, a high amount of data is available and a big multiplication effect regarding the successful implementation is expected.

Applying PriMa for components with different load/wear behaviour (cf. Figure 7), those components have been categorised into three cases: 1) load dependent correlations, 2) load independent correlations and 3) functional modules. For the load-dependent calculation, this categorisation includes the ball screws and linear guides of the main axes, as well as the bearings of the tool spindle. For the load independent behaviour, the clamping mechanism for the workpiece and the tool clamping of the main spindle is

considered, because their wear behaviour depends on the amount of switching cycles. For the functional modules, the flow sensor of the cooling system is used to demonstrate the application of PriMa for time-dependent components. Notably, for specific type of components, neither sufficient analytical nor empirical rules for lifetime (i.e. RUL) or wear are known nor statistical relevant correlation could be identified. For this reason, such components are not considered within this use-case.

4.2. Description of relevant data sources

For a defined time frame of two and a half year; data from various data sources (c.f. Table 3) has been gathered for two different reference machines. Therefore, it was possible to compare if a different production program leads to different load spectra on the respective machines. For the validation of the applied model; data from another two years' period has been gathered from the same data sources. After the model has proven to deliver

Table 3. Relevant data sources and information.

Data Source	Relevant Information	Quality/Granularity of Data
ERP System	Cost of spare parts, availability of spare parts	Real time information
ERP System	Hourly cost rates	Cost rates for skill groups
MES System	Total downtime of machine & machine performance (Overall Equipment Effectiveness (OEE))	Downtime manually entered by operator
MES System Maintenance Management Software (CMMS)	Historical production programme, (planned) future production program	Planned/Produced parts (per product type) per machine per shift
	Process parameters	Process parameters for each manufacturing job
	Periodic service plans	Service intervals for each components, planned service dates (monthly, quarterly, yearly)
Access data base for failure documentation	Documented Failure events (Report of failure event, and documentation of failure handling)	Manual documentation by operator (full-text)
Access data base for failure documentation	Time stamp (Report of failure, failure handling finished)	Manual documented by operator
Historical Knowledge Data base (Excel)	Failure classification	Rough classification (Mechanical, electrical, etc.)
	Historical Documentation of failure events	Analog to Access DB
Quality Control Database	Quality data of products	Measurement of one product of each produced product type per shift (value for each quality criteria)

significant results, the evaluation has been performed using the data for the whole time span of four and a half years.

The analysis of the before listed data sources revealed that three of them may play a key role, namely;

(1) *The documentation of failure events* represents the main basis providing information when a failure event has occurred. This information has been documented in two databases. Historically this information was documented in an Excel file. Currently documentations are stored in an Access-based Database. Therefore, these two data sources need to be aligned, consolidated, and together pre-processed for further considerations. Within this data source, the occurring failure events have been reported by operators and documented in full-text. Furthermore, the timestamps for report of the failure as well as the end of the failure handling are presented in the same data source.

(2) *The quality measurement data* are used within the quality control database. For every produced product per shift, a detailed measurement process is initiated and the results are stored in a failure protocol. Therefore, different kinds of quality factors are derived, which build a meaningful basis regarding an analysis of correlations between quality and failure effects.

(3) Finally, *historic and future production programs* using MES system provide information regarding the load spectrum and planned load on the machines. As a consequence, for load depending on machine components, such as ball-bearing, an analytical or empirical calculation of the lifetime based on the respective NC program is possible.

4.3. Methodology for applying PriMa

Considering the above discussion on the state-of-the-art in the manufacturing company as well as the objectives of the study, a methodology for industrial application of PriMa has been presented in Figure 8.

The four-step methodology is based on the Cross Industry Standard Process for Data Mining (CRISP-DM), which comprises six phases, namely i) business understanding, ii) data understanding, iii) data preparation, iv) modelling, v) evaluation and vi) deployment (Chapman et al. 2000) and (Kelleher, Mac Namee, and D'Arcy 2015). The methodology for applying PriMa merges phases (i) and (ii) and (iii) of CRIS-DM into Step 1 'Data Acquisition and Preprocessing', which involves business and domain experts of the manufacturing company as well as data and knowledge engineers of the project team. Building and modelling predictive data analytic framework (Phase iv) is distributed across Step 2 and 3. Step 2 'Data analysis and simulation' focuses on building and simulating a predictive model for failure detection and Step 3 'Reaction model' on defining a set of decision rules satisfying the given requirements. Both steps consist of several intermediate evaluations (Phase v). Finally, Step 4 'Prescriptive Maintenance Decision Support System' is aimed at creating the decision support system framework including prescriptive measures, developing a (mobile) maintenance control centre as well as evaluation and deployment (Phase v and vi) of the entire system. In particular, in the first step, data of the relevant data source has been gathered and pre-processed for further analysis. Therefore, it was necessary to perform a data transformation to a target data structure, and derive meaningful information from the unstructured data (i.e. by using text-mining methods). In the second step, the data has been analyzed in order to identify the correlations between quality and failure effect and therefore reduce the amount of significant features for the reaction model in the next step. Furthermore, a simulation-based digital shadow of the machine may derive the wear-reserve of the machine in real-time. In the third step, the results of the data analysis and wear calculation have been combined in a dynamic set of rules. These rules have been used for the prescriptive maintenance decision
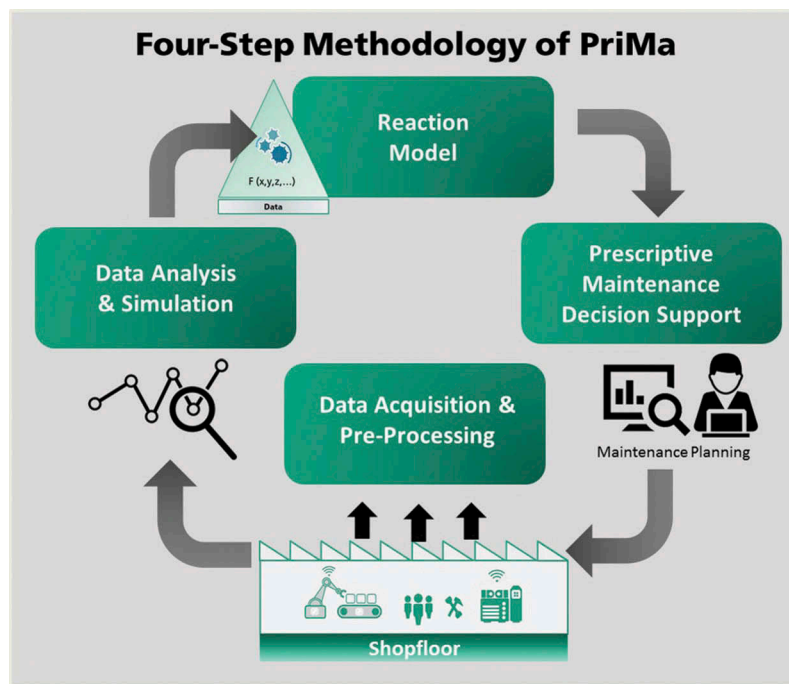
Figure 8. Four-Step methodology for applying PriMa. Adopted from (Matyas et al. 2017)

support system in the fourth step as a basis in order to derive maintenance measures.

4.3.1. Data acquisition and pre-processing

In this step, data from the relevant data sources (cf. Table 3) has been gathered, structured and analyzed. Since different sets of data usually represent a different data structure, information quality and veracity, it was essential to provide a target data structure before using the data for further analysis and simulation. Certain data sets have been generated automatically (such as product quality measures) and therefore provide unique metadata structures as well as high accuracy of data. In contrast, the other data sets that have been documented manually by the operators represent no clear structure of metadata and usually cause extra (pre-)processing time when dealing with full-text entries. Within the first meta-analysis as well as explorative analysis of the present data, a data transformation has been conducted and a new target data format has been introduced (cf. Table 4). Within this target data structure, all sets of data are linked by a unique time-stamp key, which enables further data analysis and simulation.

In order to provide a meaningful context to the data, a special focus has been laid on the operative maintenance processes. In Figure 9, the relevant systems and tools for the operative maintenance processes are shown.

As a result, important requirements and restrictions regarding the application of PriMa have been derived, which are summarised in the followings:

(1) Process parameters do not vary significantly due to the produced product types at the reference machines and thus do not lead to meaningful information. Therefore, this data source has not been further used within this use-case.
(2) For this kind of machine type, no explicit condition monitoring signals have been available. The application of additional sensors has not been in the scope of the use-case. However, the integration of motor-current signal analysis has firstly shown positive results.
(3) The already available maintenance KPI´s of the industrial company (such as Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR)) have not been used since short downtime events are neglected within their calculation. Thus, additional analysis has been carried out for the use-case, based on the actual downtime data extracted from the MES system.
(4) And finally, the documentation of the failure event do not exist in a structured format and therefore has to be

Table 4. Target data structure.

| Failure documentation	Time stamp	Machine ID	Module	Group	Component	Classification	Root cause	
Quality data	Time stamp	Machine ID	Product ID	Quality- factor	Value of Measurement	Target Value	Upper limit	Lower limit
Production Program	Time stamp	Machine ID	Product ID	# Parts				
Process data	Time stamp	Machine ID	Product ID	Process Parameter	Value	Target Value	Upper limit	Lower limit
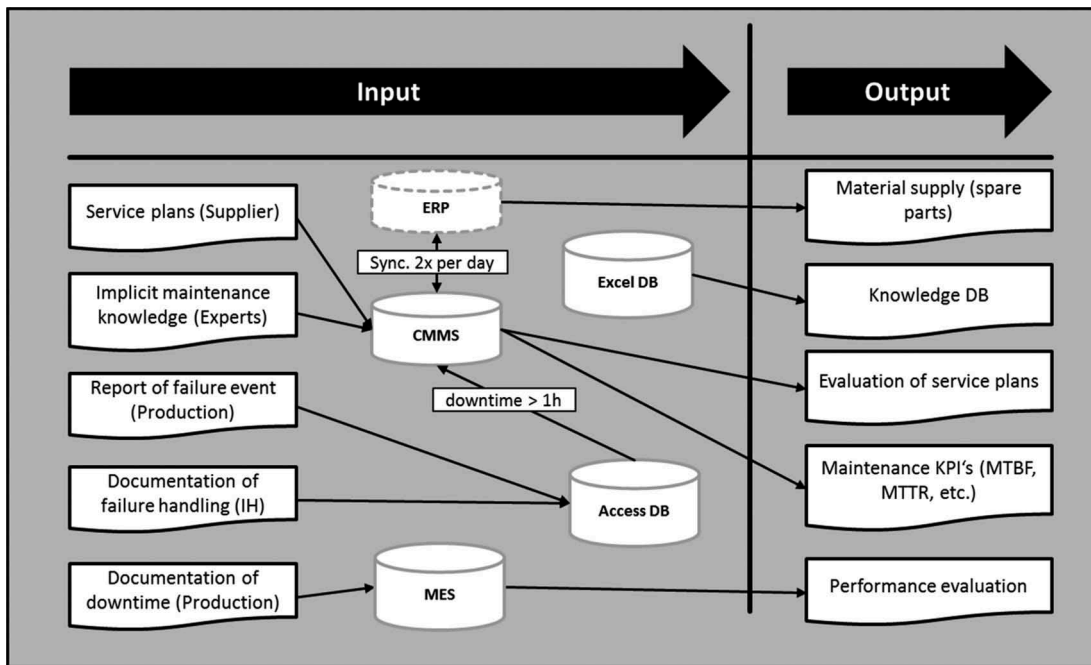
Figure 9. Relevant systems and tools for the operative maintenance processes.

further pre-processed.

4.3.2. Application of text-mining with unstructured data: pre-processing and association (gravity) measuring

In order to process unstructured data (i.e. free text passages) and extracting meaningful information from the documentation of failure events, text-mining approaches are employed. As exemplified in Figure 10, the free text passages are initially preprocessed consisting several steps, namely splitting each report to sentences, tokenizing the sentences, lowercasing each single token of the input text and removing stop words.

Afterwards, the extracted keywords are used for the purpose of meta-analysis. Firstly, CIMAWA method is used for measuring the strength of association between two words (i.e. *word (x)* and *word (y)*). CIMAWA has been introduced earlier in (Klahold et al. 2013) and applied in the context of maintenance (Ansari, Uhr, and Fathi 2014). CIMAWA combines symmetric and asymmetric co-occurrences between two words. 'Co-occurrence is a statistical measure that expresses how many times two words coexist in a defined text window' (Klahold et al. 2013). Secondly, the strength of attraction of *word (x)* in relation to *word (y)* is calculated using a statistical measure known as Associative Gravity Force (AGF). AGF has been introduced earlier in (Klahold et al. 2013). CIMAWA and AGF support the identifica-
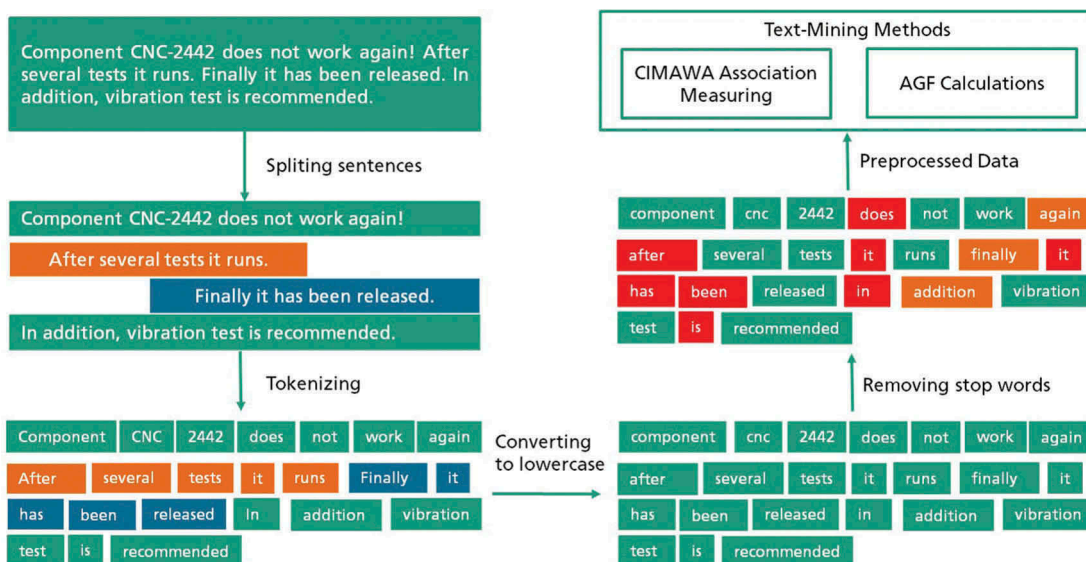

Figure 10. Example for pre-processing of free text passages.

tion of keywords relations in the maintenance text corpora, which reveal additional information. For example, the associative gravity measuring could lead to discovering a new category such as module or assembly, which was hidden. In every step, the results should be validated by the domain expert to improve the performance of the text-mining algorithms (e.g. by manually adding a new category). The information extracted from documentation of failure events has been then structured in three different layers regarding the failure events (i.e. module, assembly, and component). If possible, a layer regarding the root cause of the failure has been added. After an intensive coordination and harmonisation of the new data structure with the domain experts of the industrial partner, the new set of data has been used for further analysis and application of PriMa.

4.3.3. Data analysis and simulation

At this stage, different steps of data analysis have been carried out in order to identify relevant cause and effect coherences between product quality- and failure event data. Furthermore, the RUL of a machine component has been determined based on a simulation approach, which will be discussed later in this section. In order to be able to derive correlations, the first step was to reduce all available quality factors to just the relevant ones and therefore reduce the amount of significant measurement values for the reaction model. For this purpose, the quality factors were correlated with each other (cf. Figure 11). If two measuring points were strongly correlated, one of the affected measuring points has been excluded, because they may reflect a redundant information content.

The list of features for significant quality factors is the basis for the determination of relevant cause and effect coherences between product quality- and failure event data. Hence, a quality matrix has been created; listing all possible failure effects as well as significant quality factors and their respective measuring points (cf. Figure 12). In this matrix, two types of knowledge sources have been integrated: i) the already known coherences, based on the experience of the operators in the industrial company, and ii) results of a detailed explorative analysis of the quality data. It is important to mention that this was performed as an iterative process. On the one hand, the results of the explorative analysis have been discussed with the experts. On the other, the experts' opinions have been questioned based on the results of the analysis. Finally, a correlation matrix with four degrees of significance (very strong, strong, medium and weak correlation) has been derived. For the features with a significant correlation between quality effects, it is possible to identify statistically significant deviations in the next step.

Based on a simulation-based digital shadow of the machine the wear out of certain machine components has been derived (cf. Figure 13). The simulation approach has been extensively discussed in (Matyas et al. 2017) and (Glawar et al. 2016a, 2016b). As illustrated in Figure 13, in a first step, the preparation of the simulation requires the NC programs, the archive files of the control, the CAD data of the machine and the work piece. These data are transferred to the dynamic calculation, which determines the temporal load of the individual components such as guides and drive elements. Based on these data and the component properties, the wear calculation computes the theoretical wear. This dynamic calculation is based on the process forces derived from the kinetic data, the cutting volume and its position. In order to solve this problem, the empirical approach according to Otto Kienzle (Sekulić et al. 2014) has been chosen. It is based on a correlation of cutting volume and the direction vector. The simulated process forces have been compared to conducted measurements of the process force within the machine in order to ensure the validity of
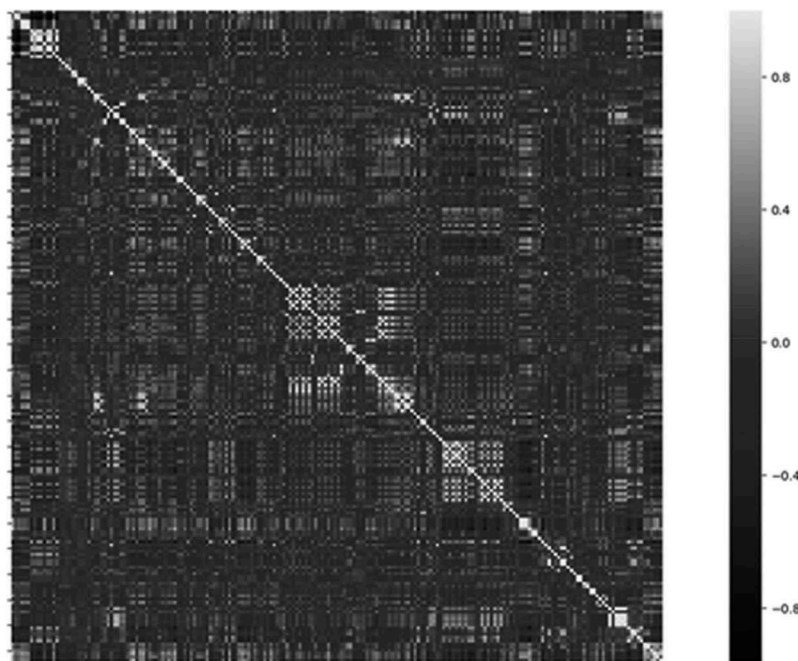

Figure 11. Correlation matrix of the quality factors.

Quality Matrix			roundness					flatness	positioning	
	Quality characteristics							flatness	positioning	
	Quality features		bearing bore					cutting surface	cutting surface	
	Related measuring point		201A	202A	204B	203A	203B	101A	102B	303B
Possible failures										
Modul	Assembly	Faulty part								
Spindel 1	Spindle cooling	flow controler	○	○	○	○	◔	○	◑	◕
		pressure regulator	◔	◔	◔	◔	○	◔	◕	◕
		nozzle	◔	○	◔	○	◐	◐	◑	◑
	Spindle seal air	air hose C	◕	◕	◕	◕	◕	○	◔	◔

Figure 12. Correlations between quality factors and failure effects as revealed in (Glawar et al. 2016b).
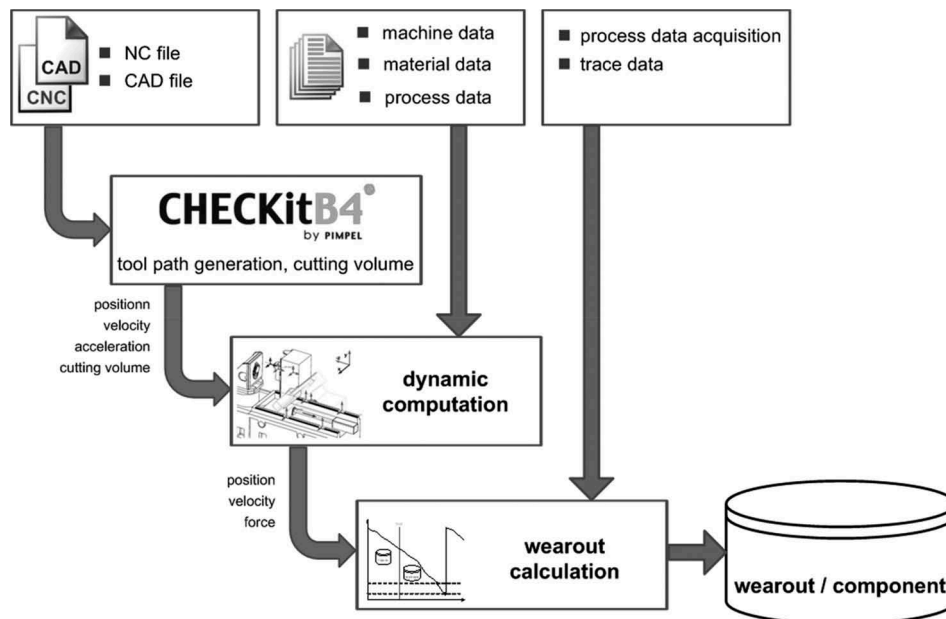
Figure 13. Dynamic calculation of wear – reproduced from (Matyas et al. 2017) & (Glawar et al. 2016a).

the approach. Based on this approach it is not only possible to derive the wear out on certain components for all historically produced parts but also to anticipate the wear out for the planned production program even for parts that have never been produced earlier (as long as a respective NC file for these parts does exist).

4.3.4. Development of the reaction model

Within the reaction model, a dynamic set of rules has been derived using i) defined single parametrised quality-based rules and ii) RUL on the basis of the dynamic wear calculation. Considering the results of the correlation analysis, individually parameterisable rules for each of the considered machine components have been derived. These rules are based on the determined failure effects, deviations and trends in the product quality. Each of these rules is represented by a mathematical function and in case of rule violation, a warning is visualised in the maintenance control centre. Four generally valid, component-independent rule-modules have been defined in Table 5.

In order to apply generally valid rules to the various components, they need to be parameterised for the respective components. This parameterisation is based on the evaluated quality data and the recorded trends in the explorative data analysis. The RUL is based on the wear of a single part, which has been calculated and stored in a database. The RUL is calculated on the basis of the production plan. Thus, a wear for a larger time span can be defined. Subsequently, it is possible to create a forecast, that provides information about when and which component should be replaced in order to

Table 5. Defined rule-modules.

Type of rule	Mathematical function	Parameters
Gradient of the regression curve of n-measuring points	$$b = \frac{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})*(y_i-\bar{y})}{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2}$$	n = number of measured values y_i = considered values x_i = 1… n (represents the date of measurements) x = arithmetic mean x_i = considered values
Mean value of n measured values	$$\bar{y} < (>)t$$ $$\bar{y} = \frac{1}{n}\sum_{i=1}^{n}y_i$$	y = arithmetical mean y_i = measured value n = amount of considered measurements t = predefined value
Comparison of variances of measured value	$$\frac{S_n^2}{S_N^2} < (>)t$$ $$S_n^2 = \frac{\sum_{i=N-n+1}^{n}(y_i-\bar{y}_n)^2}{n-1}$$ $$S_N^2 = \frac{\sum_{i=1}^{N}(y_i-\bar{y}_n)^2}{N-1}$$	s_n^2 = empirical variance of N s_N^2 = empirical variance of n t = pre-defined value n = considered values (the last n measured values out of N) N = amount of measured values y_i y_i = considered values y_n = arithmetical mean of n y_N = arithmetical mean of N
Number of limit violations	$$f_n > m$$ $$f_n\sum_{i=1}^{n}f_i$$	f_i = function describing correlation between value and pre-defined value n = amount of measured values m = amount of measured values exceeding or falling below a pre-defined value
Wear reserve	$$w_r \leq w_s$$	w_r = actual wear reserve of component w_s = pre-defined wear stock

Module: Spindel 1; **Assembly:** Spindel seal air; **Faulty part:** Air hose C

— $\bar{y} < 123{,}40 = t_1$
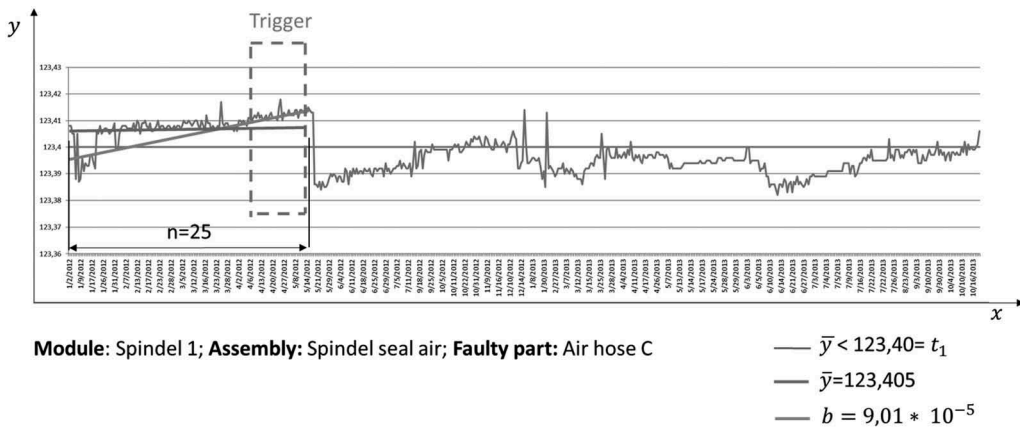— $\bar{y} = 123{,}405$
— $b = 9{,}01 * 10^{-5}$

Figure 14. Example of violation of a combination rule – Adapted from (Matyas et al. 2017).

avoid failures due to an anticipated critical wear condition. This is possible due to a combination of a known, future production program, which determines the number of the products to be manufactured, and the implemented wear calculation of the components. A rule is violated as soon as the calculated wear reserve of a component falls below a predefined value, which again has to be parameterised for each of the respective machine components (according to DIN 31051 (DIN 2012)). Based on these two sets of rules the reaction model has been established. A dynamic set of rules has been developed, which combines the defined individual rules and predicts possible failure times. The reaction model uses incoming input data sets to calculate current and future machine states and to analyze trends in the quality data in order to compare these with stored state patterns derived from historical data sets. The so-called combination rules consist of a logical combination (AND/OR) of the individual parameterised rules and have, therefore, a higher priority than the individual rules. Hence, it is ensured that maintenance actions

provided in the decision support are meaningful for the planner and do not result in a high amount of false alarms. Figure 14 shows the aforementioned violation state, which has been parameterised for the component air hose. In this example, the number of measurements is 25 (n = 25). The arithmetic mean should not exceed 123.4 and at the same time the gradient of the regression line should not be between 9.00*10−5 and 9.05*10−5; otherwise, the combination rule is violated (Matyas et al. 2017).

4.3.5. Prescriptive maintenance decision support system

The violation of one or more combination rules in the control centre provides the planner with additional information about the urgency of a corresponding countermeasure. He/she is, thus, supported in decision-making. In addition to the combination rules in the control centre, the planner will also be notified of pending (periodic) maintenance during this period. Because of this, the planner can independently decide whether to bundle the maintenance and predictive maintenance
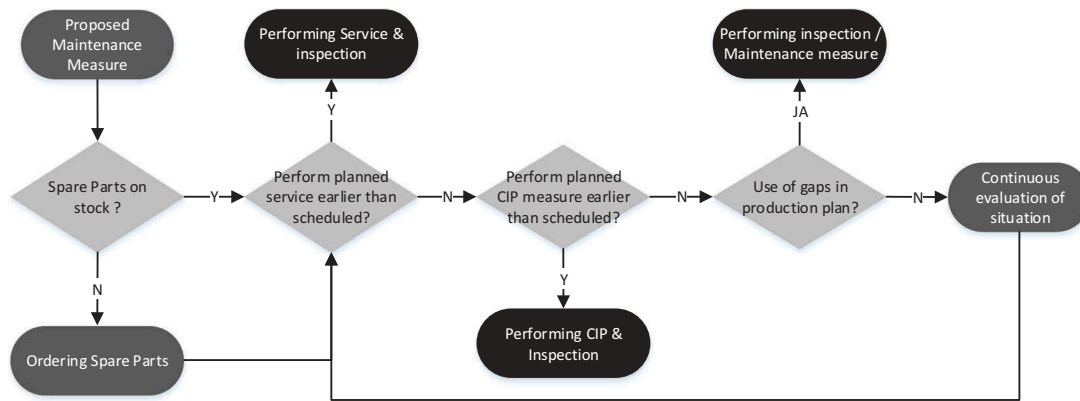
Figure 15. Decision flowchart for prescriptive maintenance decision support.

Table 6. Summary of results regarding the application of PriMa.

Machine Part	Reduction of Downtime	Planned/ Unplanned downtime	Behavior type
Tool Spindle (Ref. machine A)	12.1%	8.3%	Load dependent
Tool Spindle (Ref. machine B)	25%	12.5%	Load dependent
Clamping mechanism	14.3%	9.1%	Load independent
Ball screws	23.1%	10.0%	Load dependent

measures in order to save time and therefore may achieve cost savings according to the logic shown in Figure 15.

4.4. Achieved results

The result of the application-project is a 'maintenance control center' which has been used to derive rule-based prescriptive maintenance measures. In addition, a 'mobile control center' has been developed, which makes it possible to present relevant key figures as well as their time course and technical data of the plant and its wear stock. Thus, a real-time monitoring of the machine and the system data as a meaningful supplement to the stationary 'maintenance control center' is possible. Selected cases were used to explore and demonstrate the feasibility of applying PriMa in an industrial use-case. Occasions were identified for the machine components for which a positive effect could be achieved during test operations of the control centre demonstrator. For the identified cases, a potential reduction in downtimes of 12–25% and an improvement in the ratio of unplanned to planned downtime of 8–13% has been already achieved (cf. Table 6). Due to the improved scheduling, a realisation of savings (by targeted spare part stocking, exploitation of the wear stock, etc.) and an increase in plant availability are possible.

5. Conclusion and outlook

The undertaking paradigm shift known as Industry 4.0 and smart manufacturing technologies leads to evolution and transformation of KBM strategies and models from diagnostic to predictive and prescriptive. The main objective of this paper is to introduce PriMa in both conceptual and application

levels. In fact, there are certain technological and non-technological barriers and limitations to realize PriMa in an industrial context, including company's technology readiness level, (in-house) competency in data management and industrial data science covering predictive data analytics and knowledge engineering, historical evolution of IT-landscape, data accessibility, availability and quality, (cyber-)security and data privacy, as well as integration of PPC and maintenance systems and processes. Therefore, this paper is to pave the way for more detailed exploration and suggests some directions for future research.

In the conceptual level, the fundamental aspects of KBM have been elaborated, especially creating and learning dynamic models for predicting future events and prescribing optimal action plans considering multimodality and structural heterogeneity of maintenance data. In addition, building semantic learning and reasoning models using ontology and CBR is discussed. Previous investigations of the authors have been led to establish a methodology for building an ontological knowledge-base in maintenance problem-solving (cf. the discussion in Section 3). However, a CBR-based decision support system framework is an essential component for realisation of the semantic learning and reasoning layer of PriMa in industrial use-cases, which is currently under development. The results will be reported in a forthcoming paper.

Applying PriMa in an industrial use-case results in demonstrating and verifying its practical potential, which has been revealed by significant improvements (e.g. in the reduction of downtime and the ratio of downtime, especially for load dependent behaviour of parts). To cope with temporal characteristics of loads, it is, however, essential to extend the scope of the study and apply the model for time-dependent components. Considering load independent analysis, identifying a correlation between quality and failure effects is essential. However, it has not been achieved due to data collection problems as well as incomprehensiveness of data sources for all selected machine components. Furthermore, machine components without a frequent failure pattern (such as linear guides) do not provide the necessary information for this kind of prescriptive maintenance application. While the developed maintenance control centre provides a positive impact for the maintenance operator, there

are still a significant number of 'false alarms'. Hence, advanced machine learning approaches are required to improve the false alarm detection, support detection of false-positive and false-negative errors, and ultimately automate the decision support process.

Moreover, instantiation of PriMa for various use-cases (contexts of application) should be examined (e.g. the procedure for selection of data analytics methods tailored to the purpose of analysis or in accordance with the digital readiness of companies). In particular, the scope of unstructured data should be extended to a combination of audio, video and textual maintenance records.

Furthermore, research works should be conducted to deal with technological challenges for the realisation of CPPS in an industrial context, which directly or indirectly affect the implementation of PriMa. In particular, the major challenges are i) dealing with (cyber-)security (i.e. how to perform data analysis on encrypted data, how to make analytics platform more secured and efficient, (e.g. by means of Blockchain technology), ii) Integrating real-time data streams into simulation-based and digital models of machines for real-time (re-)configuration and online directing of machines (i.e. Digital Twin for maintenance), and iii) integrating autonomous maintenance workflow management and decision support into production control models (i.e. how to integrate prescriptive maintenance in production control models to reach a higher degree of autonomy in CPPS).

Finally, yet importantly, from knowledge management perspective, technology-oriented and human-oriented aspects of maintenance should be correlatively explored considering new division of (shared) tasks between human and machine workforce. Mutual learning strategies, models, approaches and novel didactical concepts should be developed for achieving optimal collaboration between humans and robot (AI) systems on performing maintenance tasks. Notably, the novel concept of human-machine mutual (reciprocal) learning and related reference model for realising mutual learning in smart factories has been introduced in (Ansari, Erol, and Sihn 2018) and (Ansari et al., 2018), respectively.

The outlined directions will be considered in the context of future research.

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References

Aamodt, A., and E. Plaza. 1994. "Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches." *AI Communications* 7 (1): 39–59.

Accorsi, R., R. Manzini, P. Pascarella, M. Patella, and S. Sassi. 2017. "Data Mining and Machine Learning for Condition-Based Maintenance." *Procedia Manufacturing* 11: 1153–1161. doi:10.1016/j.promfg.2017.07.239.

Aizpurua, J. I., V. M. Catterson, Y. Papadopoulos, F. Chiacchio, and D. D'Urso. 2017. "Supporting Group Maintenance through Prognostics-Enhanced Dynamic Dependability Prediction." *Reliability Engineering & System Safety* 168: 171–188. doi:10.1016/j.ress.2017.04.005.

Ansari, F. 2014. "Meta-Analysis of Knowledge Assets for Continuous Improvement of Maintenance Cost Controlling." PhD Diss., Germany: University of Siegen.

Ansari, F., M. Khobreh, U. Seidenberg, and W. Sihn. 2018. "A Problem-Solving Ontology for Human-Centered Cyber Physical Production Systems." *CIRP Journal of Manufacturing Science and Technology* 22C: 91–106. Elsevier. doi:10.1016/j.cirpj.2018.06.002.

Ansari, F., P. Hold, W. Mayrhofer, S. Schlund, and 2018. AUTODIDACT: Introducing the Concept of Mutual Learning into a Smart Factory Industry 4.0, In Proceedings of 15th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2018), October 21–23, Budapest, Hungary, 61–68.

Ansari, F., P. Uhr, and M. Fathi. 2014. "Textual Meta-Analysis of Maintenance Management's Knowledge Assets." *International Journal of Services, Economics and Management*, Inderscience Enterprises Ltd. 6: 14–37.

Ansari, F., and R. Glawar. 2018. *Knowledge Based Maintenance, Instandhaltungslogistik - Qualität Und Produktivität Steigern* (Maintenance Logistics – Enhancing Quality and Productivity). edited by K. Matyas. 7th ed., 318–342. Munich, Germany: Carl Hanser Verlag GmbH & Co. KG.

Ansari, F., R. Glawar, and W. Sihn. 2017. *Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian Networks, Machine Learning for Cyber Physical Systems*. Springer. (In Press).

Ansari, F., S. Erol, and W. Sihn. 2018. "Rethinking Human-Machine Learning in Industry 4.0: How Does the Paradigm Shift Treat the Role of Human Learning?" *Procedia Manufacturing* 23C: 117–122. doi:10.1016/j.promfg.2018.04.003.

Baars, H., and H. G. Kemper. 2008. *Management Support with Structured and Unstructured Data: An Integrated Business Intelligence Framework, Information Systems Management*, 132–148. Vol. 25. London, UK: Taylor& Francis Group.

Beierle, C., and G. Kern-Isberner. 2008. *Methoden wissensbasierter Systeme*. 4th ed. Berlin, Germany: Springer.

Belyi, D., E. Popova, D. P. Morton, and P. Damien. 2017. "Bayesian Failure-Rate Modeling and Preventive Maintenance Optimization." *European Journal of Operational Research* 262 (3): 1085–1093. doi:10.1016/j.ejor.2017.04.019.

Benttaleb, M., F. Hnaien, and F. Yalaoui. 2016. "Two-Machine Job Shop Problem for Makespan Minimization under Availability Constraint." *IFAC-PapersOnLine* 49 (28): 132–137. doi:10.1016/j.ifacol.2016.11.023.

Biedermann, H. 2014. *Anlagenmanagement im Zeitalter von Industrie 4.0 - Handlungsfelder für die industrielle Instandhaltung Instandhaltung im Wandel (Maintenace in Transition)*, 23–32. Cologne, Germany: TÜV Rheinland Group.

Bousdekis, A., B. Magoutas, D. Apostolou, and G. Mentzas. 2015. "Review, Analysis and Synthesis of Prognostic-Based Decision Support Methods for Condition Based Maintenance." *Journal of Intelligent Manufacturing* 1–14.

Bumblauskas, D., D. Gemmill, A. Igou, and J. Anzengruber. 2017. "Smart Maintenance Decision Support Systems (SMDSS) Based on Corporate Big Data Analytics." *Expert Systems with Applications* 90: 303–317. doi:10.1016/j.eswa.2017.08.025.

Chapman, P., J. Clinton, R. Kerber, T. Khabaza, T. Reinartz, C. Shearer, and R. Wirth. 2000. *Crisp-Dm 1.0*. CRISP-DM Consortium, 76 (3).

CPS Summit. 2008. "Report: Cyber-Physical Systems Summit, 2008." Technical Report. Accessed January 2 2019. http://cra.org/ccc/wp-content/uploads/sites/2/2015/05/CPS_Summit_Report.pdf

Denkena, B., M. Shanib, J. Damm, and B. Bergmann. 2017. "Selbstparametrierende Prozessüberwachungssysteme: Selbstanpassende Prozessüberwachungsstrategien Für Die Serienfertigung (Self-Parameterising Process Monitoring Systems - Self-Adjusting Process Monitoring Strategies for Series Production)." *Wt-Online* 7/8: 487–491.

DIN. 2012. *DIN 31051:2012-09:Fundamentals of Maintenance*. Berlin, Germany: Beuth Verlag.

El Khoukhi, F., J. Boukachour, and A. E. H. Alaoui. 2017. "The "Dual-Ants Colony": A Novel Hybrid Approach for the Flexible Job Shop Scheduling Problem with Preventive Maintenance." *Computers & Industrial Engineering* 106: 236–255. doi:10.1016/j.cie.2016.10.019.

Engel, G., T. Greiner, and S. Seifert. 2018. "Ontology-Assisted Engineering of Cyber-Physical Production Systems in the Field of Process Technology." *IEEE Transactions on Industrial Informatics* 14 (6): 2792–2802. doi:10.1109/TII.2018.2805320.

Famurewa, S. M., L. Zhang, and M. Asplund. 2017. "Maintenance Analytics for Railway Infrastructure Decision Support." *Journal of Quality in Maintenance Engineering* 23 (3): 310–325. doi:10.1108/JQME-11-2016-0059.

Fitouri, C., N. Fnaiech, C. Varnier, F. Fnaiech, and N. Zerhouni. 2016. "A Decison-Making Approach for Job Shop Scheduling with Job Depending Degradation and Predictive Maintenance." *IFAC-PapersOnLine* 49 (12): 1490–1495. doi:10.1016/j.ifacol.2016.07.782.

Fnaiech, N., C. Fitouri, C. Varnier, F. Fnaiech, and N. Zerhouni. 2015. "A New Heuristic Method for Solving Joint Job Shop Scheduling of Production and Maintenance." *IFAC-PapersOnLine* 48 (3): 1802–1808. doi:10.1016/j.ifacol.2015.06.348.

Franciosi, C., A. Lambiase, and S. Miranda. 2017. "Sustainable Maintenance: A Periodic Preventive Maintenance Model with Sustainable Spare Parts Management." *IFAC-PapersOnLine* 50 (1): 13692–13697. doi:10.1016/j.ifacol.2017.08.2536.

Glawar, R., C. Habersohn, T. Nemeth, K. Matyas, B. Kittl, and W. Sihn. 2016a. "A Holistic Approach for Anticipative Maintenance Planning Supported by A Dynamic Calculation of Wear Reserve." *Journal of Maintenance Engineering* 1: 313–324.

Glawar, R., M. Karner, T. Nemeth, K. Matyas, and W. Sihn. 2018. "An Approach for the Integration of Anticipative Maintenance Strategies within a Production Planning and Control Model." *Procedia CIRP* 67C: 46–51. doi:10.1016/j.procir.2017.12.174.

Glawar, R., Z. Kemeny, T. Nemeth, K. Matyas, L. Monostori, and W. Sihn. 2016b. "A Holistic Approach for Quality Oriented Maintenance Planning Supported by Data Mining Methods." *Procedia CIRP* 57: 259–264. doi:10.1016/j.procir.2016.11.045.

Gruber, T. 1993. "A Translation Approach to Portable Ontology Specifications." *Knowledge Acquisition* 5 (2): 199–220. doi:10.1006/knac.1993.1008.

Guarino, N., and P. Giaretta. 1995. *Ontologies and Knowledge Bases Towards a Terminological Clarification, Towards Very Large Knowledge Bases: Knowledge Building and Knowledge Sharing*, 25–32. Amsterdam, the Netherlands: IOS Press.

IoT Analytics. 2017. "Predictive Maintenance Market Report 2017–22." Market Report. Hamburg, Germany: IoT Analytics.

Kagermann, H., W. Wahlster, and J. Helbig. 2013. *Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0. Final Report of the INDUSTRIE 4.0 Working Group*. Edited by Forschungsunion Wirtschaft – Wissenschaft und acatech. Munich, Germany: Deutsche Akademie der Technikwissenschaften e.V.

Karim, R., J. Westerberg, D. Galar, and U. Kumar. 2016. "Maintenance Analytics–The New Know in Maintenance." *IFAC-PapersOnLine* 49 (28): 214–219. doi:10.1016/j.ifacol.2016.11.037.

Kelleher, J. D., B. Mac Namee, and A. D'Arcy. 2015. *Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies*, 1–3, 12–15, 17, 117, 153–158, 179, 247, 323. Cambridge, USA: MIT Press.

Klahold, A., P. Uhr, F. Ansari, and M. Fathi. 2013. "Using Word Association to Detect Multi-Topic Structures in Text Documents." *IEEE Intelligent Systems*. 29 (5): 40–46. IEEE Computer Society. doi:10.1109/MIS.2013.120.

Kovacs, K., F. Ansari, C. Geisert, E. Uhlmann, R. Glawar, and W. Sihn. 2019. *A Process Model for Enhancing Digital Assistance in Knowledge-Based Maintenance, Machine Learning for Cyber Physical Systems*, 87–96. Berlin, Heidelberg, Germany: Springer.

Lee, E. A. 2017. *What Is Real Time Computing? A Personal View*. IEEE Design & Test.

Lee, E. A., and S. A. Seshia. 2015. *Introduction to Embedded Systems, A Cyber-Physical Systems Approach*. 2nd ed. Cambridge, USA: MIT Press, ISBN 978-0-262-53381-2, 2017.

Legat, C., C. Seitz, S. Lamparter, and S. Feldmann. 2014. "Semantics to the Shop Floor: Towards Ontology Modularization and Reuse in the Automation Domain." *IFAC Proceedings* 47 (3): 3444–3449. doi:10.3182/20140824-6-ZA-1003.02512.

Li, J. Q., Q. K. Pan, and M. F. Tasgetiren. 2014. "A Discrete Artificial Bee Colony Algorithm for the Multi-Objective Flexible Job-Shop Scheduling Problem with Maintenance Activities." *Applied Mathematical Modelling* 38 (3): 1111–1132. doi:10.1016/j.apm.2013.07.038.

Liao, W., and T. Wang. 2018. "An Optimization Approach Using in Production Scheduling with Different Order." In *Industrial Technology and Management (ICITM), 2018 7th International Conference on,* 237-241. IEEE.

Linstedt, D., and M. Olschimke. 2015. *Building a Scalable Data Warehouse with Data Vault 2.0*, 17–32, 89–121. 1st ed. Burlington, Massachusetts, USA: Morgan Kaufmann.

Lueth, K. L., C. Patsioura, Z. D. Williams, and Z. Z. Kermani. 2016. "Industrial Analytics 2016/2017: The Current State of Data Analytics Usage in Industrial Companies." Technical Report. IoT Analytics.

Maier, R. 2009. *Knowledge Management Systems: Information and Communication Technologies for Knowledge Management*. Berlin, Germany: Springer.

Matyas, K., T. Nemeth, K. Kovacs, and R. Glawar. 2017. "A Procedural Approach for Realizing Prescriptive Maintenance Planning in Manufacturing Industries." *CIRP Annals - Manufacturing Technology* 66 (1): 461–464. doi:10.1016/j.cirp.2017.04.007. doi:10.1016/j.cirp.2017.04.007.

Miebach, T., M. Schmidt, and P. Nyhuis. 2017. "Das Intelligente Instandhaltungssystem: Ein Ansatz Zur Selbstlernenden Gestaltung Von Reaktionsbibliotheken (The Intelligent Maintenance System - an Approach for the Self-Learning Structuring of Maintenance Libraries)." *Wt-Online* 7/8: 530–535.

Mokhtari, H., and A. Hasani. 2017. "An Energy-Efficient Multi-Objective Optimization for Flexible Job-Shop Scheduling Problem." *Computers & Chemical Engineering* 104: 339–352. doi:10.1016/j.compchemeng.2017.05.004.

Mokhtari, H., and M. Dadgar. 2015. "Scheduling Optimization of a Stochastic Flexible Job-Shop System with Time-Varying Machine Failure Rate." *Computers & Operations Research* 61: 31–45. doi:10.1016/j.cor.2015.02.014.

Monostori, L., B. Kádár, T. Bauernhansl, S. Kondoh, S. Kumara, G. Reinhart, O. Sauer, G. Schuh, W. Sihn, and K. Ueda. 2016. "Cyber-Physical Systems in Manufacturing." *CIRP Annals-Manufacturing Technology* 65 (2): 621–641. doi:10.1016/j.cirp.2016.06.005.

Mourtzis, D., N. Boli, and S. Fotia. 2017. "Knowledge-Based Estimation of Maintenance Time for Complex Engineered-To-Order Products Based on KPIs Monitoring: A PSS Approach." *Procedia CIRP* 63 (1): 236–241. doi:10.1016/j.procir.2017.03.317.

Nasiri, S., M. R. Khosravani, and K. Weinberg. 2017. "Fracture Mechanics and Mechanical Fault Detection by Artificial Intelligence Methods: A Review." *Engineering Failure Analysis* 81: 270–293. doi:10.1016/j.engfailanal.2017.07.011.

Nemeth, T., F. Ansari, W. Sihn, B. Haslhofer, and A. Schindler. 2018. "PriMa-X: A Reference Model for Realizing Prescriptive Maintenance and Assessing Its Maturity Enhanced by Machine Learning." *Procedia CIRP* 72: 1039–1044. doi:10.1016/j.procir.2018.03.280.

North, K., and R. Maier. 2018. "Wissen 4.0–Wissensmanagement Im Digitalen Wande"l. *HMD Praxis der Wirtschaftsinformatik,* 1–17. Berlin, Germany: Springer.

Otto, B., S. Auer, J. Cirullies, J. Jürjens, N. Menz, J. Schon, and S. Wenzel, Industrial Data Space: Digital Souvereignity over Data, Fraunhofer White Paper, 2016.

Pawellek, G. 2013. *Integrierte Instandhaltung und Ersatzteillogistik: Vorgehensweisen, Methoden, Tools*. Berlin, Germany: Springer.

Perner, P. 2008. *Case-Based Reasoning on Images and Signals, Studies in Computational Intelligence*. Vol. 37. Berlin, Germany: Springer.

Poon, T. C., K. L. Choy, H. K. Chow, H. C. Lau, F. T. Chan, and K. C. Ho. 2009. "A RFID Case-Based Logistics Resource Management System for Managing Order-Picking Operations in Warehouses." *Expert Systems with Applications* 36 (4): 8277–8301. doi:10.1016/j.eswa.2008.10.011.

Rahmati, S. H. A., A. Ahmadi, and B. Karimi. 2018. "Multi-Objective Evolutionary Simulation Based Optimization Mechanism for a Novel Stochastic Reliability Centered Maintenance Problem." *Swarm and Evolutionary Computation* 40: 255–271. doi:10.1016/j.swevo.2018.02.010.

Reiner, J., J. Koch, I. Krebs, S. Schnabel, and T. Siech. 2005. *Knowledge Management Issues for Maintenance of Automated Production Systems, Integrating Human Aspects in Production Management, IFIP International - Federation for Information Processing*. Vol. 160. Berlin, Germany: Springer.

Reuss, P., R. Stram, K. D. Althoff, W. Henkel, and F. Henning. 2018. *Knowledge Engineering for Decision Sup-Port on Diagnosis and Maintenance in the Aircraft Domain, Synergies between Knowledge Engi-Neering and Software Engineering*, 173–196. Berlin, Germany: Springer.

Ruschel, E., E. A. P. Santos, and E. D. F. R. Loures. 2017. "Mining Shop-Floor Data for Preventive Maintenance Management: Integrating Probabilistic and Predictive Models." *Procedia Manufacturing* 11: 1127–1134. doi:10.1016/j.promfg.2017.07.234.

Russell, S., and P. Norvig. 2010. *Artificial Intelligence: A Modern Approach*. USA: Prentice Hall.

Schiuma, G. 2009. "The Managerial Foundations of Knowledge Assets Dynamics." *Knowledge Management Research & Practice* 7 (4): 290–299. doi:10.1057/kmrp.2009.21.

Schmidt, B., L. Wang, and D. Galar. 2017. "Semantic Framework for Predictive Maintenance in a Cloud Environment." *Procedia CIRP* 62: 583–588. doi:10.1016/j.procir.2016.06.047.

Seidenberg, U., and F. Ansari. 2017. "Qualitätsmanagement in Der Additiven Fertigung – Herausforderungen Und Handlungsempfehlungen (Quality Management in Additive Manufacturing - Challenges and Recommendations for Action)." In *3D-Printing: Recht, Wirtschaft und Technik des industriellen 3D-Drucks, Handbook*, edited by A. Leupold and S. Glossner, 159–214, Munich, Germany, Verlag C.H.Beck.

Sekulić, M., P. Kovač, M. Gostimirović, M. Hadžistević, and Z. Jurković. 2014. "Prediction of the Main Cutting Force in Drilling by Kienzle Equation." *Journal of Trends in the Development of Machinery and Associated Technology* 18 (1): 27.

Shamsaei, F., and M. Van Vyve. 2017. "Solving Integrated Production and Condition-Based Maintenance Planning Problems by MIP Modeling." *Flexible Services and Manufacturing Journal* 29 (2): 184–202. doi:10.1007/s10696-016-9244-8.

Studer, R., V. Benjamins, and D. Fensel. 1998. "Knowledge Engineering: Principles and Methods." *Data and Knowledge Engineering* 25 (1): 161–197. doi:10.1016/S0169-023X(97)00056-6.

Sturm, A. 2001. *Wissen basierte Betriebsführung und Instandhaltung*. Essen: VGB PowerTech Service GmbH.

Ullrich, C. 2016. "An Ontology for Learning Services on the Shop Floor." In *13th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2016)*, 17–24. Mannheim, Germany: International Association for Development of the Information Society, October 28–30.

Wagner, T., C. Herrmann, and S. Thiede. 2017. "Industry 4.0 Impacts on Lean Production Systems." *Procedia CIRP* 63: 125–131. doi:10.1016/j.procir.2017.02.041.

Wireman, T. 2014. *Benchmarking Best Practices for Maintenance and Reliability*. 3rd ed. South Norwalk, CT, USA: Industrial Press.

Wöstmann, R., P. Strauss, and J. Deuse. 2017. "Predictive Maintenance in der Produktion: Anwendungsfälle und Einführungsvoraussetzungen zur Erschließung ungenutzter Potentiale (Predictive Maintenance in production)." *Wt-Online* 7/8: 524–529.

Yan, J., Y. Meng, L. Lu, and L. Li. 2017. "Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance." *IEEE Access* 5: 23484–23491. doi:10.1109/ACCESS.2017.2765544.

Zandieh, M., A. R. Khatami, and S. H. A. Rahmati. 2017. "Flexible Job Shop Scheduling under Condition-Based Maintenance: Improved Version of Imperialist Competitive Algorithm." *Applied Soft Computing* 58: 449–464. doi:10.1016/j.asoc.2017.04.060.

Zarte, M., U. Wunder, and A. Pechmann, Concept and First Case Study for a Generic Predictive Maintenance Simulation in AnyLogic™, In Industrial Electronics Society, IECON 2017-43rd Annual Conference of the IEEE, Beijing, China, 2017. 3372–3377.

Zhang, Y., S. Ren, Y. Liu, and S. Si. 2017. "A Big Data Analytics Architecture for Cleaner Manufacturing and Maintenance Processes of Complex Products." *Journal of Cleaner Production* 142: 626–641. doi:10.1016/j.jclepro.2016.07.123.

Zühlke, D. 2008. SmartFactory – A Vision Becomes Reality. In: Proceedings of the 17thWorld Congress IFAC'08, Seoul, Korea, 14101–14108.