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PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning

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Abstract

The digital transformation already has a strong impact on manufacturing techniques and processes and requires novel data-driven maintenance strategies and models, which support prompt and effective decision-making. This poses new requirements, challenges and opportunities for securing and improving machine availability and process stability. This paper builds on the concept of prescriptive maintenance and proposes a reference model that (i) supports the implementation of a prescriptive maintenance strategy and the assessment of its maturity level, (ii) facilitates the integration of data-science methods for predicting future events, and (iii) identifies action fields to reach an enhanced target maturity state and thus higher prediction accuracy.

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Keywords: cyber physical production systems; prescriptive maintenance; data science; reference model; maturity

1. Introduction

The industrialized world is currently facing a fourth revolution through the realization of digitalized manufacturing, which is built upon cutting-edge computer science, information and communication technologies as well as manufacturing science and technology [1]. These advances have paved the way for systematical deployment of Cyber Physical Production Systems (CPPS) [2]. Utilizing CPPS significantly contributes in increasing productivity, machine availability and automation level, improving resource efficiency and ensuring product quality of a manufacturing system [1, 3]. Remote and real-time control, complete embedded systems, predictability and robustness at every level as well as safety are further expectations associated to CPPS [4, 5, 6]. As a result, increasing complexity in terms of products, processes and machines [7, 8, 9] arise, which dramatically increase the need for rethinking and reshaping maintenance management organizations, models and associated systems [10].

Hence, a paradigm shift from descriptive to predictive and prescriptive maintenance is triggered [10]. The concept of prescriptive maintenance extends beyond the mere prediction of failures. Utilizing sensing technology, modeling expert knowledge, and employing predictive data analytics, based on historical and incoming real time data, allow making predictions on when a failure occurs and ultimately recommending an optimal course of action [11, 10]. According to Ansari et. al. (2017) prescriptive maintenance of CPPS not only aims at understanding and reasoning out past events, but also at anticipating the likelihood of future events and potential effects of each decision alternative on the physical space and associated business processes [10]. The two most important complementary skills required for implementing prescriptive maintenance in practice are: production process and system knowledge on the one hand and data science methods and skills on the other hand [6].

Although several studies emphasize the importance of predictive and prescriptive maintenance to overcome current

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challenges of digitalized manufacturing [12], hardly any of these strategies have been implemented in practice. Recent empirical studies revealed that 15% of producing companies pursue partly predictive maintenance strategies, and prescriptive approaches are only applied by 4% [13]. Due to vague (not precisely determined or distinguished) or ambiguous (have two or more interpretations) definitions and descriptions of these terms, companies fail in pursuing innovative maintenance strategies [10].

In order to resolve the aforementioned challenges, a prescriptive maintenance reference model is proposed within this paper, trying to answer the following research questions: i) Which tasks and objectives should an efficient prescriptive maintenance (operational and management) process comprise? ii) Which data-science methods are most suitable for predicting future events and how can they be integrated into a prescriptive maintenance process? and ultimately iii) How can the prescriptive maintenance maturity level be assessed including operational and management parameters?

2. State of the Art

2.1. Knowledge-Based Maintenance Strategies

Prescriptive maintenance is known as the highest maturity and complexity level of knowledge-based maintenance (KBM) [10]. KBM assumes that competitive advantages for stabilizing maintenance processes and reducing unplanned costs are achieved through holistic consideration of production processes, rather than atomistic inspection of (all) influential components [10, 14]. Thus, KBM concentrates on analyzing maintenance as a non-isolated sub-domain of production systems, which, in turn, influences the organizational value creation [14]. Recent investigations show that especially the sub-domains quality management, maintenance and production planning strongly interact and jointly determine the achievement of the desired production performance, equipment availability, and product quality [8, 9].

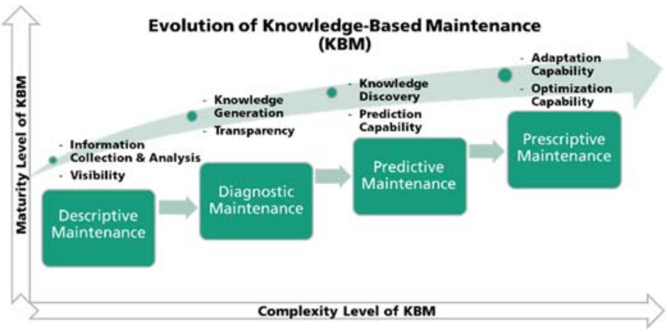

Fig. 1. Knowledge-Based Maintenance Strategies [10]

The central objective of KBM is to develop a generic concept for optimizing maintenance processes through comprehensive consideration of maintenance consequences, system conditions, organization, and processes [14]. Existing approaches for achieving the aforementioned goals of KBM can be categorized as follows (cf. Fig. 1) [10]:

- *Descriptive maintenance* answers the question "What happened?" by providing information about previous maintenance operations.
- *Diagnostic maintenance* answers the question "Why did it happen?" by analyzing cause-effect relations, reasoning, and providing further technical details about former maintenance operations.
- *Predictive maintenance* answers the question "What will happen when?" by learning from historical maintenance data, possibly in real-time, and predicting future events. This is also referred to as "Smart Maintenance", "Data-Driven Maintenance" and recently as "Maintenance 4.0".
- *Prescriptive maintenance* answers the question "How can we make it happen?" or in other words "How can we control the occurrence of a specific event?" by providing actionable recommendations for decision making and improving and/or optimizing forthcoming maintenance processes. It also refers to the recent advances in enhancing self-organization capabilities of CPPS, which ideally aim at machine self-diagnosis and scheduled maintenance.

2.2. Maintenance Decision Support Models

The state-of-the-art literature review reveals that the majority of existing maintenance models aims at supporting decision-making processes. By combining different data-sources and knowledge assets and applying data-science methods such as exploratory data analysis or machine learning, maintenance system intelligence is improved. A selection of recently developed maintenance decision support models (MDSM) is presented in this section.

Glawar et. al. (2016) outlined a holistic and anticipatory framework, which "enables the identification of maintenance-critical conditions and the prediction of failure moments and quality deviations" of tooling machines [15]. Aghezzaf et. al (2016) addressed a degradation-based selective maintenance decision problem of a continuously monitored multi-component system. By modelling components as time-dependent stochastic processes a cost-optimal set of necessary maintenance actions is found [16]. Moreover, Wang et. al (2017) investigated "a cloud-based paradigm of predictive maintenance based on mobile agent to enable timely information acquisition, sharing and utilization for improved accuracy and reliability in fault diagnosis, remaining service life prediction, and maintenance scheduling." [17]. Arab et. al (2013) solved a dynamic maintenance scheduling problem for a multi-component production system by taking into account real-time information from workstations including remaining reliability of equipment, cycle times, buffers' capacity and mean time to repair of machines [18].

Besides, Bärenfänger-Wojciechowski et. al. (2017) presented a reference integrated management approach, named smart maintenance, which combines key maintenance knowledge assets, namely humans, sensors, data-management and assistance-systems [19]. The concept "knowledge as a service", was introduced by Abramovici et. al. (2017) and supports knowledge allocation and the recommendation of possible solutions in accordance with failure causes and similarity degree between former failure descriptions stored in a semantic knowledge base [20]. Last but not least, A. K. Muchiri et. al (2017) developed a theoretical framework for evaluating the efficiency of maintenance actions based on a technical, managerial and human perspective [21], Mehairjan et. al (2016) developed a maintenance management maturity model based on five holistic dimensions including data quality [22] and Schumacher et. al (2016) developed an Industry 4.0 maturity model, which indirectly assesses aspects relevant for data-driven maintenance [23].

Although these models achieve valuable results in the area of prescriptive maintenance, they suffer from the following shortcomings: i) they consider dynamics of maintenance processes (using time variables) but do not fully or partially consider learning and prediction of the behavior of process related parameters overtime, ii) they are use-case-specific (unique problem) and hardly generalizable to similar groups of problems, iii) they do not adequately include feedback loops and efficiency assessment techniques in order to improve maintenance planning quality, and iv) they use well-established, but outdated process models for data analysis and knowledge discovery, which clearly need to be refined and extended for predictive analytics tasks.

2.3. Data Science Methods for Prescriptive Maintenance

Groundwork for prescriptive maintenance data science methods has been laid by the field of condition monitoring, which provides condition indicators and analysis methods for regular monitoring of actual mechanical conditions, operating efficiency, and other indicators of machines and process systems. These conditions feed into a wide spectrum of possible maintenance techniques, which include vibration monitoring, thermography, tribology (e.g., lubricating oil analysis), production process parameters, visual inspection, ultrasonic, or failure mode (e.g., max rotation speed) analysis.

Estimating the Remaining Useful Life (RUL) is a central task for optimizing repair intervals and minimizing costs of unscheduled outages created by machine failures. Throughout years, methods have clearly shifted from rule-based to data-driven approaches applying statistical or machine learning techniques [24] such as Support Vector Machines, Bayesian learning techniques, Hidden Markov models, similarity-based approaches, or unsupervised learning methods. However, most of these approaches heavily rely on manual investigation and identification of possible failure characteristics and subsequent feature engineering.

In order to overcome manual feature engineering, a number of Deep Learning based methods have been investigated: Convolutional Neural Networks have been applied for detection faults in rotating machinery [25] and for detecting structural damages [26]. However, both approaches have been evaluated in simulated environments, which shows that Deep Learning is still in its infancy and requires further systematic research (e.g., standard datasets, insight into black box models, transferring models, imbalance in training data, etc.) before it can be applied in the field of prescriptive maintenance [27].

Anomaly detection, which refers to the problem of finding anomalous patterns and outliers in data is a complementary, frequently used data-driven maintenance technique. Recent approaches [28, 29] apply Long-Short-Term-Memory based algorithms for that purpose. However, those existing anomaly detection approaches operate on machine sensor data only without taking into account production process parameters. Active learning [30] is a possible technique for training machine learning algorithms in settings with low availability of labelled training data (e.g., machine outages). The key idea is that an algorithm is allowed to choose data from which it learns. However, to the best of our knowledge, the application of active learning technique has not yet been investigated for real-world prescriptive maintenance problems.

2.4. Literature Synthesis: Research Gap on Maturity Assessment

Considering the literature review presented in section 2.1-2.3, we identified four dimensions, namely, KBM, MDSM, machine learning (ML) and maturity assessment (MA), which constitute the basis for prescriptive maintenance of CPPS (cf. Tab. 1). There are several papers, which either cover the three dimensions of KBM, MDSM and ML or discuss the idea of (maintenance) maturity assessment. Despite advantages, we have determined a gap on integrated data-driven maintenance maturity assessment considering multi-dimensionality of maintenance problems affected by strategic, tactical and operational processes. To the best of our knowledge, a systematic maintenance maturity model, which assesses the level of maturity from the angle of industrial data science, rather than considering only maintenance influencing factors such as organizational, cultural, IT and infrastructural factors (generic approaches), is nonexistent.

Table 1. Literature Synthesis

Literature	KBM	MDSM	ML	MA
[8], [9], [14]	✓			
[24], [25], [26], [27], [28], [29]	✓		✓	
[16]		✓		
[19]	✓	✓		
[18]		✓	✓	
[30]			✓	
[17], [15], [17], [20]	✓	✓	✓	
[21], [22], [23]	*	✓		✓

* maturity including maintenance aspects, but not specifically for KBM

Hence we build on the concept of prescriptive maintenance model (PriMa) presented in [10] and propose a reference model entitled "PriMa-X" that supports the implementation of a prescriptive maintenance strategy and the assessment of its maturity level, facilitates the integration of data-science methods for predicting future events, and identifies action fields to reach an enhanced target maturity state and thus higher prediction accuracy.

3. The PriMa-X Reference Model

3.1. Fundamentals and Scope

The PriMa-X reference model (cf. Fig. 2) constitutes a three-layer portfolio matrix, covering objectives, challenges as well as machine learning methods and necessary IT-infrastructures for realizing a prescriptive maintenance strategy within an existing production system. Each layer of the model is broken down and in-depth analyzed for each step of the introduced prescriptive maintenance process, namely, 1. Analysis and

Diagnosis, 2. Prediction Model Building, 3. Prescriptive Maintenance Decision Support, 4. Maintenance Planning and 5. Execution and Documentation.

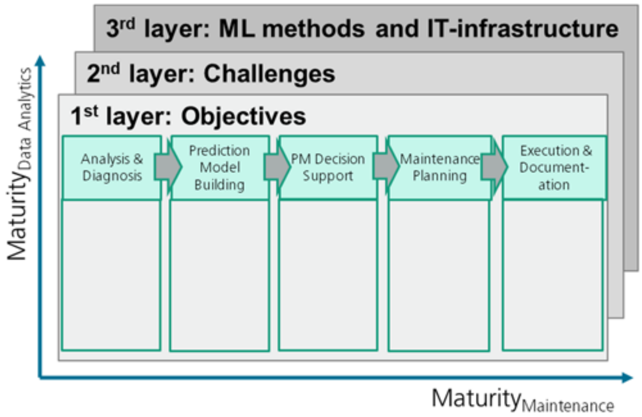

Fig. 2. PriMa-X –Three-Layer Portfolio Matrix

Prescriptive maintenance maturity is assessed for a maintenance and data analytics dimension. Both dimensions have decisive influence on the success of a prescriptive maintenance strategy, due to the strong interdisciplinary application of maintenance and production system competencies on the one hand and data analytics expertise on the other hand.

Before implementing the proposed reference model, a target application area for the realization of prescriptive maintenance within a production system has to be selected. It can be a single machine, a production line of serial and/or parallel interlinked machine associations or a whole production area, characterized by high internal criticality (due to far-reaching effects of downtimes, missing redundancies of machines etc.) and high importance (production of runner products etc.). Several concepts for assessing the equipment priority, such as the equipment index proposed in [31], are published in the scientific literature and therefore not further discussed in this paper.

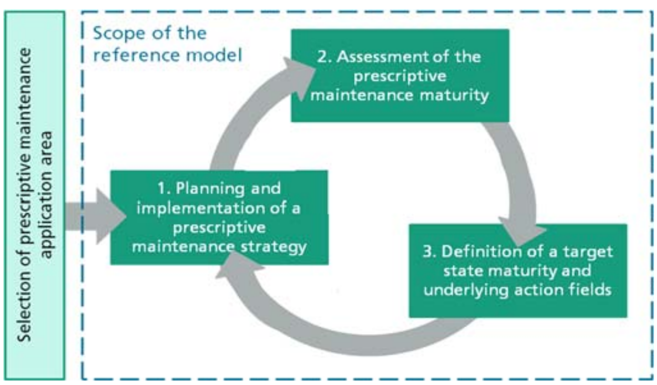

Fig. 3. Scope and elements of PriMa-X

PriMa-X builds on three iterative steps (cf. Fig. 3):

1. *Planning and implementation of a prescriptive maintenance strategy:* A planned and stepwise execution of the introduced prescriptive maintenance process enables a systematic realization of a prescriptive maintenance strategy.
2. *Assessment of the prescriptive maintenance maturity:* The current state maturity level is assessed and weaknesses are identified for each prescriptive maintenance process step.
3. *Definition of a target state maturity and underlying action fields:* A company-specific target maturity level and necessary measures for its realization are defined for each prescriptive maintenance process step and will be considered as input for the next iteration circle.

The first element is described in detail within the following sub-section. Elements 2 and 3 are outlined in the final section "Conclusion and Future Research Agenda" of this paper.

3.2. Planning and implementation of a prescriptive maintenance strategy

For each prescriptive maintenance process step, the three layers *objectives*, *challenges* and *ML methods* of the reference model are presented within this section. The focus is hereby placed on the first layer objectives. The key findings of the second and third layer are summarized within the tables 2-6.

1. Analysis & Diagnosis: The process step "Analysis & Diagnosis" firstly aims at building up ground truth datasets in order to facilitate derivation and description of patterns in stored data sets, which indicate a failure. For this purpose, historical shop floor data, including product, process and machine as well as maintenance management and cost data, has to be acquired from ERP, MES, quality or maintenance management systems, condition monitoring and PLC controls. Relevant data is aggregated, normalized and stored within a comprehensive data model. An appropriate data space infrastructure and streaming concept (supporting data batching to structured data streaming) is required to store and analyse datasets with large volume, velocity and variety. Secondly, the derived failure patterns must be inspected systematically in order to understand their technical characteristics, criticality (e.g. downtime, costs and occurrence) and their effects on maintenance key performance indicators. Thirdly, awareness of failure depended effects in interrelated functional areas (maintenance, production planning, quality management) has to be generated within this process step.

Table 2. Analysis & Diagnosis | Challenges and ML methods

Challenges	ML methods
• Missing (digital) data availability • Syntactically, structurally and semantically heterogeneity of data • Diversity of data infrastructures • Poor data quality • Lacking data storage capability - volume and complexity of data • Systematic requirements elicitation and specification • Accuracy of patterns	• Building up a ground truth • Prediction problem formalization • Expert knowledge formalization • Raw data collection and Sampling (e.g. Python, R, Shell Scripts) • Data preprocessing (e.g., cleansing, sampling, transformation, aggregation) • Exploratory data analysis (e.g. R, Python) • Hypothesis formulation

2. Prediction Model Building: In the second process step, future machine failures are predicted based on the previously derived failure patterns and incoming data sets in order to determine their probability of occurrence. Besides the defined input data sets of process step 1, further prediction relevant input data shall be acquired in order to enhance the prediction accuracy. The future production program, which indirectly reveals future machine loads, can, for example, serve as a valuable additional input parameter for the prediction. As a result, transparency of the expected impact of future machine failures (e.g. downtime, maintenance KPIs and costs) is generated and mechanical conditions and quality deviations can be monitored in their current and future state.

Table 3. Prediction Model Building | Challenges and ML methods

Challenges	ML methods
• Real-time access to actual planning data • Fast data processing capability • Successful and significant predictions: • High prediction accuracy • High probability of occurrence	• Definition of training, test, and validation datasets • Selection of suitable machine learning and optimization algorithms • Model building / Training • Systematic model evaluation and validation using standard machine learning quality assessment metrics • Packaging model as data product

3. Prescriptive Maintenance Decision Support: The main objective of this step lies in the systematic prioritization and prescription of maintenance activities. By defining company specific operational (e.g. environmental factors, downtime) and management decision parameters (e.g. risk disposition, budget targets, strategic prioritization) a dynamic set of decision rules is derived and integrated into a multi criteria decision model. The decision model automatically prioritizes the predicted machine failures of process step 2. Considering the current service plan, availability of spare parts and resources a specific maintenance activity can be prescribed in order to avoid the machine failure and its associated negative impacts.

Table 4. Prescriptive Maintenance Decision Support | Challenges and ML methods

Challenges	ML methods
• Fast data processing capability • Successful and significant prescriptions of maintenance activities: o High accuracy of results o Prioritization of results o Interpretability of results • Dynamic nature of operational and business workflows and related decision preferences and parameters	• Application of trained and evaluated prediction models on live-data • Visualization and reporting of prediction results • Contextualization of prediction results (data sources, timeliness, etc.) • Expert feedback collection (Active Learning)

4. Maintenance Planning: The fourth process step aims at the creation of concrete maintenance orders within the company´s maintenance management system (MMS). Therefore, domain experts manually accept (or reject) the previously prescribed maintenance activities in order to integrate their implicit knowledge and context sensibility within the prescriptive maintenance process. By bundling maintenance activities, e.g. a prescribed maintenance activity and a regular preventive task, an additional efficiency improvement on operational and management level can be achieved within all interrelated functional areas (maintenance, production planning, and quality management).

Table 5. Maintenance Planning | Challenges and ML methods

Challenges	ML methods
• Data access to MMS • Fast data processing capability • Establishment of feedback loops to process the final judgement of the user • High confidence of planner in the prescribed actions	• Data visualization and interactive user interfaces (concept maps, dashboards, networks, etc.) • Online analytical processing (OLAP) • Meta-analysis • Similarity-based learning (e.g. case-based reasoning) • Information-based learning (e.g. decision trees)

5. Execution & Documentation: Besides the obvious task of timely executing a maintenance order, the last step "Execution & Documentation" includes the measurement and control of the share of successful predictions and effective recommendations as well as the a-posteriori specification and concretization of machine failures due to the operator´s feedback. This information is used for the semi-automatic refinement of the machine learning methods and the decision model. Finally, the improvement of maintenance key performance indicators due to the prescribed and bundled maintenance activities is quantified.

Table 6. Execution & Documentation | Challenges and ML methods

Challenges	ML methods
• Provision of relevant information for maintenance execution • Integration of comprehensive process understanding and feedback of employees into the model • High effectiveness of recommended actions • High confidence of maintainer in prescribed actions • Measuring and controlling the number of highly effective recommendations	• Data product deployment • Data product scaling and real-time streaming connection • Communication and automatic report generation • Interactive interfaces • Continuous monitoring of prediction accuracy and effectiveness

4. Conclusion and Future Research Agenda

The presented reference model constitutes a comprehensive approach for systematically realizing a prescriptive maintenance strategy in both operational and management process levels of a production system. Besides, typical challenges (e.g. multiplicity of data sources, lacking data quality, and variety of process interrelations) within each prescriptive maintenance process step and appropriate ML methods to overcome these challenges are highlighted. As a result of applying the model, companies benefit from optimized intervals between repairs, minimized costs of unscheduled machine breakdowns and prevented unexpected consequential impacts on associated functional areas.

In order to further enhance an existing prescriptive maintenance strategy in a targeted way, there is a clear need of prescriptive maintenance maturity assessment, which is one major task on the author´s future research agenda. The concept is outlined within the next paragraph.

We pursue an analytical, rather than an empirical approach (based on guided interviews with domain experts) to assess the current state maturity level of each prescriptive maintenance process step. For each prescriptive maintenance process step, relevant and measureable key indicators for the data analytics and maintenance dimension are derived, e.g.:

- *Maintenance dimension:* maintainability, reliability, availability, repair- and downtime, cost and human resource effectiveness
- *Data analytics dimension:* data quality metrics (structure, information and veracity), accuracy of failure patterns, certainty and reliability of predictions

By quantifying the defined key indicators, the current state maturity level is assessed, and weaknesses are identified. These results serve as a basis for the third element of the reference model: A company specific target maturity state is defined based on strategic priorities of the company. Due to the quantified key indicators and a set of prescriptive maintenance influencing factors on operational, tactical and strategic level, action fields to achieve the target state can be specified.

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