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Jürgen Beyerer
Alexander Maier
Oliver Niggemann *Editors*

Machine Learning for Cyber Physical Systems

Selected papers from the International Conference ML4CPS 2017

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Preface

Cyber Physical Systems are characterized by their ability to adapt and to learn. They analyze their environment, learn patterns, and they are able to generate predictions. Typical applications are condition monitoring, predictive maintenance, image processing and diagnosis. Machine Learning is the key technology for these developments.

The third conference on Machine Learning for Cyber-Physical-Systems and Industry 4.0 - ML4CPS - was held at the Fraunhofer IOSB in Lemgo, on September 25th - 26th 2017. The aim of the conference is to provide a forum to present new approaches, discuss experiences and to develop visions in the area of data analysis for cyber-physical systems. This book provides the proceedings of selected contributions presented at the ML4CPS 2017.

The editors would like to thank all contributors that led to a pleasant and rewarding conference. Additionally, the editors would like to thank all reviewers for sharing their time and expertise with the authors. It is hoped that these proceedings will form a valuable addition to the scientific and developmental knowledge in the research fields of machine learning, information fusion, system technologies and industry 4.0.

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Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian Networks

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Keywords: Maintenance, CPPS, Prescriptive Analytics, Cause-Effect Analysis, Data Model, Bayesian Network.

Abstract. The complexity and data-driven characteristics of Cyber Physical Production Systems (CPPS) impose new requirements on maintenance strategies and models. Maintenance in the era of Industry 4.0 should, therefore, advances prediction, adaptation and optimization capabilities in horizontally and vertically integrated CPPS environment. This paper contributes to the literature on knowledge-based maintenance by providing a new model of prescriptive maintenance, which should ultimately answer the two key questions of "what will happen, when? and "how should it happen?", in addition to "what happened?" and "why did it happen?". In this context, we intend to go beyond the scope of the research project "Maintenance 4.0" by i) proposing a data-model considering multimodalities and structural heterogeneities of maintenance records, and ii) providing a methodology for integrating the data-model with Dynamic Bayesian Network (DBN) for the purpose of learning cause-effect relations, predicting future events, and providing prescriptions for improving maintenance planning.

1 Introduction

1.1 Key Terms of Knowledge-Based Maintenance

The emergence of cyber physical production systems (CPPS) and the transition to Industry 4.0 trigger a paradigm shift from descriptive to predictive and prescriptive maintenance, colloquially known as the highest maturity level of knowledge-based maintenance (KBM). Figure 1 elaborates on the four maturity and complexity levels of KBM. Notably, maintenance professionals and researchers use different terms to describe the four maturity levels of KBM, which in some cases remain either vague (not precisely determined or distinguished) or ambiguous (have two or more interpretations), such as the concepts of smart maintenance and maintenance 4.0. In this paper, we use the overarching term of KBM that refers to multiple concepts, which can be distinguished from one another (Cf. Figure 1). In particular, prescriptive maintenance involves modeling expert knowledge, machine learning, predictive data analytics and semantic reasoning to enhance and automatize 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. Prescriptive

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maintenance of CPPS 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 on the physical space and associated business processes.

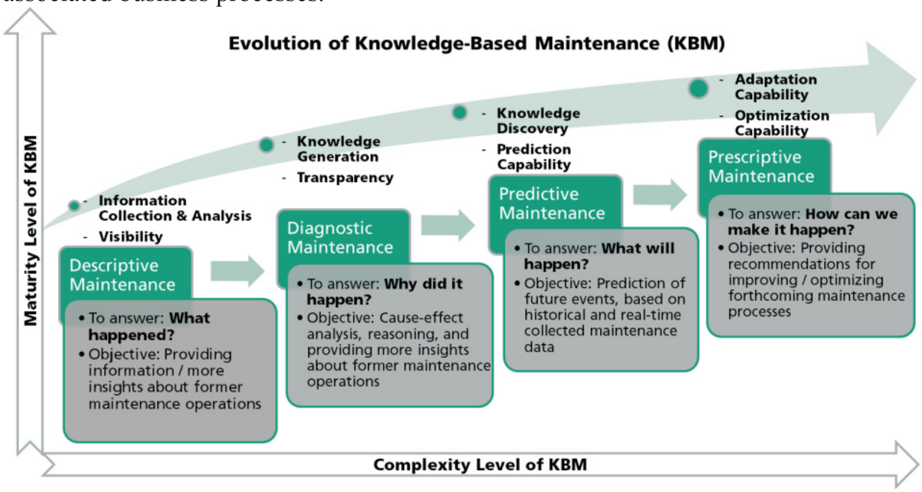

Fig. 1. Four Maturity Levels of KBM – From Descriptive to Prescriptive Maintenance

1.2 State-of-the-Art – Knowledge-Driven and Integrated Approaches

The state-of-the-art literature review on KBM reveals different approaches, which can be categorized into one of two general groups: i) *Knowledge-Driven Approaches* i.e. set of data-mining, machine learning and knowledge representation methods, which are evaluated in the context of diagnostic, predictive or prescriptive maintenance, including maintenance planning, monitoring and controlling activities, and ii) *Integrated Knowledge-Intensive Approaches or Reference Models*, including assistance systems, which aim at combining multiple data-sources and knowledge assets towards enhancing maintenance system intelligence. An overview of selected novel approaches is presented in this section.

Azadeh et. al. (2016) proposed an integrated multi-criteria approach, i.e. AHP-TOPSIS, to consider various parameters and non-linear characteristics of maintenance planning and ultimately optimize maintenance activities [1]. Windmann et. al. (2016) employed the Hidden Markov models and clustering-based condition monitoring for “comparing the actual process behavior with the behavior as predicted from the process models” especially for strictly continuous systems [2]. Moreover, Li and Niggemann (2016) proposed an approach for improving cluster-based anomaly detection on the process data to deduce the health status of systems and automatically detect anomalous statuses [3]. Paschke et. al. (2016) developed a generic data-driven model for active condition monitoring of automation systems, in particular for detecting wear-out or faulty situations “in machine subsystems, each consisting of a servomotor driving different parts of the machine” [4]. Ansari et. al. (2014), Dienst et. al. (2015) and Ansari and Fathi (2016) firstly proposed and then advanced an integrated concept for applying