Digital Transformation Trends: Industry 4.0, Automation, and AI
Industrial Track at ISoLA 2018

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1 Topic and Goal

The industrial track at ISoLA 2018 provided a platform for presenting industrial perspectives on digitalization and for discussing trends and challenges in the ongoing digital transformation. The track continued two special tracks at ISoLA conferences focused on the application of learning techniques in software engineering and software products [3], and industrial applications of formal methods in the context of Industry 4.0 [5]. Topics of interest included but were not limited to Industry 4.0, industrial applications of formal methods, and applications of machine-learning in industrial contexts.

Industry 4.0. Since the "Umsetzungsempfehlung für das Zukunftsprojekt Industrie 4.0" was published in 2012, industries and enterprises are trying to define and implement their Industry 4.0 and digitalization strategy [4]. The past years are embossed by papers, conferences, speeches, tracks and all kinds of information. But what is Industry 4.0 and what does that mean for businesses of tomorrow? The early history teaches us that a lot of money is spent and a lot is said but the real change is missing! Who will make the race towards Industry 4.0 and the digitalization? How will companies with long mechanical background look like in 5–10 years from now?

Formal Methods. The adoption of formal methods in industrial contexts has a huge potential for reducing the effort that is necessary for developing systems and for making systems more save and more secure (e.g., model-based approaches or automated verification techniques). However, the transfer of results of academic research in many instances is not straightforward: Developed methods are abstract and generic and have to be concretized and tailored to concrete problems. Is it possible to identify best practices and structured methods for applying formal methods in practice?

Machine Learning. We are entering the age of learning systems! On the one hand, we are surrounded by devices that learn from our behavior [1]: household appliances, smart phones, wearables, cars, etc. On the other hand, man-made systems are becoming ever more complex, requiring us to learn the

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behavior of these systems: Learning-based testing [2,6,7], e.g., has been proposed as a method for testing the behavior of systems systematically without models and at a high level of abstraction. Advances in both areas raise the same questions cornering properties of inferred models: *How accurate are the descriptions that can be obtained of some behavior?* and: *How can we reason about and assure the safety of such systems?*

The industrial track aimed at bringing together practitioners and researchers to explore the practical impact and challenges associated with the trends sketched above.

2 Contributions

The track featured three contributions with accompanying papers and two invited talks. Contributions focused on Industry 4.0, automated synthesis of workflows and factory layouts. The invited talks reported on applications of machine-learning techniques in automotive systems.

The first contribution *"GOLD: Global Organization aLignment and Decision - Towards the Hierarchical Integration of Heterogeneous Business Models"* by Barbara Steffen and Steve Bosselmann [9] (in this volume) presents a multi-perspective framework for supporting organizations in analyzing their business strategy in the context of Industry 4.0 at multiple levels and discusses technological requirements as well as challenges for the development of modeling tools that support hierarchical integration of analyses and models, allowing to converge on an organization-wide aligned business strategy.

The second contribution *"Automatic composition of rough solution possibilities in the target planning of factory planning projects by means of combinatory logic"* by Jan Winkels, Julian Graefenstein, Tristan Schäfer, David Scholz, Jakob Rehof, and Michael Henke [10] (in this volume) presents an automated approach for generating meaningful alternative factory floor plans at an early stage of the planning process. The method enables an efficient planning process in terms of time and cost: With the help of a constraint-based variant compilation on the basis of previously defined target and frame parameters as well as information on the factory system, various possible solution variants for target planning are generated through combinatory synthesis. A specific use case scenario is used to evaluate the presented methodology.

The third contribution *"A Methodology for Combinatory Process Synthesis: Process Variability in Clinical Pathways"* by Tristan Schäfer, Frederik Möller, Anja Burmann, Yevgen Pikus, Norbert Weißenberg, Marcus Hintze, and Jakob Rehof [8] (in this volume) develops a structured method for the industrial application of combinatory process synthesis for the automated generation of workflows. The presented approach is based on the Design Science Research principles. The approach is evaluated in an industrial case study, in which combinatory process synthesis was used for generating workflows in a hospital.

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