

Special Issue: Design Engineering in the Age of Industry 4.0

This special issue is motivated by the trend of smart factories of the future toward the fourth Industrial Revolution, which makes it possible to better leverage capabilities and resources in a human-cyber-physical production environment. This emerging paradigm of Industry 4.0 poses new systems design problems at the interface of smart manufacturing, robust and flexible automation, distributed and reconfigurable production systems, industrial IoT, and supply chain integration. Recent advances in design engineering in the age of Industry 4.0 are presented in this special issue. More than 40 papers were received and peer-reviewed, out of which 14 papers were selected for publication. These papers are both theoretical and practical, as well as state-of-the-art reviews, new perspectives, and outlook for future research directions in the field. The papers span a range of design aspects and Industry 4.0 technologies. There are three intersecting clusters in this category: design principles and techniques for Industry 4.0, smart manufacturing technologies, and machine learning and data-driven techniques for Industry 4.0.

There are four papers on design principles and techniques for Industry 4.0. Wang et al. performed a detailed review of the literature to identify the needs for decision support in designing complex systems for Industry 4.0. In their paper titled “Knowledge-Based Design Guidance System for Cloud-Based Decision Support in the Design of Complex Engineered Systems,” they presented an architecture of a Knowledge-Based Design Guidance System (KBDGS) for cloud-based decision support. This architecture is used to support integrated management of complexity, uncertainty, and knowledge in complex decision workflows that are typical in Industry 4.0 scenarios.

In the paper titled “Are Two Heads Better Than One for Computer-Aided Design?” Phadnis et al. evaluated the effects of work process-related choices in the Industry 4.0 context. The authors compared three working styles using human subject experiments. The working styles include individuals working by themselves, pairs sharing control of one CAD model instance and input, and pairs able to simultaneously edit a CAD model from two inputs. The authors concluded that Industry 4.0 technologies alone do not influence designer output; however, these process-related choices have a major effect on design outcomes.

Crowdsourcing is an important trend for Industry 4.0. It can be applied to new strategies and practices of design innovation and product realization. The Internet+ economy and cyber-physical platform technologies are important for crowdsourced design and manufacturing. Hwang et al. in their paper titled “Design Principles for Additive Manufacturing: Leveraging Crowdsourced Design Repositories” proposed some practical design principles for additive manufacturing for successfully creating and building customized design artifacts. The authors exploited a crowd-sourced repository of additively manufacturable components from a website.¹

In the paper titled “Prototyping Human-Centered Products in the Age of Industry 4.0,” Ahmed et al. addressed the design needs for Industry 4.0 by focusing on customer-oriented mass customization, simulating human-machine interactions early in design, and injecting human factors throughout the value chain. The authors presented a human-centered computational prototyping framework for the ergonomic assessment of products during the early stages of design. The authors concluded that understanding the intricacies of the relationships among the fidelity level, type of ergonomic assessment, and human-product interaction level helps designers in advancing the objectives of Industry 4.0.

There are five papers on this special issue on smart manufacturing technologies. The use of a digital twin to establish a real-time mapping between physical space and virtual space has emerged as a powerful technique for decision support to design in the era of Industry 4.0, such as real-time analysis, reliability assessment, predictive maintenance, and design optimization of products.

In the paper titled “Designing Shape-Performance Integrated Digital Twin Based on Multiple Models and Dynamic Data: A Boom Crane Example,” Lai et al. developed a shape-performance integrated digital twin (SPI-DT) technology and illustrated how to design the SPI-DT step by step for structural analysis of complex heavy equipment using a boom crane as an example. The SPI-DT employs an analytical model, a numerical model, and an artificial intelligence (AI) model to leverage multisource dynamic data obtained from different sensors located at multiple measurement positions. This significantly improves the computational efficiency of the digital twin used for the structural analysis of complex heavy equipment, making the digital twin computationally affordable, and thus, it can be used for the safety assessment and damage protection of the equipment in operation, as well as for the design optimization of next-generation products.

Sensor integration is one of the critical challenges in the transition to Industry 4.0. In their paper titled “Barriers for Industrial Sensor Integration Design—An Exploratory Interview Study,” Juul-Nyholm et al. presented an interview study among practitioners in different industrial contexts. The authors highlighted five general challenges and four contextual challenges in sensor system design and find that one of the key reasons for the slow adoption of Industry 4.0 is a lack of tools and experience in the development of connected consumer and industrial products.

The coordination of autonomous resources within a smart manufacturing enterprise is an important enabler for Industry 4.0. Decentralized cooperative manufacturing for 3D printing results in increased throughput and efficiency but poses new coordination challenges. To address these challenges, Poudel et al. presented a method for scheduling multi-robot cooperative 3D printing in their paper titled “Resource-Constrained Scheduling for Multi-Robot Cooperative Three-Dimensional Printing.” The authors demonstrated the algorithms using different geometrical shapes.

Building on the theme of collaborative robotics, Chen et al. addressed the problem of knowledge transfer across different yet interrelated tasks in a manufacturing shop floor. In the paper titled “Levering Task Modularity in Reinforcement Learning for

¹Thingiverse.com

Adaptable Industry 4.0 Automation,” the authors presented a meta-reinforcement learning framework to enhance the adaptability of collaborative robots to new tasks. They combined modular design techniques that are widely used in engineering design with reinforcement learning techniques to achieve a high degree of adaptability, flexibility, and resilience in manufacturing systems.

A key benefit of IoT technologies for Industry 4.0 is intelligent fault detection and recovery. Zinn et al. in their paper titled “Fault-Tolerant Control of Programmable Logic Controller-Based Production Systems with Deep Reinforcement Learning” presented a machine learning approach to design fault-tolerant control policies that automatically restart PLC-based production systems during fault recovery.

There are four reports of machine learning and data-driven techniques for Industry 4.0. The increasingly connected devices, systems, and humans in Industry 4.0 raise new challenges related to the security and privacy of information exchange. In the paper titled “Design of Trustworthy Cyber-Physical-Social Systems with Discrete Bayesian Optimization,” Wang addressed the problem of incorporating the perception of trust in architecting cyber-physical social systems. The author described a surrogate-based discrete Bayesian optimization method to apply quantitative trustworthiness metrics as design criteria in system architecture design.

Exploiting product usage data has attracted much attention recently. Li et al. in their paper titled “A Data-Driven Methodology to Improve Tolerance Allocation Using Product Usage Data” emphasized such product usage data as geometric deviation, position deviation, and angular deviation that lead to product functional performance degradation which is continuously collected during the product usage stage. A data-driven methodology based on the deviation for tolerance analysis is proposed to optimize the tolerance allocation. Based on a feature graph of mechanical assembly relationships, a graph neural network (GNN) algorithm is developed to identify hidden relations between nodes in the feature graph and to calculate labels of all nodes. The case study of optimal tolerance allocation of a press machine is an application that identifies the to-be-modified tolerance values offering high priorities for product improvement.

With the ongoing automation of manufacturing as a part of Industry 4.0, there is a greater need for advancing methods to handle challenges such as high input dimensionality, data paucity, or big data problems, these methods consist primarily of proposing efficient experimental designs, optimal data acquisition strategies, and other mathematical procedures. Focusing on the challenges of efficiently training a Gaussian Process (GP), Pandita et al. in the paper titled “Scalable Fully Bayesian Gaussian Process Modeling and Calibration With Adaptive Sequential Monte Carlo for Industrial Applications” compared an Adaptive Sequential Monte Carlo sampling algorithm to classic Markov Chain Monte Carlo sampling strategies. Effective computational time savings for large-scale problems is demonstrated by helping push the boundary of GP regression applicability and scalability in various domains of Industry 4.0, including but not limited to design automation, design engineering, predictive maintenance, manufacturing planning, and supply chain management.

Data-driven decision-making has an important role in predictive maintenance and equipment health management in the age of Industry 4.0. Focusing on the design and maintenance of a gas turbine compressor vane carrier, the paper titled “Low-Cycle Fatigue Lifetime Estimation and Predictive Maintenance for a Gas Turbine Compressor Vane Carrier Under Varying Operating Conditions” by Han et al. presented a probabilistic method to estimate the low-cycle fatigue (LCF) life under varying operating conditions. The authors proposed a new data processing technique inspired by the cumulative sum (CUSUM) control chart for identifying the first ramp-up period as well as the shutdown period of each cycle

from noisy operational data. The authors demonstrated an effective sequential convolution strategy adapted from Miner’s rule to compute the probability distribution of accumulated LCF damage, and hence LCF life, from single-cycle damage distribution data. With the gas turbine case study, the authors showed that this is an approximative, quick estimation method to reduce computational expense in dealing with large operating data.

As the guest editorial team, we co-authored a review and positioning paper by Jiao et al. titled “Design Engineering in the Age of Industry 4.0” that is included in this Special Issue. In this paper, we reviewed the state of the art in Design Engineering and offer Design Engineering 4.0 as an emerging contemporary paradigm for consideration by the design research community. It is our hope that our review and prospect will spur dialog, leading to impactful research and associated new horizons in the national and international research funding landscape related to the new frontiers in this important and fascinating emerging field.

Finally, we take this opportunity to thank all authors for submitting their contributions and all reviewers for their efforts in reviewing the manuscripts. We appreciate the Editor-in-Chief, Professor Wei Chen, for her supportive guidance and Amy Suski for her timely, constant support throughout the editorial process.

Janet K. Allen
Systems Realization Laboratory,
University of Oklahoma,
Norman, OK 73019
e-mail: janet.allen@ou.edu

Sesh Commuri
Electrical and Biomedical Engineering,
University of Nevada Reno,
Reno, NV 89557
e-mail: scommuri@unr.edu

Roger Jiao
George W. Woodruff School of Mechanical Engineering,
Georgia Institute of Technology,
Atlanta, GA 30332
e-mail: rjiao@gatech.edu

Jelena Milisavljevic-Syed
Civil Engineering and Industrial Design,
University of Liverpool,
Liverpool, L69 3BX, UK
e-mail: J.Milisavljevic-Syed@liverpool.ac.uk

Farrokh Mistree
Systems Realization Laboratory,
University of Oklahoma,
Norman, OK 73019
e-mail: farrokh.mistree@ou.edu

Jitesh Panchal
Department of Mechanical Engineering,
Purdue University,
West Lafayette, IN 47907
e-mail: panchal@purdue.edu

Dirk Schaefer
Civil Engineering and Industrial Design,
University of Liverpool,
Liverpool, L69 3BX, UK
e-mail: Dirk.Schaefer@liverpool.ac.uk