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Editorial

Smart Manufacturing and Industry 4.0

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Smart manufacturing processes and systems have received great attention through the latest innovations, ongoing efforts, and best practices in the Industry 4.0 era. The era that we currently live in is undergoing a revolutionary transition in the ways that data and information are collected, accessed, analyzed, and employed in completing industrial tasks. Specifically, manufacturing has greatly benefited from this transition toward forming new generations of manufacturing considered "smart" or "intelligent" [1]. Smart manufacturing is considerably agile in satisfying design requirements with higher levels of accuracy and reliability while the cost is maintained at a minimum; moreover, there are provisions for product customization and adaptation to the environment and the needs of the other machines/processes. In addition, today's smart manufacturing integrates machines and humans. These benefits of smart manufacturing result in the cost-effective use of manufacturing resources and a reduction in the time to market. This transition gradually started several years ago. For example, the Intelligent Manufacturing Systems (IMS) Working Group, a scientific network affiliated with the IFAC Technical Committee 5.1 (namely, TC 5.1 Manufacturing Plant Control), discussed this topic in a series of IFAC international IMS Workshops starting in 1992 (in Austria, Romania, Korea, Brazil, Poland, Hungary, Spain, Portugal, USA, Canada, and Israel) [2,3]. The 15th IMS is scheduled to be held in Poland in 2025. Smart Manufacturing appeared after Intelligent Manufacturing [2]; however, both terms are used in conjunction with Industry 4.0.

This issue considers three application areas in Industry 4.0:

(1) Intelligent Design and Manufacturing;
(2) Intelligent Process and Production Control;
(3) Intelligent Maintenance.

This invited issue has been developed based on the contributions of researchers in different countries. The area of Intelligent Design and Manufacturing includes three papers: (1) Najafabadi et al. addressed the usage of topology optimization in design considering manufacturing constraints, and they applied simulated annealing with crystallization heuristics as an optimization tool. The proposed method resulted in geometries nearly those of organics [4]. (2) Duran et al. proposed feedback strategies for simulated annealing and applied them to airplane design. It is relevant to point out that the design was constrained in this problem since the airplane had to carry a maximum load under a group of restrictions [5]. (3) Pastor et al. described the application of a genetic algorithm to optimize the design process. The article showed that using this optimization in kinematics analyses and automated Computer-Aided Design (AD) of robotic arms was viable and could speed up the design process [6].

The area of Intelligent Process and Production Control includes three papers: (1) Ferro et al. proposed a process for production analysis through discrete event simulation and optimization using genetic algorithms and presented a case study in the textile industry [7]. (2) Kim et al. used machine learning to predict the demand of small and medium enterprises.

Usually, small and medium enterprises have poor inventory data, which typically causes the prediction model to fail. The authors proposed predicting inventory data by modeling the volatility stochastically [8]. (3) Cieplinski et al. proposed a methodology for production scheduling considering production resources as tools and humans. The methodology could use any generic optimization algorithm to solve the problem [9].

The area of maintenance has one paper: 1. Neupane et al. proposed an intelligent method for detecting and classifying bearing faults using a convolutional neural network. The authors used vibration data as a temporal sequence. The temporal sequence was processed to determine fault detection [10].

We believe that some main trends will emerge shortly: (1) Smart manufacturing will be a key feature in coordinating operations for manufacturing plant control; integrating design and manufacturing activities; and organizing and synchronizing operations in different domains, such as logistics, production, maintenance, safety, and quality. (2) Cyber-physical integration will serve as the basis for manufacturing by cooperatively combining employees and machines (mobile and autonomous robots and drones). (3) Intelligence will continue to be the core tool in this development.

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