Editorial

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Biographical notes: Fazleena Badurdeen is the Earl Parker Robinson Chair Professor in Mechanical Engineering in the Department of Mechanical Engineering, University of Kentucky, UK. She serves as the Director of Manufacturing Systems Engineering MS Program and is a core member of UK's Institute for Sustainable Manufacturing. Her research focuses on circular and sustainable product design, modelling and analysis of manufacturing systems and supply chains, and development of decision support tools in these areas. She is the Technical Vice President at the Institute of Industrial and Systems Engineers, an editor for *Resources, Conservation and Recycling*, and serves in several other journal editorial boards.

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The increased complexity of modern manufacturing systems has led to an exponential growth of data generated during various stages of manufacturing operations. The emerging Industry 4.0 technologies offer significant capabilities for manufacturers to better use data and manage the complexities. Efficient use of manufacturing big data would provide intelligence for modelling and optimisation at the product, process, and system levels, to facilitate optimised product design, to improve manufacturing productivity and energy efficiency, and to reduce material waste and eliminate hazardous working environments, towards achieving the goal of sustainable manufacturing (SM). Emerging artificial intelligence (AI) techniques have been widely investigated in academia and applied by industry for manufacturing big data analysis and learning. These AI techniques offer numerous capabilities, including processing multi-modal data (e.g., time series, images, and video), correlating input-output variables in a complex system, optimising system behaviour in a high-dimensional space, and so on. All these capabilities contribute to better data analysis to enable more SM. Digital integration of data generated across different stages of a product's lifecycle by various stakeholders can help to increase the visibility and accessibility of that information for more informed, sustainability-driven decision making. This special issue showcases a selection of articles addressing the application of the emerging Industry 4.0 techniques for enhancing SM.

In their paper titled 'A critical review of Industry 4.0 technologies for sustainable manufacturing in remanufacturing development', Chong et al. review existing studies and knowledge gaps of Industry 4.0 technologies for implementing remanufacturing for SM. Through a review of 36 recently published relevant studies in the remanufacturing context, it is identified that the existing studies of integrating Industry 4.0 techniques into SM consider only the application at the product, processes, or the system level separately, but not the combined application across all these three levels. The paper concludes by underscoring the need to identify methods for integrated product and process data-driven decision-making methods for improving the efficiency of remanufacturing operations and developing an implementation framework for promoting SM advancement toward circular economy.

Rumsa and Biswas developed a novel framework to assess the sustainability of ammonia production by using the triple bottom line (TBL) methodology in their paper titled 'Sustainability performance of ammonia production: the contribution of Industry 4.0 and renewables to enhance the triple bottom line'. After consulting with professionals in the ammonia production process, industry and academia, nine performance indicators and one aggregated sustainability index are generated. A local case study is performed, and the results validate that SM process improves with increasing levels of integrating automation and Industry 4.0 technologies into blue ammonia production.

Huang et al. review the literature related to Industry 4.0 with a focus on advancing smart and SM in their paper titled 'A review of research on smart manufacturing in support of environmental sustainability'. The benefits of Industry 4.0 techniques and applications in the manufacturing sector are reviewed at three levels, machines/process, production systems, and supply chains. Knowledge gaps and future research directions are also identified at the three levels. The authors identify the need for more research in a variety of areas, including improving machine health diagnosis by integrating physics into machine learning models, investigating various dynamic scheduling techniques in production systems, and automated data collection and processing for improving supply chains.

Schimanek et al. present a framework for improving circularity through data fusion methods in product inspection in their paper titled 'Data fusion for improved circularity through higher quality of prediction and increased reliability of inspection'. Different data fusion methods, including statistical analysis and machine learning techniques, are demonstrated as effective in fusing sensor and business data for improving prediction quality and stability in inspection. The paper also reviews AI-enhanced applications for inspection in reverse logistics and return management, as well as resource efficiency and circularity.

Bhatia et al. present work that combines smart phone-based imaging and machine learning-enabled image processing for detecting production quality of parts printed via fused deposition modelling in their paper titled 'Automated quality detection of resource efficient 3D printing'. For processing the images, a Sobel filter with adaptively determined threshold is applied to detect part edges. Gaussian process regression and support vector machines are investigated and compared for correlating process parameters to part surface roughness and energy consumption. Based on the correlation modelling, optimal process windows are recommended to achieve the desired part quality while avoiding excess energy consumption.

Badurdeen et al. present an approach to develop an interoperable digital thread to integrate data from different sources across the total lifecycle in their paper titled 'Digital integration of total lifecycle tools for sustainable product design'. The digital thread is connected to a range of decision support tools aimed at optimising product design and conducting simulations, sensitivity analysis, and risk assessments. An industrial case study exemplifies the practical implementation of this digitally integrated capability. The outcomes clearly illustrate that the digital thread serves as a powerful platform for gathering data across various lifecycle stages and conducting sustainability analyses to identify the most appropriate product configuration designs.