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Editorial

Smart Manufacturing—Theories, Methods, and Applications

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1. Smart Manufacturing (SM) Theories

Smart manufacturing (SM) distinguishes itself from other system paradigms by introducing '*smartness*' as a measure to a manufacturing system; however, researchers in different domains have different expectations of system smartness from their own perspectives. In this *Special Issue* (SI), SM refers to a system paradigm where digital technologies are deployed to enhance system smartness by (1) empowering physical resources in production, (2) utilizing virtual and dynamic assets over the internet to expand system capabilities, (3) supporting data-driven decision making at all domains and levels of businesses, or (4) reconfiguring systems to adapt changes and uncertainties in dynamic environments. System smartness is measured by one or a combination of system performance metrics, such as the degree of automation, cost-effectiveness, leanness, robustness, flexibility, adaptability, sustainability, and resilience. This SI aims to present the most representative works in advancing the theories, methods, and applications of SM.

Rapidly developed digital technologies have continuously stimulated shifts of manufacturing system paradigms; most recently, the study of SM has attracted numerous researchers in academia and practitioners in industry [1–5]. However, people in different domains have highly diversified expectations of system smartness, leading to the ambiguity, diversity, and inconsistency of SM concepts in terms of system architecture, reference models, enabling technologies, and evaluation matrices. Bi et al. [6] generalized the definition of SM by unifying diversified expectations of system smartness as customizable measures, and they presented two concepts of *digital triad* (DT-II) and the *Internet of Digital Triad Things* (IoDTT) to emphasize the *functional requirements* (FRs) of SM to accommodate changes and uncertainties in sustainable and cost-effective ways. Bányai [7] analyzed the needs of adaptability and flexibility in *matrix production*; he argued that flexible manufacturing systems could be the correct solutions to deal with changes in production. He emphasized the importance of effective models and methods in optimizing system controls. In particular, he proposed a hybrid metaheuristic algorithm based on multiphase black hole and flower pollination to plan and schedule manufacturing resources in material handling systems using robots.

Sahal et al. [8] investigated the roles of *digital twins* (DTs) in modelling physical assets and supporting decision-making activities in decentralized and distributed manufacturing. They found that DTs required collaboration among stakeholders to reach the consensuses of decisions and predict risks; the critical FRs of collaborations were defined in terms of interoperability, authentication, scalability, and the avoidance of single-point failures. A ledger-based collaborative framework was proposed to fulfill the identified FRs in smart transportation systems, and the incorporated technologies included blockchain technologies (BCTs), predictive analysis techniques, and other digital technologies. Ubiquitous smart things in the *Internet of Things* (IoT) make it feasible to collect real-time data of the conditions of any manufacturing resources from anywhere at any time; Tan et al. [9] adopted DTs to synchronize and utilize real-time data in a cyber space; the challenges of

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integrating DTs with smart things in IoT were explored, and a new scheme and framework were constructed to simulate DTs with real-time data.

2. System Design Methods

SM has benefited greatly from rapidly developed information technologies, such as DTs, BCT, IoT, *cloud computing* (CC), *big data analytics* (BDA), *cyber-physical systems* (CPSs), and *edge-computing*. These technologies have been changing the landscape of the research and development of SM radically, in a sense that (1) solutions of acquiring and transferring data become increasingly more affordable in regards to implementing, deploying, and integrating 'smarter' things in a system; (2) business-relevant data become increasingly bigger in terms of '*volume*', '*variety*', and '*velocity*', where advanced data analytics can be used to capture, store, process, and utilize data to cope with changes in dynamic environments; (3) the system boundary becomes increasingly vaguer, and system architecture has to be dynamically adaptable to physical and virtual collaborations of business partners over time [10–13].

System design methods are used to select system elements, configure these elements into components and systems, and model, evaluate, and compare design options against *key performance indicators* (KPIs) for system optimization. However, traditional system design methods are mostly for the design of static systems with clear system boundaries. There are needs required for the advancement of system design methods so that a smart manufacturing system can be reconfigurable to achieve high-level smartness in its system lifecycle. The configurations of a smart system must be customized to the constraints of manufacturing resources and the prioritized KPIs. Bi et al. [14,15] proposed a systematic design methodology as the guide for designs of smart manufacturing systems in specified applications. The *axiomatic design theory* (ADT) was adopted and expanded to design, analyze, and assess smart manufacturing systems, and the applicability of the proposed methodology was verified using three case studies. Erasmus et al. [16] proposed an information architecture to integrate CC and IoT with smart devices for human–robot collaboration; the architecture was modularized for *small- or medium-sized enterprises* (SMEs) to access extensible cloud services, and it was used as a reference architecture for information management systems in Industry 4.0. The architecture was tested and evaluated with the information systems of ten real-world factories. Kim and Lee [17] extended the SM concept to a maintenance system in ship building and servicing; the framework, procedure, and architecture of a smart maintenance system were developed to systematically design large-scale SM systems.

3. Applications

SM is expected to meet some emerging requirements of automation, adaptability, sustainability, and resilience of modern manufacturing systems in the digital era at numerous aspects, including (1) dealing with any level of system complexity relating to the number and variants of system elements, the interactions of system elements, and anticipated and unanticipated changes over time; (2) maximizing system entropy to adopt changes in a dynamic environment; (3) responding to real-time changes in the shortest possible time; (4) monitoring, diagnosing, and predicting system states and trends, generating preventive solutions for adverse changes, and upgrading systems to adapt preferable changes; (5) supporting the seamless coordination, collaboration, and cooperation of stakeholders; (6) orchestrating manufacturing resources across enterprise bounds to seize novel opportunities; (7) providing generic architecture applicable to different products, functions, and regions [1,18–20].

Cutting-edge digital technologies have been widely explored in regard to solving various engineering problems in real-world applications. For examples, Hou et al. [21] developed a function–structure model to evaluate performance and cost in product development; products were characterized in functional and structural domains, respectively, and an evolutionary algorithm (EA) was used to map functions into corresponding structures for the verification of design constrains and the evaluation of design solutions. Kang et al. [22] discussed various challenges of using vibrioses to protect the environment during fossil fuel exploration; numerical simulation models were developed to analyze the response of a vibriosis subjected to specific boundary conditions and excitations, and simulation results were used to identify the weakest vibriosis junctions. Liu et al. [23] proposed an integrated robotic system for its application in an ill-structured on-site environment with the purpose of cost-efficiency. The proposed system consisted of two-terminal manipulators for parallel sorting processes, and it was seamlessly integrated in an automated assembly system to perform sorting tasks consistently in a shortened cycle time. Yung et al. [24] discussed the challenges in designing and manufacturing highly diversified space instruments. The specifications of space instruments were greatly distinguished from those of products on Earth, and careful considerations had to be determined on the size, weight, cost, complexity, and extreme space environments. A systematic literature search method was used to look into the impact of product design and innovation on the development of space instruments; the survey provided important information and critical considerations for using cutting-edge digital technologies in designing and manufacturing space instruments.

4. Future Research Directions

Increasingly more manufacturing enterprises are ready to incorporate newly developed technologies, such as DTs, CPSs, IoT, BDA, and BCT, with traditional manufacturing technologies, such as *flexible manufacturing systems* (FMSs), *total quality management* (TQM), *supply chain management* (*SCM*), *enterprise resource planning* (*ERP*), and *computer-integrated manufacturing* (*CIM*). However, existing theories, methods, and tools still exhibit limitations in supporting cost-effective *vertical integration*, *decentralization*, *smart sensing and actuating*, *autonomy and self-organization*, and uses of *semantic models* [25]. The research of SM in theories, methods, and applications should be advanced to transfer integrated digital technologies into productivity, profitability, and sustainability of systems. This Editorial Team anticipated that future research in SM would mainly incorporate areas of (1) ubiquitous sensing, (2) fusing and integrating data from heterogeneous sources, (3) effective BDA methods, (4) data visualization methods for human interactions, (5) data-driven decision-making supports, (6) workflow composition methods, (7) the standardization and specifications of smart modules, and (8) quantified criteria such as adaptability, sustainability, and resilience for system evaluation [1,6,14].

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