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Editorial

Advanced Digital Design and Intelligent Manufacturing

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1. Introduction

This Special Issue was initiated to reflect how digital technologies, data, and intelligence are reshaping mechanical engineering and production systems across the entire product life cycle [1–3]. Advanced computer aided design (CAD), high-fidelity simulations, and automation are now central to achieving higher precision, efficiency, and innovation in products and processes, while artificial intelligence (AI), machine learning (ML), and the Industrial Internet of Things (IIoT) enable real-time monitoring, predictive maintenance, and adaptive optimization in smart factories [4–7]. This Closing Editorial situates the contributions of the Special Issue within current research on Industry 4.0, digital twins, and intelligent manufacturing, highlighting their impact and outlining future directions for both research and industrial practice.

2. Digital Design, Modeling, and Simulation

Digital design is increasingly grounded in multi-domain modeling and simulation, which together form the backbone of "design for intelligent manufacturing". This Special Issue shows how general purpose environments such as MATLAB/Simulink R2025b and Simscape can be exploited beyond classical control design to support structural analysis and evaluation of mechatronic systems, thereby reducing dependence on labor-intensive analytical calculations [8–11]. This trend is aligned with the broader shift toward simulation-driven design, where virtual models are iteratively refined before physical prototyping, effectively establishing a digital thread from conception to realization.

A key contribution in this context is the conceptually simple method for optimizing model computations in MATLAB Simulink, which focuses on solver selection, time step control, and numerical settings to improve accuracy without altering the underlying physical model. Similar numerical concerns have been addressed in hybrid simulation frameworks for cyber physical systems, where inappropriate integration schemes or step sizes can compromise stability and reliability of simulation-based decisions. By providing a practical, well-structured procedure, the article supports wider industrial adoption of advanced simulation, and is compatible with model-based systems engineering (MBSE) approaches that integrate models across disciplines and life-cycle stages [12–14].

More generally, robust simulation is a prerequisite for trustworthy digital twins and virtual commissioning, where the virtual representation must faithfully capture dynamic behavior, constraints, and interactions among system components. The works in this Special Issue demonstrate that when numerical configuration is treated as a first-class design variable, multi-body and system-level simulations can provide reliable guidance for later stages of manufacturing system design and operation [15,16].

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3. Digital Twins and Data-Driven Integration

Digital twins have emerged as a cornerstone of intelligent manufacturing, providing dynamic, data-enriched virtual representations of physical assets, processes, and systems. This Special Issue presents implementations of digital twins for CNC machining centers and entire production systems, where simulation models are coupled with real-time and historical data from sensors, controllers, and manufacturing execution systems (MES). Such implementations resonate with established frameworks for digital-twin-based sustainable intelligent manufacturing, which emphasize closed-loop interactions between design, production, and service to support continuous performance improvement and life-cycle optimization.

A distinctive feature of the reported work is the integration of heterogeneous data sources—including CSV logs, database connections, OPC-based communication, and scenario files—into coherent digital twin environments that support monitoring, planning, and decision support. Similar architectures have been proposed in the literature to enable flexible and scalable data pipelines for Industry 4.0 applications, particularly in small and medium-sized enterprises (SMEs) that require cost effective solutions [14,17]. By validating their approaches on different manufacturing systems, the contributions in this Special Issue illustrate concrete pathways for SMEs to adopt digital twin technologies, complementing conceptual surveys and reference frameworks reported elsewhere [17–19].

Beyond individual factories, there is growing attention to industrial data spaces and standardized reference architectures, such as the Asset Administration Shell (AAS), which aim to ensure secure, interoperable data exchange across organizational boundaries. Contributions to this Special Issue that demonstrate automatic registration and synchronization of AAS-based digital twins within data space infrastructures align with ongoing research on federated industrial data management and cross company value networks [19]. These developments are tightly coupled with research on AI-enabled digital twins, where generative and predictive models are orchestrated across cloud and edge resources to support diagnostics, optimization, and decision making in distributed manufacturing ecosystems.

4. Intelligent Monitoring, Control, and Process Optimization

Intelligent manufacturing is closely associated with advanced monitoring and control strategies that leverage ML and data-driven models to enhance process performance, quality, and reliability. In this Special Issue, several contributions examine condition monitoring of robotic systems and intelligent control of forming and machining processes, thereby extending the reach of AI-based analytics into domains that have historically relied on heuristic or rule-based approaches. These efforts echo a broader body of work demonstrating the effectiveness of deep learning and statistical learning for fault diagnosis and predictive maintenance in complex industrial systems [20].

Vibration-based monitoring of industrial robots, for instance, combines statistical feature selection methods (such as ANOVA and t tests) with classification algorithms to detect loosening of robot bases during operation, providing an example of data-driven condition monitoring tailored to sequential and multi-axis machinery. Similar strategies have been widely applied to rotating machines, where carefully engineered features and supervised learning have yielded significant improvements over traditional threshold-based approaches. Extending these methods to robots addresses a recognized gap in the diagnostics literature and supports the development of predictive maintenance programs for highly automated production lines [20,21].

Process optimization is further illustrated by studies on robotic milling and metal forming, where the influence of parameters like feed rate, depth of cut, and forming angles on product quality and springback is systematically analyzed. These works are in

line with research on data-driven process optimization and virtual machining, which use simulation and experimental data to build models that predict surface quality, dimensional accuracy, and energy consumption for different parameter combinations. In particular, the application of reinforcement learning (RL) for springback compensation in V bending demonstrates how "learning in the loop" strategies can adapt to uncertainties in material properties and tooling, reflecting a wider trend toward integrating RL into industrial process control [22–24].

Collectively, these contributions show that intelligent monitoring and control can be integrated into existing manufacturing systems incrementally, augmenting rather than replacing established automation and control architectures.

5. Conclusions

The contributions gathered in this Special Issue collectively demonstrate that advanced digital design and intelligent manufacturing are deeply intertwined dimensions of the emerging cyber physical production paradigm [1–3]. Multi-domain modeling, numerically robust simulation, and digital twins form the foundation upon which intelligent monitoring, AI-based control, and data-driven optimization are built. At the same time, developments in industrial data spaces, standardized architectures, and MBSE provide the structural and organizational scaffolding needed to integrate these technologies across life-cycle stages and organizational boundaries.

Looking ahead, several research challenges and opportunities can be identified. First, there is a need for interoperable reference architectures that support modular digital twin components, hybrid physics-based and data-driven models, and standardized interfaces for analytics and control services. Second, robust AI methods that can cope with non-stationary conditions, limited labeled data, and strict safety requirements are essential to move from prototypes to large-scale, mission-critical deployments. Third, specific attention should be paid to SMEs, ensuring that digital twin and AI solutions are economically viable, scalable, and compatible with existing equipment and skills. Finally, education and training in digital design, data science, and AI for manufacturing will be crucial to fully exploit the potential of these technologies and to foster a workforce capable of working effectively in data rich, highly automated environments.

As Guest Editors, we believe that the contributions collected in this Special Issue provide a timely and representative snapshot of ongoing developments in advanced digital design and intelligent manufacturing [1–3]. We hope that the presented concepts, methods, and case studies will stimulate further interdisciplinary collaboration between academia and industry, and will support the transition towards more intelligent, sustainable, and resilient manufacturing systems in line with the vision of Industry 4.0 and beyond.

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