machines

MDPI

Editorial

Recent Developments in Machine Design, Automation and Robotics

Raul D. S. G. Campilho [1,2]

[1] CIDEM, ISEP—School of Engineering, Polytechnic of Porto, 431, 4200-072 Porto, Portugal; raulcampilho@gmail.com

[2] INEGI—Institute of Science and Innovation in Mechanical and Industrial Engineering, Pólo FEUP, 400, 4200-465 Porto, Portugal

This editorial introduces a Special Issue of *Machines* entitled "Recent Developments in Machine Design, Automation and Robotics". This Special Issue arrives at an important time in industrial evolution, when digital transformation, sustainability, and productivity optimization are redefining how machines and systems are conceived, built, and operated [1–3]. Modern industrial competitiveness depends not only on production output or cost efficiency, but also on the ability to rapidly adapt to changing demands and ensure high levels of reliability and traceability while incorporating environmentally responsible practices to help businesses achieve their goals [4]. These objectives can only be achieved by integrating automation, robotics, and intelligent system design into the industrial processes [5,6]. As the fourth industrial revolution (Industry 4.0) continues to progress, the design and deployment of machines and manufacturing systems is facing significant changes [7]. Concepts such as cyber–physical systems, real-time data processing, artificial intelligence (AI), and the Internet of Things (IoT) are giving rise to smart factories—environments in which automation and robotics are not isolated functions but act together to promote autonomous operation and continuous improvement [8,9]. This transformation provides new opportunities and presents novel challenges: the implemented production systems must be increasingly flexible, decentralized, safe for human interaction, and resilient to disturbances [10]. On the other hand, global pressures regarding sustainability and energy efficiency also affect machines' design and operation during their life cycle, influencing material selection, maintenance, and recycling [11]. This Special Issue aims to address these needs by collecting innovative scientific and technological contributions that describe the evolution of machine design, automation, and robotics. The 32 accepted papers cover a wide range of innovative topics in the form of review and research papers, which are organized into five main areas. Each area represents a distinct dimension of the current research and developments in intelligent industrial systems.

check for updates

Received: 29 July 2025
Accepted: 31 July 2025
Published: 3 August 2025

Citation: Campilho, R.D.S.G. Recent Developments in Machine Design, Automation and Robotics. *Machines* **2025**, *13*, 683. https://doi.org/10.3390/machines13080683

Copyright: © 2025 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Artificial Intelligence and Machine Learning in Automation

The increasing user experience and accessibility of AI tools have revolutionized how industrial automation is applied in real settings [12,13]. Machine learning (ML) techniques currently play a major role in improving machine performance, adaptability, and fault tolerance by applying techniques/tools such as advanced diagnostic systems, predictive control, and autonomous decision-making [14]. These tools allow systems to read and act in dynamic environments, enabling self-optimization and proactive maintenance strategies [15]. AI is becoming increasingly prevalent in hardware and edge devices, creating intelligent machines capable of learning from their own operation and improving over time [16,17]. Fabiocchi et al. [18] introduced a vision-based virtual sensor that estimates ground reaction forces in mechanical systems without the need for physical sensors. Using

AI models trained on dynamic behavior data, the system analyzed video input to infer force trends in real time. Validated under realistic conditions, the method was considered both accurate and robust, and it offered a non-invasive and cost-effective solution for force monitoring in industrial machinery. Haque et al. [19] proposed a lightweight and interpretable framework for fault diagnosis in electric vehicle drive motors. By combining optimized ML models with feature selection and a soft voting ensemble, the approach achieved high diagnostic accuracy with low computational demands. The framework was validated using both simulated and real-world datasets, demonstrating strong generalizability and transparency. Al-refai et al. [20] developed two deep learning models for surface classification using internal measurement unit (IMU) time-series data from ground robots as a cost-effective alternative to vision-based systems. A cascaded convolutional neural network-long short-term memory (CNN-LSTM) attention model and a parallel fusion variant were proposed and evaluated. While the cascaded model achieved higher accuracy, the parallel model offered faster processing, making it better suited for real-time applications. Both models benefited from the inclusion of multi-head attention mechanisms. Bougoffa et al. [21] introduced a hybrid deep learning framework combining stacked sparse auto-encoders with an optimized multilayer perceptron to detect faults in photovoltaic systems. Trained and validated on real-world data, the model achieved near-perfect accuracy for various fault types and environmental conditions. It outperformed conventional methods, thus providing a scalable and efficient solution to enhance system reliability and reduce maintenance costs. Silaa et al. [22] proposed an adaptive sliding-mode controller with a forgetting factor to improve trajectory tracking in a two-degrees-of-freedom (DOF) robotic arm. The adaptive mechanism enhanced robustness and reduced chattering, while the forgetting factor helped to prevent gain drift. Stability was proven via Lyapunov theory, and simulations confirmed superior performance over conventional sliding-mode controls (SMCs) in terms of accuracy and noise resilience. Lisauskas and Maskeliunas [23] presented a Transformer-based model for road scene segmentation which was designed to improve object detection and environmental understanding in autonomous systems. A custom decoder with attention-based fusion was developed to preserve spatial detail and enhance contextual awareness. The model achieved strong performance on the Cityscapes dataset and, with its lightweight architecture, was considered suitable for memory-constrained devices. Osan and Drenţa [24] applied artificial neural networks (ANNs) to optimize metal machining processes by predicting surface quality and estimating machining time. One model forecasted surface roughness based on machining parameters, while another estimated operation duration for cost planning. The results showed accurate predictions, supporting improved efficiency and process control in manufacturing. Ochoa et al. [25] introduced a type-3 fuzzy system (T3FS) to dynamically adapt the crossover parameter in differential evolution algorithms. Applied to an inverted pendulum control task, the approach improved optimization accuracy and consistency compared to static parameter settings. The results demonstrated lower error and variance, highlighting the potential of T3FS in tuning controllers for uncertain nonlinear systems.

2. Robotics and Human–Machine Interaction

Modern robotics is shifting to higher levels of collaboration, mobility, and contextual awareness [26,27]. Human–robot interaction (HRI) is no longer limited to industrial safety or physical assistance. It now involves intuitive interfaces, augmented reality, shared decision-making, and accessibility [28]. This area includes developments in collaborative robots (cobots), multi-robot coordination, mobile robotics for specialized tasks, and sensor-driven interaction [29,30]. This research is essential for automating tasks that are traditionally occupied by human labor, while maintaining safety, flexibility, and ergonomic

considerations [31]. As robotics becomes universal, designing systems that can understand and respond to human intentions becomes central to successful implementation and co-existence in manufacturing [32]. Subramanian et al. [33] reviewed the role of augmented reality (AR) in HRI, particularly in manufacturing contexts. It identified the main challenges, such as situational awareness and communication, and proposed a framework to guide the design and evaluation of AR systems. The framework, supported by case studies, emphasized safety, collaboration, and user-centered principles from human–computer interaction (HCI). Pham et al. [34] proposed a path-planning model (named the Multi-ST model) for multi-robot coverage path planning in environments with static and dynamic obstacles. Based on a spiral-spanning tree algorithm with intelligent reasoning, the method improved coordination, obstacle avoidance, and coverage efficiency. The experimental results showed superior performance compared to existing approaches in terms of robustness, scalability, and adaptability to dynamic conditions. Voutsakelis et al. [35] developed and evaluated a smartphone app for blind users that combined real-time object detection with haptic and audio feedback. Using the EfficientDet-lite2 model and the common objects in context (COCO) dataset, the app enabled users to interact with detected objects through touch and sound. Usability tests confirmed that the haptic feedback significantly improved user experience, accessibility, and independence. Pan et al. [36] presented the design and testing of a robot to install spacers on six-split transmission lines, aiming to reduce manual labor and safety risks. The system included a wire-following mechanism, spacer storage, and an assembly arm. The experimental results showed efficient operation with low error rates, demonstrating its potential for use in power line maintenance under complex conditions. Florescu [37] developed a digital twin for a flexible manufacturing system integrating intelligent machine tools and robots, supporting the goals of Industry 4.0. The digital replica was used for system design, simulation, and virtual commissioning of a real cylindrical-part production process. Simulations enabled error detection, collision avoidance, and process optimization through collaborative robotics. Tissot-Daguette et al. [38] introduced flexure-based rectilinear stages using coupled serial revolute joint (RRR) planar parallel mechanisms to minimize parasitic shifts without sacrificing stiffness or range. Finite element method (FEM) simulations and experimental tests confirmed sub-micron precision and robust support stiffness. A silicon prototype with thermally preloaded buckling beams further reduced translational stiffness, demonstrating the design's suitability for high-precision micro- and nano-positioning applications. Foiani et al. [39] evaluated a robotic C-arm manipulator as a passive attitude control device for a 1U CubeSat. Simulations showed that while gravity gradient stabilization and magnetic control were feasible, pointing accuracy was limited and affected by instabilities due to the lack of damping. The approach proved suitable for missions with relaxed attitude requirements typical of CubeSat platforms.

3. Smart Manufacturing and Control Systems

Control strategies play a central role in the architecture of automated operations. In the context of smart manufacturing, they evolve into adaptive, real-time, and often AI-assisted mechanisms that ensure high precision, energy efficiency, and system resilience [40]. This area explores advanced manufacturing cells, digital twins for simulation and optimization, and automated quality assurance techniques [41,42]. It also embraces the design of software architectures and communication protocols that enable interoperability, decentralization, and modularity, which are the main characteristics of Industry 4.0-compliant environments [43]. Overall, smart control systems enhance productivity and are fundamental for integrating sustainability and flexibility into modern production [44]. Jia and Pei [45] reviewed recent advances in multi-agent reinforcement learning (MARL) applied to the

intelligent control of water environment systems. The authors examined core algorithm types, cooperative strategies for tasks like water scheduling and monitoring, and challenges such as communication instability and system heterogeneity. The study also highlighted emerging solutions for generalization and robustness, which provided insights for future applications in water infrastructure. Tzimas et al. [46] presented the design and implementation of a controller for a flexible manufacturing cell with heterogeneous equipment and communication interfaces. Focusing on integration, extensibility, and interoperability, the system was applied to microfluidic device production. Open-source technologies enabled effective control and communication, supporting reusability and reducing dependence on proprietary protocols. Curralo et al. [47] designed semi-automatic equipment to replace manual connector assembly in the automotive sector, aiming to reduce cycle time and labor costs. The system automated component insertion and used AI-based vision for quality control. Structural verification, cost analysis, and validation confirmed the design's effectiveness and adaptability to other industries such as electronics and aerospace. Rashed et al. [48] addressed the lack of sound-based diagnostics in intelligent transportation systems by developing a specialized audio dataset and proposing a multi-model classification framework. Using advanced feature extraction and a Bayesian-optimized ensemble method, the system accurately identified vehicle faults and emergency sounds. The results showed strong potential for real-time diagnostics and accessibility enhancements in smart city environments. Paduraru et al. [49] proposed a hybrid testing framework for robotic process automation (RPA) workflows, which combined symbolic execution and concolic testing to improve validation. The open-source solution enhanced test coverage, reduced manual effort, and supported multiple RPA platforms. Industry-based evaluations confirmed its effectiveness in improving reliability and aligning with best testing practices. Puri et al. [50] addressed agricultural safety by analyzing terrain slope data with terrestrial Light Detection and Ranging (LiDAR) and correlating it with machinery tilt specifications to assess tip/roll-over risks. Conducted in alpine vineyards in Trento, the research supported safer decision-making for machinery use on steep terrain. The findings aimed to improve occupational health and safety in agriculture by informing both operators and manufacturers. Klein Fiorentin et al. [51] addressed challenges in ultrasonic fatigue testing, focusing on specimen design and heat generation during high-frequency loading. A methodology was proposed to quantify heat severity based on material properties and to guide geometric design for resonance at 20 kHz. The work provided practical insights into managing temperature effects and thermal gradients in fatigue testing.

4. Electric Machines, Drives, and Mechatronics

Despite the growing role of software and AI, mechanical and electromechanical components remain the core of industrial systems [52]. Innovations in electric machines, powertrains, sensors, and actuation mechanisms enable more compact, efficient, and robust machines adapted to specific applications [53]. The field of mechatronics, combining mechanical engineering, electronics, and computing, continues to produce highly integrated and responsive systems [54,55]. In this area, attention is given to the design, modeling, and optimization of electric motors, dynamic analysis of mechanical transmissions, and advanced diagnostics for condition monitoring and system reliability [56]. Zhang et al. [57] proposed a modeling approach for gear tooth profile errors using both systematic and random distribution components to better reflect real machining conditions. A mathematical model was developed to assess their impact on contact stress and transmission accuracy. The results showed a 13.8% reduction in output accuracy due to these errors, which showed the importance of precise error prediction during the design stage. Zhang et al. [58] developed a non-destructive device to detect dynamic unbalance in small cylindrical rollers

using air flotation support and resonance amplification. A dynamic model was created and validated through modal and harmonic response analyses. Experimental tests confirmed the system's ability to measure unbalance accurately without damaging the roller surface. Ahmed et al. [59] presented a hybrid brushless wound-rotor synchronous machine with an outer rotor and integrated permanent magnets for enhanced performance. A centrifugal switch enabled dual-mode operation, allowing the machine to function as a permanent magnet synchronous motor (PMSM) at high speeds. Designed for dual-speed applications like washing machines, the concept was validated through two-dimensional (2D) simulations using ANSYS®. Vlachou and Karakatsanis [60] developed a fault-tolerant PMSM for elevator systems and validated its performance through simulation and real-world testing. Operational data were analyzed using a Random Forest classifier, achieving 94% accuracy in detecting motor health states. The integration of robust design with ML enabled effective predictive maintenance and improved system reliability. Kim et al. [61] proposed a 2D equivalent analysis method for outer rotor brushless DC (BLDC) motors, addressing challenges posed by the permanent magnet (PM) overhang structure. The approach incorporated spatial harmonics and Carter coefficients to accurately evaluate electromagnetic performance. Optimization using the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) enhanced efficiency and power density, and the results were validated against FEM simulations for accuracy.

5. Green Design, Machining, and Sustainability

Sustainable engineering is no longer a side consideration but a guiding principle in the design of industrial systems [62,63]. This area addresses green manufacturing processes, energy-efficient machining, environmentally conscious machine design, and multi-criteria decision-making, facilitating the selection of technologies with minimal environmental impact [64]. Concepts such as minimum quantity lubrication (MQL), recycling of materials, and energy-aware optimization are central in this area [65]. As industries face increasing regulatory pressure and societal expectations to implement sustainable practices, the development of machines that support circular economy principles is becoming a strategic imperative [66]. Kokkinis et al. [67] reviewed current trends and emerging technologies in mining exploration and drilling, highlighting the shift toward fully autonomous, infrastructure-independent machines. Advances in AI, IoT, robotics, and computational modeling were shown to be transforming mining equipment design. Their study emphasized the need for new approaches in deep and near-to-face exploration, especially as interest in re-opening abandoned mines grows. Buldum et al. [68] evaluated the turning performance of AZ91D magnesium alloy under dry, MQL, and nano-reinforced MQL (NanoMQL) conditions using carbon nanotube additives. The NanoMQL setup significantly improved surface quality and reduced tool wear compared to other methods. Enhanced lubrication and thermal conductivity led to lower built-up edge formation, making NanoMQL ideal for demanding machining conditions. Maurya et al. [69] analyzed energy consumption and electrode wear in die-sinking electrical discharge machining (EDM) using real-time monitoring under varied machining parameters. High discharge currents significantly reduced machining time and specific energy consumption, improving both efficiency and sustainability. The findings offered practical insights to optimize EDM processes in advanced manufacturing. Ramírez-Jiménez and Torres Valencia [70] presented the design and simulation of a low-cost fly-cutting plant prototype for academic training in automation and control. A three-dimensional (3D) model was created in SketchUp and simulated using Matlab and Simulink, incorporating a conveyor and continuous cutting system. Performance and cutting tests validated the setup, making it suitable for hands-on process control education. Raman et al. [71] proposed a technique for order of preference by similarity to ideal solution

(TOPSIS)-based methodology to support the selection of Fused Filament Fabrication (FFF) machines based on multiple weighted criteria. Sensitivity analysis using Monte Carlo simulations evaluated the effects of decision variability and scoring uncertainty. The approach was tested on three case studies, showing robust and consistent machine rankings for specific part requirements.

This Special Issue presents an innovative and forward-looking compilation of research showcasing the coverage and interdisciplinarity of machine design, automation, and robotics that defines the next generation of industrial technologies. By presenting rigorous theoretical analyses, experimental investigations, numerical simulations, and practical implementations, the contributing authors have collectively advanced the understanding of automation, robotics, and machine design in meaningful and application-oriented ways. As the Guest Editor of this Special Issue, I wish to express my sincere appreciation to all authors for their high-quality contributions, and to the reviewers whose critical evaluations and expert insights were essential to ensuring the high scientific standard of this issue. I also gratefully acknowledge the editorial staff of *Machines* for their support throughout the publication process. It is my strong belief that this Special Issue, facilitated by the open access publication system offered by MDPI, will serve as a valuable reference for academic researchers and as a source of technical guidance for industry professionals dealing with the design, control, and integration of intelligent manufacturing systems.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Li, L. Digital transformation and sustainable performance: The moderating role of market turbulence. *Ind. Mark. Manag.* **2022**, *104*, 28–37. [CrossRef]
2. Han, Y.; Li, Z.; Feng, T.; Qiu, S.; Hu, J.; Yadav, K.K.; Obaidullah, A.J. Unraveling the impact of digital transformation on green innovation through microdata and machine learning. *J. Environ. Manag.* **2024**, *354*, 120271. [CrossRef] [PubMed]
3. Turan, E.; Konuşkan, Y.; Yıldırım, N.; Tunçalp, D.; İnan, M.; Yasin, O.; Turan, B.; Kerimoğlu, V. Digital twin modelling for optimizing the material consumption: A case study on sustainability improvement of thermoforming process. *Sustain. Comput. Inform. Syst.* **2022**, *35*, 100655. [CrossRef]
4. Leng, J.; Liu, Q.; Ye, S.; Jing, J.; Wang, Y.; Zhang, C.; Zhang, D.; Chen, X. Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model. *Robot. Comput. Integr. Manuf.* **2020**, *63*, 101895. [CrossRef]
5. Duro, R.; Kondratenko, Y. *Advances in Intelligent Robotics and Collaborative Automation*; CRC Press: Boca Raton, FL, USA, 2022.
6. Mineo, C.; Vasilev, M.; Cowan, B.; MacLeod, C.; Pierce, S.G.; Wong, C.; Yang, E.; Fuentes, R.; Cross, E. Enabling robotic adaptive behaviour capabilities for new industry 4.0 automated quality inspection paradigms. *Insight Non Destr. Test. Cond. Monit.* **2020**, *62*, 338–344. [CrossRef]
7. George, A.S.; George, A.H. Industrial revolution 5.0: The transformation of the modern manufacturing process to enable man and machine to work hand in hand. *J. Seybold Rep. ISSN NO* **2020**, *1533*, 1525.68128.
8. Ren, L.; Dong, J.; Liu, S.; Zhang, L.; Wang, L. Embodied intelligence toward future smart manufacturing in the era of AI foundation model. *IEEE/ASME Trans. Mechatron.* **2024**, 1–11, *early access*. [CrossRef]
9. Czimmermann, T.; Chiurazzi, M.; Milazzo, M.; Roccella, S.; Barbieri, M.; Dario, P.; Oddo, C.M.; Ciuti, G. An autonomous robotic platform for manipulation and inspection of metallic surfaces in industry 4.0. *IEEE Trans. Autom. Sci.* **2021**, *19*, 1691–1706. [CrossRef]
10. Leng, J.; Ruan, G.; Xu, C.; Zhou, X.; Xu, K.; Qiao, Y.; Liu, Z.; Liu, Q. Deep reinforcement learning of graph convolutional neural network for resilient production control of mass individualized prototyping toward industry 5.0. *IEEE Trans. Syst. Man Cybern. Syst.* **2024**, *54*, 7092–7105. [CrossRef]
11. Zhai, J.; Chen, X.; Sun, X.; Xie, H. Economically and thermodynamically efficient pressure-swing distillation with heat integration and heat pump techniques. *Appl. Therm. Eng.* **2023**, *218*, 119389. [CrossRef]
12. Lazarenko, B. Manufacturing evolution: The intelligent automation revolution. *Quality* **2025**, *64*, 43.
13. Ghulaxe, V. Robotic process automation with ML and artificial intelligence: Revolutionizing business processes. *Int. J. Eng. Technol. Manag. Sci.* **2024**, *4*, 107–112.

14. Li, L.; Liu, J.; Wei, S.; Chen, G.; Blasch, E.; Pham, K. Smart robot-enabled remaining useful life prediction and maintenance optimization for complex structures using artificial intelligence and machine learning. In Proceedings of the Sensors and Systems for Space Applications XIV, Online, 12–16 April 2021; pp. 100–108.
15. Zhang, Y.; Cai, B.; Gao, C.; Zhao, Y.; Shao, X.; Yang, C. A system-centred predictive maintenance re-optimization method based on multi-agent deep reinforcement learning. *Expert Syst. Appl.* **2025**, *274*, 127034. [CrossRef]
16. Tsochev, G.; Sharabov, M. Artificial intelligence methods used in industry 4.0 in particular industrial control systems. *AIP Conf. Proc.* **2021**, *2333*, 070017. [CrossRef]
17. Yang, T.; Yi, X.; Lu, S.; Johansson, K.H.; Chai, T. Intelligent manufacturing for the process industry driven by industrial artificial intelligence. *Engineering* **2021**, *7*, 1224–1230. [CrossRef]
18. Fabiocchi, D.; Giulietti, N.; Carnevale, M.; Giberti, H. AI-driven virtual sensors for real-time dynamic analysis of mechanisms: A feasibility study. *Machines* **2024**, *12*, 257. [CrossRef]
19. Haque, M.E.; Zabin, M.; Uddin, J. EnsembleXAI-Motor: A lightweight framework for fault classification in electric vehicle drive motors using feature selection, ensemble learning, and explainable AI. *Machines* **2025**, *13*, 314. [CrossRef]
20. Al-refai, G.; Karasneh, D.; Elmoaqet, H.; Ryalat, M.; Almtireen, N. Surface classification from robot internal measurement unit time-series data using cascaded and parallel deep learning fusion models. *Machines* **2025**, *13*, 251. [CrossRef]
21. Bougoffa, M.; Benmoussa, S.; Djeziri, M.; Palais, O. Hybrid deep learning for fault diagnosis in photovoltaic systems. *Machines* **2025**, *13*, 378. [CrossRef]
22. Silaa, M.Y.; Barambones, O.; Bencherif, A.; Rougab, I. An adaptive control strategy with switching gain and forgetting factor for a robotic arm manipulator. *Machines* **2025**, *13*, 424. [CrossRef]
23. Lisauskas, B.; Maskeliunas, R. Efficient transformer-based road scene segmentation approach with attention-guided decoding for memory-constrained systems. *Machines* **2025**, *13*, 466. [CrossRef]
24. Osan, A.R.; Drenţa, R.F. Application of artificial neural networks in predicting surface quality and machining time. *Machines* **2025**, *13*, 561. [CrossRef]
25. Ochoa, P.; Peraza, C.; Melin, P.; Castillo, O.; Geem, Z.W. Type-3 fuzzy dynamic adaptation of the crossover parameter in differential evolution for the optimal design of type-3 fuzzy controllers for the inverted pendulum. *Machines* **2025**, *13*, 450. [CrossRef]
26. Olszewski, M. Modern industrial robotics. *Pomiary Autom. Robot.* **2020**, *24*, 5–20. [CrossRef]
27. Elwin, M.L.; Strong, B.; Freeman, R.A.; Lynch, K.M. Human-multirobot collaborative mobile manipulation: The omnid mocobots. *IEEE Robot. Autom. Lett.* **2022**, *8*, 376–383. [CrossRef]
28. Liang, H.; Zheng, H.; Lu, Y. Context-aware cognitive assistive assembly system based on online human action recognition. In Proceedings of the 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE), Bari, Italy, 28 August–1 September 2024; pp. 381–387.
29. Jin, L.; Qi, Y.; Luo, X.; Li, S.; Shang, M. Distributed competition of multi-robot coordination under variable and switching topologies. *IEEE Trans. Autom. Sci.* **2021**, *19*, 3575–3586. [CrossRef]
30. Hu, K.; Zou, L.; Chen, Z.; Jiang, J.; Jiang, F.; Tao, X. Wireless multi-robot collaboration: Communications, perception, control and planning. *IEEE Netw.* **2024**, *39*, 302–311. [CrossRef]
31. Mitterberger, D.; Dörfler, K.; Sandy, T.; Salveridou, F.; Hutter, M.; Gramazio, F.; Kohler, M. Augmented bricklaying: Human–machine interaction for in situ assembly of complex brickwork using object-aware augmented reality. *Constr. Robot.* **2020**, *4*, 151–161. [CrossRef]
32. Jokinen, K.; Homma, K.; Matsumoto, Y.; Fukuda, K. Integration and interaction of trustworthy ai in a virtual coach–an overview of EU-Japan collaboration on eldercare. In Proceedings of the Annual Conference of the Japanese Society for Artificial Intelligence, Online, 8–11 June 2021; pp. 190–200.
33. Subramanian, K.; Thomas, L.; Sahin, M.; Sahin, F. Supporting human–robot interaction in manufacturing with augmented reality and effective human–computer interaction: A review and framework. *Machines* **2024**, *12*, 706. [CrossRef]
34. Pham, H.V.; Do, H.Q.; Nguyen Quang, M.; Asadi, F.; Moore, P. Proposed multi-ST model for collaborating multiple robots in dynamic environments. *Machines* **2024**, *12*, 797. [CrossRef]
35. Voutsakelis, G.; Dimkaros, I.; Tzimos, N.; Kokkonis, G.; Kontogiannis, S. Development and evaluation of a tool for blind users utilizing AI object detection and haptic feedback. *Machines* **2025**, *13*, 398. [CrossRef]
36. Pan, J.; Cheng, Y.; Hu, C.; Jiang, M.; Ma, Y.; Meng, F.; Shi, Q. The innovative design and performance testing of a mobile robot for the automated installation of spacers on six-split transmission lines. *Machines* **2025**, *13*, 432. [CrossRef]
37. Florescu, A. Digital twin for flexible manufacturing systems and optimization through simulation: A case study. *Machines* **2024**, *12*, 785. [CrossRef]
38. Tissot-Daguette, L.; Vallat, C.; Nijenhuis, M.; Cosandier, F.; Henein, S. Near-zero parasitic shift rectilinear flexure stages based on coupled n-RRR planar parallel mechanisms. *Machines* **2025**, *13*, 530. [CrossRef]

39. Foiani, F.; Morettini, G.; Palmieri, M.; Carletta, S.; Cianetti, F.; Dionigi, M. Multibody simulation of 1U CubeSat passive attitude stabilisation using a robotic arm. *Machines* **2025**, *13*, 509. [CrossRef]
40. Simmons, N. Design of robust manufacturing systems: A systemic approach. *Am. J. Ind. Prod. Eng.* **2025**, *6*, 10–14.
41. Banerjee, S.; Jesubalan, N.G.; Kulkarni, A.; Agarwal, A.; Rathore, A.S. Developing cyber-physical system and digital twin for smart manufacturing: Methodology and case study of continuous clarification. *J. Ind. Inf. Integr.* **2024**, *38*, 100577. [CrossRef]
42. Rossi, A.; Moretti, M.; Fravolini, M.; Senin, N. Autonomous learning of digital twins for intelligent extrusion optimisation in MEX. *J. Manuf. Process.* **2025**, *143*, 321–334. [CrossRef]
43. Lu, Y.; Asghar, M.R. Semantic communications between distributed cyber-physical systems towards collaborative automation for smart manufacturing. *J. Manuf. Syst.* **2020**, *55*, 348–359. [CrossRef]
44. Musaeva, K.; Vyachina, I.; Aliyeva, M. Smart factories and their impact on modern manufacturing enterprises: Prospects and challenges in the era of the digital economy. In Proceedings of the E3S Web of Conferences, Les Mureaux, France, 21–22 November 2024; p. 07010.
45. Jia, L.; Pei, Y. Recent advances in multi-agent reinforcement learning for intelligent automation and control of water environment systems. *Machines* **2025**, *13*, 503. [CrossRef]
46. Tzimas, E.; Papazetis, G.; Benardos, P.; Vosniakos, G.-C. Design and development of a flexible manufacturing cell controller using an open-source communication protocol for interoperability. *Machines* **2024**, *12*, 519. [CrossRef]
47. Curralo, P.M.P.; Campilho, R.D.S.G.; Pereira, J.A.P.; Silva, F.J.G. Design of connector assembly equipment for the automotive industry. *Machines* **2024**, *12*, 731. [CrossRef]
48. Rashed, A.; Abdulazeem, Y.; Farrag, T.A.; Bamaqa, A.; Almaliki, M.; Badawy, M.; Elhosseini, M.A. Toward inclusive smart cities: Sound-based vehicle diagnostics, emergency signal recognition, and beyond. *Machines* **2025**, *13*, 258. [CrossRef]
49. Paduraru, C.; Cernat, M.; Staicu, A.-N. A unified framework for automated testing of robotic process automation workflows using symbolic and concolic analysis. *Machines* **2025**, *13*, 504. [CrossRef]
50. Puri, D.; Vita, L.; Gattamelata, D.; Tulliani, V. Roll/tip-over risk analysis of agricultural self-propelled machines using airborne LiDAR data: GIS-based approach. *Machines* **2025**, *13*, 377. [CrossRef]
51. Klein Fiorentin, F.; Dantas, R.; Wolfs Gil, J.; Piga Carboni, A.; Fiorentin, T.A.; de Jesus, A.M.P. On the specimen design, physical properties and geometry effect on heat generation and thermal gradient in ultrasonic fatigue. *Machines* **2025**, *13*, 380. [CrossRef]
52. Berezin, L.; Oliinyk, O.; Rubanka, M. Innovative trends in industrial machinery engineering and education. *Actual Probl. Mod. Sci.* **2021**.
53. Luo, Y.; Wu, K.; Spielberg, A.; Foshey, M.; Rus, D.; Palacios, T.; Matusik, W. Digital fabrication of pneumatic actuators with integrated sensing by machine knitting. In Proceedings of the Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, New Orleans, LA, USA, 30 April–5 May 2022; pp. 1–13.
54. Chen, X. Application of intelligent control in mechatronics system. *Eng. Adv.* **2023**, *3*, 182–185. [CrossRef]
55. Oomen, T.; Steinbuch, M. Model-based control for high-tech mechatronic systems. In *Proceedings of the Mechatronics and Robotics*; CRC Press: Boca Raton, FL, USA, 2020; pp. 51–80.
56. Hammood, A.S. Towards condition monitoring: Fabrication and finite element analysis of a helical gear transmission rig for fault simulation. *Jordan J. Mech. Ind. Eng.* **2024**, *18*, 219–226. [CrossRef]
57. Zhang, M.; Zhang, Z.; Xiong, J.; Chen, X. Accuracy analysis of complex transmission system with distributed tooth profile errors. *Machines* **2024**, *12*, 459. [CrossRef]
58. Zhang, Z.; Yang, B.; Duan, M.; Gu, R.; Liang, S.; Chen, Y. Design and experimental research of a non-destructive detection device for high-precision cylindrical roller dynamic unbalance. *Machines* **2024**, *12*, 684. [CrossRef]
59. Ahmed, S.; Ali, Q.; Sirewal, G.J.; Kumar, K.; Choi, G. Hybrid brushless wound-rotor synchronous machine with dual-mode operation for washing machine applications. *Machines* **2025**, *13*, 342. [CrossRef]
60. Vlachou, V.I.; Karakatsanis, T.S. Development of a fault-tolerant permanent magnet synchronous motor using a machine-learning algorithm for a predictive maintenance elevator. *Machines* **2025**, *13*, 427. [CrossRef]
61. Kim, T.-S.; Yang, J.-W.; Shin, K.-H.; Jang, G.-H.; Han, C.; Choi, J.-Y. Analysis of electromagnetic characteristics of outer rotor type BLDC motor based on analytical method and optimal design using NSGA-II. *Machines* **2025**, *13*, 440. [CrossRef]
62. Yakovenko, I.; Permyakov, A.; Dobrotvorskiy, S.; Basova, Y.; Kotliar, A.; Zinchenko, A. Prospects for the development of process equipment in aggregate-modular design for sustainable mechanical engineering. *Int. J. Mechatron. Appl. Mech.* **2023**, *13*, 145–156.
63. Goodfellow, H.D.; Wang, Y. *Industrial Ventilation Design Guidebook: Volume 2: Engineering Design and Applications*; Academic press: Cambridge, MA, USA, 2021.
64. Khanna, N.; Shah, P.; Sarikaya, M.; Pusavec, F. Energy consumption and ecological analysis of sustainable and conventional cutting fluid strategies in machining 15–5 PHSS. *Sustain. Mater. Technol.* **2022**, *32*, e00416. [CrossRef]
65. Babu, M.N.; Anandan, V.; Babu, M.D. Performance of ionic liquid as a lubricant in turning inconel 825 via minimum quantity lubrication method. *J. Manuf. Process.* **2021**, *64*, 793–804. [CrossRef]

66. Hagedorn, W.; Jäger, S.; Wieczorek, L.; Kronenberg, P.; Greiff, K.; Weber, S.; Röttger, A. More than recycling–The potential of the circular economy shown by a case study of the metal working industry. *J. Clean. Prod.* **2022**, *377*, 134439. [CrossRef]
67. Kokkinis, A.; Frantzis, T.; Skordis, K.; Nikolakopoulos, G.; Koustoumpardis, P. Review of automated operations in drilling and mining. *Machines* **2024**, *12*, 845. [CrossRef]
68. Buldum, B.B.; Leksycki, K.; Cagan, S.C. Comparative analysis of dry, minimum quantity lubrication, and nano-reinforced minimum quantity lubrication environments on the machining performance of AZ91D magnesium alloy. *Machines* **2025**, *13*, 430. [CrossRef]
69. Maurya, S.K.; Campatelli, G.; Veracini, M.; Arcioni, M.; Clori, D. Balancing productivity and sustainability in EDM: A comprehensive analysis of energy consumption and electrode degradation. *Machines* **2025**, *13*, 469. [CrossRef]
70. Ramírez-Jiménez, D.F.; Torres Valencia, C.A. Experimental design and simulation of a fly-cutting plant for academic environment practices. *Machines* **2025**, *13*, 15. [CrossRef]
71. Raman, V.V.; Badarinath, R.; Prabhu, V.V. TOPSIS-based methodology for selecting fused filament fabrication machines. *Machines* **2025**, *13*, 574. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.