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Editorial

Advanced Manufacturing Processes and Technologies: Trends and Innovations

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Advanced manufacturing processes and technologies have transformed various industries by enabling more efficient, sustainable, and precise production methods. These methods can lead both design and manufacturing to a new era when studied from a modern perspective [1–7].

- Advanced manufacturing process optimization, e.g., ultrasonic-based fabrication processes, worm grinding, thin-wall parts, etc.;
- Use of algorithmic modeling of manufacturing processes based on advanced methodologies, e.g., Support Vector Regression, Random Forest, Ridge Regression, Hierarchical Graph Neural Network, and CatBoost;
- Application of feature recognition in 3D CAD-based intelligent manufacturing;
- Additive Manufacturing (AM) and 3D printing (3DP) technologies as mainstream fabrication processes;
- CAD/CAM/CAE, Computational Design and Artificial Intelligence (AI);
- Implementation of production scheduling based on advanced algorithms, e.g., distributed resource-constrained hybrid flow shop scheduling with machine breakdowns.

When the methods and tools listed above are combined, following Industry 4.0 and 5.0 approaches, most product manufacturing issues can be solved in a way that benefits both manufacturers and customers. Across the papers in this Special Issue, a series of fabrication problems are tackled throughout the complete product life cycle, thus reducing the cost and optimizing the performance [8–15].

Meso-scale ultrasonic vibration-assisted end milling supports the latest trends in the manufacturing industry. Zahid et al. introduced a machine learning framework that systematically compares Gaussian Process Regression (GPR), Support Vector Regression (SVR), Random Forest (RF), and Ridge Regression for predicting cutting forces, tool wear, and surface roughness. As a result, they contribute to the sustainability aspects of the manufacturing process. The experimental work is based on a Taguchi L16 orthogonal array, and all cases are duplicated for increased accuracy. The fabrication parameters used are the cutting speed, the feed rate, the depth of cut, the vibration amplitude and the tool coating. SVR and GPR are recommended as reliable surrogate models for process optimization in UVAEM of Inconel 718.

Worm grinding is used for face-gear high-precision fabrication. He et al. proposed a compensation method applicable to complex topological surfaces in face-gear grinding, with the aim to reduce both pitch and tooth thickness deviations. The method was applied successfully in a case study. The compensation strategy reduced both pitch and tooth thickness deviations in the face gear, with reduction rates ranging from 48.57% to 96.80%.

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A dual-graph fusion network was proposed by Wang et al. to address the gap where the existing GNN-based methods often neglect the inherent geometric relationships present in the B-Rep data structure. Given how important machining feature recognition in 3D CAD-based intelligent manufacturing is, the proposed methodology uses a GatedGCN-based graph encoder and a FiLM-based cross-stream fusion mechanism to jointly encode topological and geometric information from the B-Rep model. Successful verification tests were performed on open-source synthetic datasets, including MFInstSeg and MFRCAD.

Customized product design requires the support of fully personalized design methodologies based on individual anthropometric characteristics. Minaoglou et al. developed an application for automatically designing custom-fit sunglasses by combining Artificial Intelligence (AI) and Computational Design (CD) principles. Both textual and visual programming tools were used, while a validation procedure provided a solid basis for the success of the product design application. At the same time, it was proven that combining both AI-driven feature extraction and parametric Computational Design constitutes a reliable tool for automating the production of personalized wearable products.

Xu et al. studied a distributed resource-constrained hybrid flow shop scheduling problem with machine breakdowns, with two optimization objectives (makespan and total energy consumption). To solve the problem, a block–neighborhood-based multi-objective evolutionary algorithm was developed. The proposed methodology was compared with a series of other advanced multi-objective algorithms, and the results indicated its superior performance.

Li et al. proposed a manufacturability analysis method based on a graph neural network so that the process engineer can detect defects that are difficult/impossible to manufacture or have high manufacturing costs early enough in the design cycle. Several verification tests were performed and the manufacturability analyses together with the experimental results prove that the proposed method could be successfully implemented.

Harishbabu et al. explored the reinforcement of PLA with boron nitride nanoplatelets (BNNPs) in order to improve its mechanical properties when the FDM process is used. At the same time, the research contributes towards the optimization of the reinforcement content, the nozzle temperature, the printing speed, the layer thickness, and the sample orientation, using a Taguchi L27 design. Both statistical analysis and machine learning models were used for the prediction of the process's mechanical properties.

Min et al. studied the effect of vibration on high tool wear rate, severe deterioration of machining accuracy, and surface integrity in thin-walled-part cutting processes. The results provide a solid basis for the significant reduction in the acceleration response amplitude of thin-walled parts and decrease in their vibration decay time. The study contributes towards reduced milling force and machining vibration.

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List of Contributions

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