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SUSTAINABLE PROCESS OPTIMIZATION IN MANUFACTURING USING GREEN MANUFACTURING APPROACHES

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Abstract

Green manufacturing (GM) integrates environmental considerations into process design and operation to minimize ecological footprint while maintaining economic performance. This article synthesizes current theoretical and methodological advances in optimizing manufacturing processes through GM principles, emphasizing waste reduction, energy efficiency, integration with the circular economy (CE), digital technologies, and product life-cycle orientation. We propose an integrated framework that combines the design for circularity, energy-aware process optimization, digital twin and predictive analytics, and end-of-life (EOL) strategies. The framework is illustrated with representative models and decision variables drawn from the literature, highlighting how material and energy efficiency, remanufacturing, recycling, and disassembly can be co-optimized with traditional production objectives. We discuss challenges, data needs, and measurement metrics, and outline a research agenda to advance GM-based optimization across diverse manufacturing contexts.

Keywords: *Green Manufacturing, Circular Economy, Energy efficiency, Product Life Cycle orientation.*

1. Introduction

Manufacturing sectors face mounting pressure to reduce environmental impacts while sustaining productivity and competitiveness. Green manufacturing (GM) offers a principled approach to embed sustainability into manufacturing decisions, aligning with circular economy (CE) concepts that aim to keep materials in use and minimize waste [8,9,12]. Optimization methods are central to realizing GM, enabling decisions that lower energy consumption, material waste, and emissions, while enhancing product lifespan, re-manufacturability, and resource recirculation [14, 20, 23]. Recent work showcases how digital technologies, artificial intelligence (AI), and digital twins (DTs) can support GM and CE synergies by providing real-time data, predictive insights, and lifecycle visibility [5,7,20,22]. Integrating CE indicators into inventory, lot-sizing, and production planning models further demonstrates the economic viability of circular strategies under uncertainty and carbon constraints [3,13,16]. This article synthesizes these strands to present a cohesive framework for optimizing manufacturing processes under green manufacturing principles, with attention to nuance and where consensus is evolving.

2. Green Manufacturing Principles and Their Role in Optimization

Energy efficiency and resource use: GM emphasizes substantial reductions in energy use and efficient use of materials across the production life cycle. Digital twins and predictive analytics can drive energy-aware scheduling and process control, yielding measurable energy savings and lower emissions [5,20]. Material use efficiency (MUE) concepts provide quantitative targets and metrics to guide process improvements and design choices toward waste minimization and compatibility with recycling [6].

2.1. Design for circularity

Early design decisions can substantially influence end-of-life recovery, remanufacturing, and recyclability. PLC (product life cycle) optimization across the planning, design, production, and reassembly stages helps identify trade-offs that improve circularity while maintaining cost-effectiveness [14]. Integrated cost modeling for re-assembly and remanufacturing supports decision-makers in evaluating lifecycle economics of circular strategies [13].

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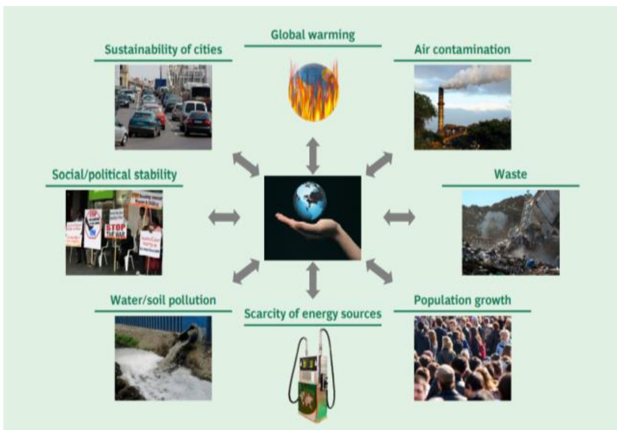

Fig. 1. Green encompasses many different concerns.

2.2. End-of-life and disassembly:

CE-oriented optimization considers optimal disassembly sequences, depths, and strategies to maximize recoverable value and minimize processing costs. Efficient disassembly is recognized as a bottleneck without automation and intelligent planning, which motivates the development of optimization models for planning and execution [17,19,21].

2.3. Digital technologies and predictive analytics:

DTs, AI, IOT, and blockchain enable data-driven optimization for GM, including real-time energy management, predictive maintenance, and traceability for circular supply chains. Studies show potential energy reductions of roughly 10–12% through DT-based optimization and improved recycling metrics when these technologies are integrated with CE practices [5,20]. An Integrated Optimization Framework for GM in Manufacturing We propose a modular framework consisting of four interlocking layers:

3. Circularity-aware design and production planning

Decision variables: product design options affecting material selection, part count, and standardization; production lot sizes; choice between traditional manufacturing and remanufacturing; scrap capture rate for recycling; disassembly depth and sequencing for EOL items (for batteries, electronics, and complex assemblies) [14,19,21]. The Objectives are to maximize the circularity index, minimize the total lifecycle cost, minimize carbon emissions, and meet demand while tolerating CE constraints [3,14,19]. And the Constraints: capacity, lead times, quality requirements, legal/regulatory CE obligations, and reliability of disassembly/recovery operations [13,17].

3.1. Energy- and resource-efficient process optimization

Decision variables include process temperatures, machining strategies, cutting parameters, energy-optimizing sequencing, and the use of hybrid manufacturing (combining subtractive/additive methods) to reduce waste and the energy footprint [1,7,14]. The objectives are to minimize energy consumption and material waste; minimize emissions; maximize material yield; improve resource utilization efficiency (RUE) indicators [6,14]. The tools are used for DTs, AI-based predictive maintenance, and real-time optimization to adapt to supply-and-demand fluctuations while maintaining green targets [5,20].

3.2. Digital twins and predictive analytics for sustainable operations

Role: DTs provide a digital counterpart for real-time monitoring, simulation, and optimization of energy performance, circularity, and end-of-life outcomes. They support ISO 50001-aligned energy management and CE actions [5,20].

Outputs:

i. Energy reduction estimates,
ii. LEAN-friendly waste reduction plans, and
iii. End-of-life decision support (e.g., when to refurbish, remanufacture, or recycle) [5,20,7].

3.3. End-of-life and disassembly optimization

Decisions: optimal disassembly order, depth, and sequencing; identification of components suitable for reuse, refurbishment, or recycling; integration of disassembly planning with initial product design and production planning to enable cost-effective recovery [17,19,21].

Metrics:

i. Disassembly time,
ii. Tooling and safety requirements,
iii. Recovery value, and
iv. Impact on overall lifecycle costs.

4. Circular economy inventory and production models

Economic Production Quantity (EPQ) with circularity indicator: a finished-product EPQ variant that treats circularity as a variable, coupling production quantity with remanufacturing/recycling decisions and including carbon costs. This framework demonstrates that investing in CE activities can be advantageous even when incumbents favor conventional production [3].

Multi-variable optimization across PLC stages: selecting PLC-level decisions that optimize sustainability and circularity rather than optimizing stages in isolation yields better CE outcomes and can be compatible with profitability goals [14].

4.1. Energy and material-efficiency optimization

Material use efficiency (MUE) metrics guide decision-making across production and disposal stages, including measurement approaches such as life-cycle assessment (LCA) and material flow analysis, to identify key levers for improvement [6].

Integrated design-to-disassembly optimization: considerations of disassembly depth and sequence, coupled with product design changes to facilitate recovery, offer a path to lower total costs and higher recoveries [13,19].

4.2. Digital twin and AI-enabled optimization

DT frameworks with AI/predictive analytics can drive energy reductions and circularity improvements in manufacturing processes, supporting continuous improvement and alignment with CE policies [5,20].

Predictive analytics-based optimization supports material and energy efficiency by forecasting demand, waste, and maintenance needs, enabling proactive decision-making across the supply chain [16,20].

Additive manufacturing (AM) within a CE lens: AM can enable material-efficient designs and repair/remanufacturing, though energy intensity and process qualification remain concerns. Hybrid manufacturing and recycling of AM-derived parts can improve circularity when accompanied by automated, digitalized process controls [1].

Digital twins in CE-enabled factories: A DT-based framework can realize energy savings and enhanced reuse/recycling metrics by enabling real-time optimization and end-of-life decision-making, aligning with ISO standards and CE action plans [5,20].

Low-friction design as an energy-reduction lever in circular manufacturing: by reducing mechanical resistance and enabling smarter digital workflows, it can contribute to substantial energy savings in CE-driven production [15].

Disassembly optimization for EV batteries: automated, optimized disassembly strategies are essential for scalable CE in high-value product streams such as EV batteries, underscoring the need to incorporate disassembly planning into early design and production strategy [17,18,21].

4.3. Challenges, Opportunities, and Measurement

Data availability and interoperability: Realizing GM optimization requires high-quality data across design, process, and end-of-life stages, alongside interoperable data standards to enable DTs and AI systems [22].

4.4. Model integration and tractability

Coupling design, production planning, energy optimization, and disassembly into a single tractable model remains challenging; modular approaches with explicit interfaces can mitigate complexity [14,16]. Economic and regulatory considerations: CE incentives, carbon pricing, and regulatory requirements influence optimization outcomes; cost models for re-assembly and remanufacturing are critical for decision support [13,17]. Metrics Such as Circularity indices, MUE, LCA-based footprints, energy intensity, and carbon emissions are essential for evaluating GM optimization performance; ongoing refinement of CE metrics is needed to reflect diverse industry contexts [6,14].

5. Conclusion

This synthesis underscores that optimizing manufacturing processes through green manufacturing principles requires an integrative stance across design, production, and end-of-life management, supported by digital technologies and CE thinking. The reviewed literature indicates robust evidence that circularity-oriented optimization can achieve energy and material reductions while preserving economic viability, particularly when CE indicators are embedded in decision models and when digital infrastructures (DTs, AI, IoT) enable data-driven optimization. Developing standardized CE-embedded optimization frameworks applicable across industries. Advancing modular optimization architectures that integrate PLC design, production planning, energy management, and disassembly with scalable data pipelines. Expanding empirical validation across sectors and product

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types, including high-value, complex assemblies such as EV batteries. Investigating governance and organizational practices that enable rapid adoption of GM optimization paradigms.

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Conflict of Interest

The authors of this work declare that they have no conflicts of interest.

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