Energy Optimization Strategies in Low-carbon Manufacturing

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Abstract. This article introduces 5 optimization strategies to enhance energy efficiency and reduce carbon emissions in low-carbon manufacturing. Key focus areas include algorithmic optimization models and technological frameworks. The Grey Wolf Algorithm (GWO) and Chromosome Hierarchical Coding Genetic Algorithm (GA) are highlighted as advanced multi-objective optimization tools for minimizing energy consumption and emissions in manufacturing processes. Practical case studies are listed to demonstrate their effectiveness. To be specific, GWO achieved a 12-15% improvement in Pareto front solutions for gear manufacturing, while GA reduced standby energy by 83% in mechanical part production. The National Energy Technology-Aluminum (NET-AL) model addresses China's aluminum industry. It plans a 5.3% cumulative CO_2 reduction by 2050 through phased technology deployment and energy structure optimization. Digital transformation (DT) is emphasized as a trigger for low-carbon innovation due to its role in reconstructing and sharing knowledge, thereby enhancing sustainability outcomes. The Design for Energy Minimization (DfEM) framework integrates energy metrics into product development, achieving 15-20% energy savings in automotive and plastics sectors through simulation tools and supply chain collaboration. Collectively, these strategies underscore the potential of data-driven algorithms, digital integration and policy alignment to balance energy-carbon trade-offs while maintaining industrial productivity.

Keywords: Energy optimization, Low-carbon manufacturing, Data-based algorithm.

1 Introduction

In the contemporary society, environmental protection and energy shortage challenges have become hot topics guiding the public to focus on energy consumption and the negative impacts (e.g., global warming) brought by the use of fossil fuels [1]. This concern is particularly pertinent to the industrial sector, which contributes nearly 18% of global carbon emissions. Since nearly 18% of global carbon emissions come from industry, exploring effective ways to optimize energy use and carbon emission in manufacturing has become unavoidable [2].

So far, the governments have introduced several energy auditing and accreditation standards (e.g., "Energy End Use Efficiency and Energy Services") [3]. Meanwhile,

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the development of computer science is driving energy optimization towards a new era. Energy optimization in low-carbon manufacturing is increasingly being shaped by the integration of data-driven algorithms. For example, the use of random forests and evolutionary algorithms is particularly effective in multi-objective combinatorial optimization problems, where traditional analytic methods fall short due to the absence of explicit objective functions [4]. Moreover, the transition to net-zero emissions energy systems underscores the urgency of decarbonizing difficult-to-abate sectors. The development and deployment of data-driven algorithms can play a crucial role in overcoming these barriers by optimizing energy systems to meet future demands without adding carbon dioxide to the atmosphere [5].

Therefore, to discuss feasible solutions for energy conservation and emissions reduction in modern manufacturing, this article presents detailed examples of advanced algorithms and effective policies. Based on this analysis, key energy-saving pathways (e.g., data-driven algorithms) for low-carbon manufacturing can be identified.

2 Current Energy Optimization Strategies

2.1 Grey Wolf Algorithm (GWO)

A multi-objective optimization strategy for low-carbon and low-energy gear machining processes using an enhanced GWO was developed in 2019, by a research team of Qiannan Normal University [6]. The model mainly considers three decision variables (equipment selection, tool allocation and process sequencing) to minimize energy consumption and carbon emissions.

The improved GWO incorporated two-point crossover (rate: 0.8) and mutation operations (rate: 0.1) to enhance global search capability. Parameters were set to a population size of 100 and 500 iterations. Convergence analysis revealed stable energy and emission reductions after 300 iterations, as shown in Figures 1-2. Applied to machining a 20CrMnTiH steel automotive transmission gear (outer diameter: 97.25 mm, modulus: 1.75 mm, weight: 0.665 kg), the model adhered to constraints including cutting force limits (≤1,700 N), surface roughness (Ra ≤ 1.6 μm), and machine power (≤10 kW). Carbon emission factors for materials (steel: 2.653 kg CO_2/kg), energy (electricity: 8.292 kg CO_2/kWh), and waste (scraps: 8.221 kg CO_2/kg) were quantified to refine boundary conditions. Compared to prior methods (e.g., genetic algorithms, PSO), the hybrid GWO achieved 12–15% higher accuracy in Pareto front solutions, enabling manufacturers to balance energy-carbon trade-offs effectively while maintaining machining quality.

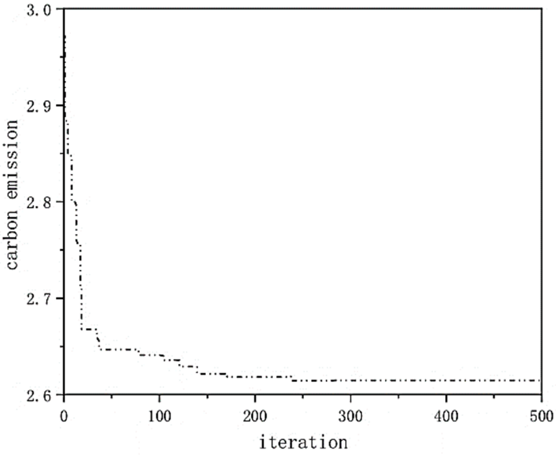

Fig. 1. Carbon emission convergence algebraic diagram [6]

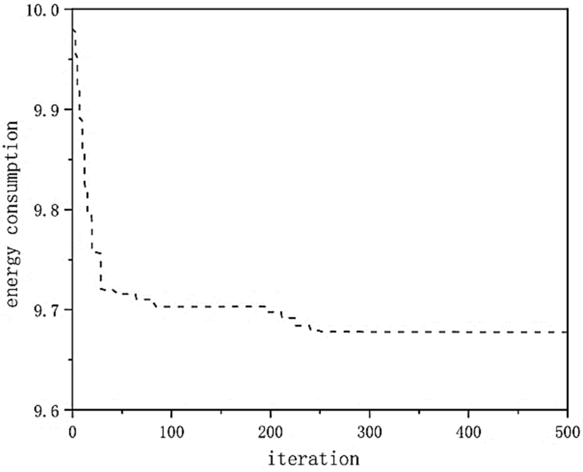

Fig. 2. Energy consumption convergence algebraic diagram [6]

Key quantitative outcomes include the following aspects. Firstly, the optimal scheme achieved 9.989 kWh per gear, compared to 10.064 kWh for low-carbon-only and 9.689 kWh for low-energy-only approaches, showing a clear reduction from conventional methods. Secondly, it comes to carbon emission. Combined optimal strategy yielded 2.975 kg CO_2, balancing trade-offs between low-carbon-only (2.612 kg) and low-energy-only (2.813 kg) approaches, with a clear reduction over traditional strategies. The study offers a probable algorithm to meet the goal of balancing carbon emission and energy saving.

2.2 Chromosome Hierarchical Coding Genetic Algorithm (GA)

This model used to optimize energy consumption in machining manufacturing process was established based on the GA [7]. The core method addresses multi-objective optimization, including energy efficiency, total completion time, and machine tool status, ensuring a comprehensive approach to sustainable manufacturing.

It starts from energy consumption modeling, a comprehensive model quantifies energy use in both processing and idle states, incorporating machine tool power and kinematics-based energy calculations. Secondly it's the nonlinear process planning. Represented by an AOS tree, alternative process routes are generated through feature mapping, enabling flexible machine tool and parameter selection. Thirdly, its genetic algorithm optimization: chromosomes encode process routes, machine tools, and scheduling sequences. With a population size of 50, crossover rate of 0.74, and mutation rate of 0.26, the GA balances objectives using weighted fitness functions (weights: 0.20 for machine status, 0.48 for time, and 0.32 for energy).

It turns out that with the help of optimization strategy, both energy saving and time saving are achieved. Integrated scheduling reduced machine tool standby energy by 83% (Case 2 vs. Case 1). Total energy consumption decreased by 7.1% compared to conventional methods. Meanwhile, total completion time was shortened by 24.43% (from 3,391s to 2,451s) in multi-objective optimization scenarios (Case 4). Moreover, the average machine status score improved from 0.5769 to 0.6132, indicating enhanced operational efficiency and longevity.

When applied to a batch of 45-steel mechanical parts (5 workpieces, 3 machine types), the optimized scheme achieved 5,892,451 J total energy use (0 J standby) and 2,451s completion time. This performance greatly outperforms traditional approaches in both energy efficiency and processing speed. This method provides a solution for sustainable manufacturing, effectively balancing energy-carbon trade-offs while maintaining production quality.

2.3 National Energy Technology-Aluminum (NET-AL)

This study proposes a highly accurate bottom-up NET-AL model (its accuracy is shown in Fig. 3.) to explore low-carbon pathways for China's primary aluminum industry [8]. The model integrates material and energy flows across the entire production chain—from bauxite mining to aluminum ingot casting—while incorporating 22 advanced technologies and regional power structure optimization. Three scenarios were designed: Business-as-Usual (BAU), Advanced Technology Promotion (AT), and Energy Structure Optimization (ES). The "S-curve" method projected China's primary aluminum demand to peak at 40.99 million tons by 2025. Using the algorithm model, the following conclusions can be generated.

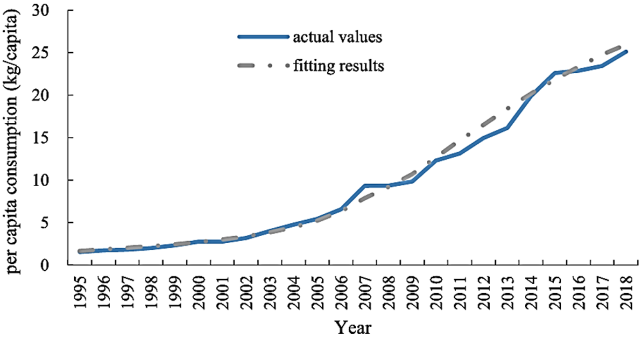

Fig. 3. Comparison between fitting results and actual values [8]

Firstly, it's the carbon emission. Under all scenarios, CO_2 emissions peak in 2025 at 545–569 Mt. By 2050, cumulative reductions are projected to reach 5.3%. Secondly, it's the technology impact. Advanced technologies, particularly seven-effect tube evaporation (gibbsite bauxite) and energy-saving conductive structures, contribute 31.1% and 15.8% of energy savings, respectively. Large-scale electrolytic cells (≥500kA) reduce electricity consumption by 334 TWh cumulatively. Thirdly, it's the power structure. Hydropower-aluminum integration (6.5% penetration) cuts indirect emissions by 2.3%. However, the cost advantages of self-owned coal power plants hinder further decarbonization efforts.

The NET-AL model highlights the necessity of phased technology deployment (like prioritizing cost-effective innovations short-term and subsidizing high-impact technologies long-term) and stricter coal-power phase-out policies. This work provides an actionable road map for aligning China's aluminum industry with carbon neutrality goals.

2.4 Digital transformation in Chinese manufacturing industry

This study investigates how digital transformation (DT) drives low-carbon technology innovation (LCTI) in Chinese manufacturing firms, with a focus on the mediating role of knowledge reconstruction (KR) and the moderating role of knowledge sharing (KS) [9]. Using survey data from 270 manufacturing enterprises across 30 Chinese provinces (392 valid responses), the authors employed a multi-stage analytical approach. Variables including DT, KR, KS, and LCTI were measured via Likert-5 scales. Control variables such as firm age and R&D investment were incorporated to enhance robustness. Structural equation modeling (SEM) and hierarchical regression analysis were applied to test hypotheses. Key findings include 3 aspects.

Firstly, it's the direct effect. DT significantly enhances LCTI (β=0.414, $p<0.001$), confirming its role as a catalyst for green innovation in the context of sustainable industrial transitions. Secondly, it's the mediation. KR partially mediates the DT-LCTI relationship (indirect effect β=0.126, 95% CI [0.081, 0.178]), indicating that DT fosters innovation by restructuring knowledge systems. Lastly, it's the moderation. KS amplifies both the DT-KR linkage (β=0.098, $p<0.01$) and the DT-LCTI pathway (β=0.102, p<0.01). High KS levels strengthen these effects, underscoring the importance of cross-organizational collaboration in innovation ecosystems.

The study's Bootstrap tests (5,000 samples) and model fit indices (CFI=0.978, RMSEA=0.043) validated the reliability of results. Practically, the research highlights that manufacturing firms should prioritize DT-driven knowledge management, build KS networks, and invest in KR capabilities to achieve carbon neutrality, particularly under the "dual carbon" policy framework. Theoretically, it advances the understanding of digital-green synergy by integrating knowledge dynamics into innovation frameworks, offering a roadmap for sustainable industrial transitions under the “dual carbon” policy.

2.5 Material Optimization in the Manufacturing Process

A research team from Loughborough University proposes the Design for Energy Minimization (DfEM) framework, a groundbreaking methodology to systematically address energy consumption in manufacturing by embedding energy optimization into every stage of product development—from conceptual design to production [10]. By aligning environmental objectives with industrial practicality, DfEM bridges the gap between traditional design practices and the urgent need for decarbonization in manufacturing.

The framework begins with a Streamlined Life Cycle Assessment (S-LCA) tool, which simplifies energy evaluation during early design stages. This tool leverages databases of material and process energy footprints to guide designers in selecting low-impact options. For instance, when designing a plastic chair, S-LCA enables rapid comparison between materials like ABS and polypropylene (PP). It highlights PP's lower energy demand in extraction (15% reduction) and processing. Additionally, the tool evaluates manufacturing routes (e.g., traditional vs. gas-assisted injection molding) to prioritize energy-efficient processes.

The Energy Simulation Model (ESM) forms the core of DfEM's technical innovation. By integrating theoretical energy data (e.g., unit process inventories from databases like CO_2PE!) with empirical measurements, the ESM predicts energy consumption for specific production scenarios, allowing targeted energy optimizations. For example, in automotive component manufacturing, the model simulates energy flows across machining, assembly, and facility services, identifying "hotspots" such as high-energy grinding or inefficient HVAC systems. A House of Quality (HoQ) matrix further translates these insights into actionable design improvements, balancing energy reduction with functional requirements (e.g., surface finish quality, structural integrity). This phase enables "what-if" scenario testing, such as adjusting cutting speeds or machine configurations to optimize energy efficiency without compromising product performance.

The Advanced Energy Metering System (AEMS) provides real-time monitoring of energy consumption at the production facility level. Deploying sensors and IoT-enabled devices, AEMS tracks granular data on energy consumption. This includes machine-specific power use (e.g., CNC milling) and facility-wide utilities (e.g., lighting, compressed air). This empirical data validates ESM predictions and supports iterative process optimization. For instance, in a case study on plastic chair production, AEMS revealed that 30% of energy waste stemmed from idle machine time, prompting adjustments in production scheduling and equipment shutdown protocols.

Key achievements and innovations involves 3 aspects, which are energy reduction, supply chain synergy and tool reliability. From the aspects of energy reduction, case studies demonstrated tangible outcomes. For a plastic chair, selecting PP over ABS and optimizing injection molding parameters reduced embodied energy by 15–20%, demonstrating the potential for significant energy savings in small-scale production. In automotive supply chains, hierarchical energy specifications cascaded from OEMs to suppliers cut total vehicle manufacturing energy by 12% through standardized low-energy component designs. When it comes to the supply chain synergy, DfEM's distributed design approach facilitated cross-supplier collaboration. A centralized energy database allowed tiered suppliers to share process data, ensuring compliance with energy targets while maintaining design flexibility. For example, a German automotive OEM achieved a 10% reduction in assembly-line energy use by coordinating with 20+ suppliers on standardized machining parameters. Lastly, when focuses on the tool reliability, the ESM's simulation accuracy was validated against AEMS data, showing less than 5% deviation in energy predictions. This precision enables industries to trust simulation-driven decisions, reducing reliance on costly trial-and-error adjustments.

DfEM's phased tools address both centralized (simple products) and distributed (complex supply chains) manufacturing contexts, offering scalability under regulations like ISO 50001 and the EU EcoDesign Directive. Its integration of energy metrics into conventional design workflows represents a paradigm shift, empowering industries to meet decarbonization targets without sacrificing productivity, as is shown in Fig. 4.

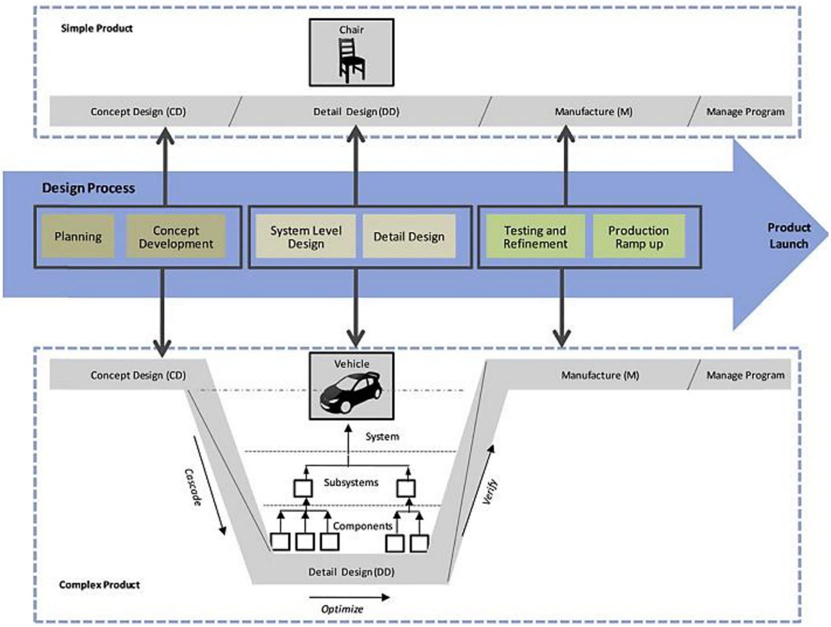

Fig. 4. Characterization of the product development process for simple and complex manufactured products [10]

Future research should expand DfEM's scope to encompass logistics and end-of-life phases, such as incorporating transportation energy models and circular design principles like modular disassembly. For instance, incorporating transportation energy models or circular design principles (e.g., modular disassembly) could further reduce lifecycle impacts. Additionally, enhancing interoperability between DfEM tools and existing Industry 4.0 platforms (e.g., digital twins) would strengthen real-time energy management. By advancing these aspects, DfEM can evolve into a holistic framework for sustainable manufacturing, guiding the transition to a low-carbon industrial future.

3 Conclusion

By listing a series of current optimization strategies in manufacturing, the potential of algorithms, digital tools, and systemic models in optimizing low-carbon manufacturing can be demonstrated. The GWO and GA algorithms effectively reconcile energy-carbon trade-offs, while the NET-AL model and DfEM framework provide practical pathways for sector-wide decarbonization. Specific case studies, such as those involving the GWO and GA algorithms, validate significant reductions in energy use and emissions, underscoring the scalability of these strategies. Future research should expand the integration of circular economy principles, such as modular design and end-of-life recycling, to address full life-cycle impacts. Enhancing interoperability between energy optimization tools and Industry 4.0 platforms could enable real-time, adaptive manufacturing systems. Policy frameworks must encourage cross-supplier collaboration and subsidize high-impact technologies, particularly in energy-intensive sectors like aluminum production. Exploring AI-driven predictive maintenance and renewable energy integration in manufacturing processes could enhance sustainability gains.

Ultimately, achieving carbon neutrality demands a holistic approach—combining technological innovation, digital transformation, and regulatory alignment. By prioritizing these synergies, industries can transition toward resilient, low-carbon futures while maintaining global competitiveness.

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