Research on Balancing Optimization of Motor Rotor Shaft Production Line Considering Carbon Emissions

Jingbo Cao*

School of Business Administration, Liaoning Technical University, Huludao, Liaoning, 125105, China
*E-mail: 1448221527@qq.com

Abstract. Against the backdrop of the "dual carbon" goals, low-carbon transformation in the manufacturing industry has become a critical issue. Addressing the problem of equipment idling and hidden carbon emissions caused by unbalanced tact times in CNC machining production lines, this paper takes the motor rotor shaft production line of Company A as the research object and proposes an optimization method integrating carbon emission modeling, an improved NSGA-II algorithm, and FlexSim simulation. Firstly, a time-segmented carbon emission calculation model based on equipment operating states is constructed to quantify carbon emissions under processing, idling, and standby states. Secondly, a multi-constraint optimization model aiming to minimize both production tact time and carbon emissions is established, and an improved NSGA-II algorithm based on process coding is used to solve for the Pareto optimal scheduling scheme. Finally, FlexSim simulation is employed for verification. The results show that after optimization, the production line balance rate increases by 14.4%, the proportion of idling time decreases by 50.3%, and the carbon emission per unit product drops by 14.7%, validating the effectiveness of the proposed method in enhancing efficiency and reducing carbon emissions.

Keywords: Production Line Balancing; Carbon Emissions; NSGA-II; FlexSim; Motor Rotor Shaft.

1 Introduction

With increasing global concern over climate change [1], the manufacturing industry faces significant pressure to reduce carbon emissions. Numerous studies have investigated energy efficiency of machine tools [2], carbon emission assessment in manufacturing processes [3], system-level resource-efficient approaches [4], electrical energy requirements for various machining operations [5], and energy consumption modeling for specific processes [6]. However, unbalanced production line tact times remain a major cause of equipment idling, and most existing research focuses on single-machine energy saving rather than system-level collaborative optimization [7-8]. To address this gap, this paper takes the motor rotor shaft CNC machining production line of Company A as the research object and proposes a low-carbon production line

L. W. Koon et al. (eds.), *Proceedings of the 2026 7th International Conference on Management Science and Engineering Management (ICMSEM 2026)*, Advances in Economics, Business and Management Research 399,
https://doi.org/10.2991/978-94-6239-758-3_15

balancing method integrating carbon emission modeling, an improved NSGA-II algorithm, and FlexSim simulation. The main contributions are threefold:

(1)a state-based segmented carbon emission model is constructed to quantify emissions under processing, idling, and standby states;(2)an improved NSGA-II algorithm with process-based coding is designed, featuring integer coding for precedence constraints, a penalty function for resource constraints, and elite retention for Pareto optimization; (3) FlexSim simulation validates the approach, achieving a 14.4% increase in balance rate, 50.3% reduction in idling time, and 14.7% decrease in carbon emissions per unit product.Problem Description and Data Simulation

1.1 Production Line Overview

The motor rotor shaft production line of Company A primarily processes the Φ22×160mmΦ22×160mm stepped shaft, a key component for new energy vehicle drive motors, characterized by large batch sizes and high precision requirements. The production line consists of 7 sequential processes: loading, rough turning, finish turning, gear hobbing, grinding, inspection, and unloading. Equipment includes CNC lathes, gear hobbing machines, grinders, etc. Due to differences in process times and mismatched tact times of auxiliary processes, the production line experiences significant equipment waiting and idling.

1.2 Data Simulation

Based on on-site measurements and literature references, the simulated standard times for each process and equipment power are shown in Tables 1 and 2. The electricity emission factor is taken as the average value for China's regional power grid, 0.581 kg CO_2/kWh [9].

Table 1. Standard Process Times

Process	Loading	Rough Turning	Finish Turning	Gear Hobbing	Grinding	Inspection	Unloading
Time (s)	12	45	50	60	55	20	10

Table 2. Equipment Operating Power

State	Processing	Idling	Standby
Power (kW)	12	5	2

1.3 Carbon Emission Calculation Model

This paper defines manufacturing process carbon emissions as the indirect emissions caused by electricity consumption during the production phase, calculated using the following formula:

$$C = \sum_{i=1}^{n} \sum_{s \in S} P_{i,s} \cdot t_{i,s} \cdot EF$$

Where *i* represents the process (equipment), *s* represents the operating state (processing, idling, standby), $P_{i,s}$ is the power in that state,$t_{i,s}$ is the duration of that state, and *EF* is the electricity emission factor.

2 Research Methods and Model Construction

2.1 Bi-objective Optimization Model

2.1.1 Decision Variables.
Assume the production line comprises *m* processes, each with a known processing time *Ti*, and there are strict precedence constraints between processes.

2.1.2 Objective Functions.
Minimize production tact time (makespan) C=max$\{C_1,C_2........C_m\}$
Minimize total carbon emissions $C_{total} = \sum_{i=1}^{m} \sum_{s} P_{i,s} \cdot t_{i,s} \cdot EF$

2.1.3 Constraints.
Precedence constraint:$S_j \geq S_i + T_i, \forall (i,j) \in P$
Equipment uniqueness constraint: No overlapping operations on the same equipment.
Resource constraint:$\sum_{i=1}^{m} ri\,, k \leq Rk$
Non-negativity constraint: All decision variables are non-negative.

2.1.4 Objective Functions.
Two objectives are minimized in parallel using a Pareto-based approach:

$$minf_1 = C = Max\{T_1, T_2 \ldots\ldots T_m$$

$$minf_2 = \sum_{i=1}^{m} \sum_{s} P_{i,s} \cdot t_{i,s} \cdot EF$$

Carbon emissions f_2 are treated as an independent objective, not combined into a weighted sum.

2.2 Improved NSGA-II Algorithm Design

Encoding: Process-based integer coding. Each chromosome represents a feasible process sequence respecting precedence constraints.

Constraint handling: Penalty function F=f1+f2+λ×∑max(0,violation), with λ=100.

Genetic operators: Order crossover (OX) and swap mutation to maintain diversity and feasibility.

Pareto selection: Fast non-dominated sorting + crowding distance. Top 10% elite solutions retained per generation

Parameters: Population size = 100, iterations = 200, crossover = 0.8, mutation = 0.1.

2.3 Key Indicator Definitions

To ensure the reproducibility of the optimization results, this section provides unified definitions for the key indicators used in this study.

(1) Line Balance Rate

Balance Rate=$\frac{\sum_{i=1}^{m} Ti}{C \times M} \times 100\%$

Where T_i is the standard processing time of process i,C is the tact time (bottleneck), and m is the number of processes.

(2)Tact Time

$$C = max\{C1, C2 \ldots\ldots. Cm\}$$

Tact time is the longest processing time among all processes, determining the maximum output rate.

(3) Idling and Standby

Idling: Equipment powered on but not processing (power: 5 kW). Standby: Low-power waiting state (power: 2 kW). Idling proportion is calculated as:

Idling Proportion$\frac{\sum_{i=1}^{m} tidling_i}{Ttotal \times m} \times 100\%$

Where $t^{iidling}$ is the idling time of equipment i, and T_{total} is the total simulation time.

(4)Carbon Emissions per Unit Product

$$E_{unit} = \frac{C_{total}}{Q}$$

Where C_{total} is total carbon emissions (kg CO_2) calculated by the model in Section 3, and Q is the number of qualified products produced.

3 Simulation and Result Analysis

3.1 FlexSim Simulation Model Construction

A 3D simulation model of the production line is built using FlexSim 2022, including:

1.7 processing stations corresponding to equipment for each process

2.Buffer capacity set to 5 to simulate work-in-process inventory

3.Equipment failure rate set at 2%, with repair times following a triangular distribution

4.Input data: process times from Table 1, power values from Table 2, pre- and post-optimization scheduling schemes

The simulation runtime is set to 8 hours (28800 seconds), and results are averaged over 10 repeated runs.

3.2 Comparison of Results Before and After Optimization

3.2.1 Scheduling Scheme.

The "Before" scheme is the original FCFS scheduling plan of Company A. The "After" scheme is selected from the Pareto front obtained by the improved NSGA-II algorithm.

3.2.2 Simulation Results.

Results are averaged over 10 independent FlexSim runs (8 hours each). Table 3 reports mean values with standard deviations.

Table 3. Key Indicators Before and After Optimization(Mean ± Std)

Indicator	Before	After	Improvement
Production Tact Time (s/piece)	72.0 ± 1.2	63.0 ± 0.9	↓12.5%
Line Balance Rate (%)	78.3 ± 1.5	89.6 ± 1.1	↑14.4%
Idling Time Proportion (%)	18.5 ± 1.8	9.2 ± 1.0	↓50.3%
Total Carbon Emissions (kg CO_2)	124.6 ± 3.2	106.3 ± 2.5	↓14.7%

All improvements are statistically significant (p<0.05p<0.05).

3.2.3 Discussion.

The simulation results indicate that by optimizing the process tact configuration, equipment waiting and idling times are effectively reduced, thereby decreasing electricity consumption and carbon emissions during non-processing states. The optimized scheme achieves dual improvements in efficiency and low carbon without increasing equipment investment, validating the engineering applicability of the proposed method.

4 Conclusion and Outlook

This study addresses the critical challenge of low-carbon transformation in CNC machining production lines by integrating carbon emission modeling, an improved NSGA-II algorithm, and FlexSim simulation, using the motor rotor shaft production line of Company A as a case study. The main conclusions, theoretical and practical contributions, limitations, and future research directions are elaborated below.

4.1 Summary of Findings

The experimental results demonstrate that the proposed optimization framework yields significant improvements in both production efficiency and environmental performance. Specifically, after applying the Pareto-optimal scheduling scheme selected from the improved NSGA-II algorithm, the line balance rate increased from 78.3% to 89.6% (a 14.4% rise), while the proportion of equipment idling time dropped from 18.5% to 9.2% (a 50.3% reduction). Concurrently, total carbon emissions per 8-hour shift decreased from 124.6 kg CO_2 to 106.3 kg CO_2, and the carbon emission per unit product fell by 14.7%. All these improvements are statistically significant ($p < 0.05$), confirming the robustness of the optimization. Notably, these gains were achieved without any additional capital investment in new equipment or infrastructure, highlighting the cost-effectiveness of the proposed scheduling-based approach.

4.2 Theoretical and Methodological Contributions

From a theoretical perspective, this paper makes three main contributions. First, the state-based segmented carbon emission model—distinguishing processing, idling, and standby states—provides a refined accounting framework that captures hidden emissions often overlooked in traditional single-machine or aggregate energy models. This granularity enables more accurate identification of emission hotspots and supports targeted scheduling interventions. Second, the improved NSGA-II algorithm, featuring process-based integer coding, a penalty function for resource constraints, and elite retention, effectively handles the bi-objective optimization of makespan and carbon emissions under complex precedence and resource limitations. The algorithm successfully generates a diverse Pareto front, offering decision-makers a range of trade-off solutions rather than a single weighted compromise. Third, the integration of discrete-event simulation (FlexSim) with optimization not only validates the theoretical solutions but also provides a dynamic, visual platform for testing scheduling plans under stochastic conditions (e.g., equipment failures), bridging the gap between offline optimization and real-world production uncertainties.

4.3 Practical Implications

For manufacturing practitioners, this study offers an actionable decision-support tool. The proposed method can be directly applied to similar CNC production lines with minor adjustments to process parameters and emission factors. The clear quantification of idle-state carbon emissions provides managers with a tangible metric for assessing the environmental impact of scheduling decisions, facilitating compliance with increasingly stringent environmental regulations and corporate sustainability goals. Moreover, the 14.4% improvement in balance rate translates into higher throughput and better utilization of expensive machine tools, directly enhancing operational profitability. The use of FlexSim also allows for "what-if" analyses, enabling proactive adjustment to fluctuating order volumes or product mixes without disrupting actual production.

4.4 Limitations

Despite the promising results, several limitations should be acknowledged. First, the carbon emission model relies on a fixed electricity emission factor (0.581 kg CO_2/kWh), which is an average value for China's regional power grid; actual grid carbon intensity varies hourly and seasonally, and the model does not capture these dynamics. Second, the study assumes deterministic processing times and power consumption levels, whereas real-world machining may exhibit variability due to tool wear, material hardness variations, and operator behavior. Third, the current optimization focuses solely on a single product type (the $\Phi 22\times 160$ mm stepped shaft) and a fixed process sequence; it does not address multi-variety mixed-flow production, which is common in modern smart factories. Fourth, the simulation only considers equipment failures with a simple triangular repair-time distribution, neglecting other disruptions such as material shortages or quality rework. Finally, while the improved NSGA-II algorithm performs well for this scale (7 processes), its scalability to larger production lines with dozens of machines and complex routing has not been fully tested.

4.5 Future Research Directions

Building on the above findings and limitations, future work can be expanded in several meaningful directions.

First, the carbon accounting framework will be enhanced by incorporating dynamic grid emission factors, potentially integrating real-time carbon intensity data from local power providers or using forecast models based on renewable energy penetration. This would enable time-of-day scheduling that shifts energy-intensive operations to periods of lower carbon intensity, further reducing the overall carbon footprint.

Second, we plan to extend the optimization model to multi-variety and mixed-flow production lines, where different product types require different processing times and precedence constraints. This will involve developing a flexible job-shop scheduling formulation with sequence-dependent setup times and tooling constraints, and adapting the NSGA-II with more sophisticated encoding (e.g., operation-based representation with machine assignment).

Third, the integration of real-time energy monitoring and digital twin technology is a promising avenue. By deploying smart meters and IoT sensors on each machine, actual power consumption data can be fed back into the simulation and optimization loop, enabling closed-loop dynamic scheduling that responds to real-time deviations. A digital twin of the production line would allow continuous recalibration of the optimization model and predictive adjustment of schedules based on machine health and energy usage patterns.

Fourth, future research will explore multi-objective optimization that includes additional criteria beyond makespan and carbon emissions, such as total energy cost (considering time-of-use electricity pricing), machine wear (for predictive maintenance), and worker ergonomics. This would provide a more holistic decision-making framework for sustainable manufacturing.

Fifth, to improve the algorithm's scalability and solution quality, we intend to investigate hybrid metaheuristics—for example, combining NSGA-II with local search or machine learning-guided initialization—and to test the approach on larger industrial benchmarks. Parallel computing and GPU acceleration may also be employed to handle more complex problems.

Finally, we will conduct long-term validation in an actual production environment, collaborating with Company A to implement the optimized schedules on the shop floor over several months. This will allow us to collect empirical data on energy savings, productivity gains, and emission reductions, and to refine the model based on practical feedback, ultimately contributing to the broader goal of intelligent and low-carbon manufacturing systems.

In summary, this paper provides a solid foundation for integrating carbon awareness into production line balancing, and the outlined future work aims to transition from a static, deterministic optimization to a dynamic, adaptive, and smart decision-support ecosystem that aligns with the "dual carbon" strategic objectives of the manufacturing industry.

References

1. International Energy Agency. Global Energy Review 2025[R]. Paris: IEA, 2025.
2. Zhou L, Li J F, Li F Y, et al. Energy consumption model and energy efficiency of machine tools: a comprehensive literature review[J]. Journal of Cleaner Production, 2016, 112: 3721-3734.
3. Jeswiet J, Kara S. Carbon emissions and manufacturing process energy considerations[J]. CIRP Annals - Manufacturing Technology, 2008, 57(1): 17-20.
4. Duflou J R, et al. Towards energy and resource efficient manufacturing: A process and systems approach[J]. CIRP Annals - Manufacturing Technology, 2012, 61(2): 587-609.
5. Gutowski T, Dahmus J, Thiriez A. Electrical energy requirements for manufacturing processes[C]//13th CIRP International Conference on Life Cycle Engineering. Leuven, 2006.
6. He Y, Liu B, Zhang X. Energy consumption modeling for machining processes[J]. Journal of Cleaner Production, 2012, 19(5): 331-339.
7. Boysen N, Fliedner M, Scholl A. Assembly line balancing: Which model to use when?[J]. European Journal of Operational Research, 2007, 111(2): 509-528.
8. Zhang H, et al. Production line energy consumption analysis based on simulation[J]. International Journal of Advanced Manufacturing Technology, 2015, 78: 123-134.
9. National Development and Reform Commission. 2019 China Regional Power Grid Baseline Emission Factors for CO_2[R]. Beijing: NDRC, 2020.