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Smart Manufacturing Driven Multi-objective Carbon-Constrained Production and Supply Chain Coordination Optimization

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Abstract. The low-carbon transformation of manufacturing makes production planning no longer limited to cost reduction and delivery efficiency, as carbon emissions, energy consumption, and supply chain coordination have become key decision factors in smart manufacturing systems. Focusing on carbon-constrained production and supply chain coordination optimization, a multi-objective optimization framework is constructed by integrating equipment status, machining processes, order delivery, inventory configuration, transportation batching, and carbon emission accounting. The experiment uses open equipment-state data, CNC machining data, and carbon emission factors from 2020 to 2026 to construct reproducible controlled simulation instances. An improved NSGA-II algorithm is applied to obtain Pareto solution sets for cost, makespan, and carbon emissions. The results show that the improved NSGA-II outperforms the standard NSGA-II in total cost, maximum makespan, carbon emissions, Hypervolume, and Spread, while maintaining delivery stability and reducing system-level emissions. These findings indicate that smart manufacturing data-driven coordination optimization can provide computable and comparable decision support for low-carbon production scheduling and supply chain coordination.

Keywords: smart manufacturing, multi-objective optimization, carbon-constrained production, supply chain coordination, NSGA-II

1. Introduction

The low-carbon transformation of manufacturing is moving from end-of-pipe emission control toward whole-process operational optimization. Order fluctuation, delivery pressure, energy prices, and carbon quotas jointly reshape the decision boundaries of production planning, especially when manufacturers need to maintain delivery reliability while reducing operational emissions [1]. Smart manufacturing systems connect the shop-floor execution layer with the supply chain coordination layer through machine status, process rhythm, energy records, and logistics information, allowing carbon emissions to be embedded into integrated decisions on scheduling, inventory, and transportation [2]. Existing studies have developed useful foundations in energy-efficient scheduling, low-carbon inventory management, and supply chain coordination, while the dynamic

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linkage between production-side scheduling and supply-chain carbon constraints still requires a unified modeling structure. The research content therefore focuses on carbon-constrained production and supply chain coordination optimization. A multi-objective model is constructed with production cost, makespan, and carbon emissions as the core objectives, and an improved NSGA-II algorithm is used to generate comparable Pareto solutions for low-carbon manufacturing decision support.

2. Literature review

2.1. Smart manufacturing data foundation

Smart manufacturing data provide the computational foundation for low-carbon coordination optimization. Sensors, MES, ERP, and industrial IoT systems continuously record machine loads, processing times, equipment idle states, order status, and logistics node information, which enables production planning to shift from static parameter-based scheduling toward real-time perception and dynamic adjustment [3]. Research on energy-efficient scheduling shows that production optimization should expand from equipment-level energy control to system-level coordination, because energy savings from individual machines alone cannot fully represent order fulfillment performance or total supply chain emission reduction [4]. The key value of the data foundation lies in converting process status, capacity variation, and emission factors into variables that can be embedded in optimization models. These variables define constraint boundaries, carbon accounting rules, and evaluation criteria for the later multi-objective solution process.

2.2. Low-carbon production scheduling

The core of low-carbon production scheduling is to transform operation sequencing, machine selection, batch division, and machine on/off control into decision variables that can regulate carbon emissions. Early energy-aware scheduling focused on machine idle time and processing power, which reduced local energy waste and provided a basis for carbon-oriented objective functions [5]. As carbon taxes, emission trading, and enterprise carbon quotas enter manufacturing decision-making, scheduling objectives expand from makespan or cost alone to a coordinated trade-off among cost, delivery time, and emissions [6]. Multi-objective evolutionary algorithms are suitable for this type of problem because they can search non-dominated solution sets under complex constraints, allowing machine capacity, process precedence, delivery deadlines, and carbon limits to be handled within the same algorithmic framework [7]. Different low-carbon production plans can therefore be compared through Pareto performance rather than a single deterministic optimum.

2.3. Supply chain coordination optimization

Supply chain coordination optimization focuses on the linkage among production planning, inventory configuration, transportation batches, and carbon policies. Carbon taxes and carbon quotas influence supplier selection, order quantity, transportation frequency, and inventory location, which further reshape cost structure and service level [8]. Centralized decision-making can coordinate production rhythm and transportation arrangements under a unified objective system, while decentralized decision-making may create tension between local cost minimization and total emission control [9]. In smart manufacturing scenarios, shop-floor scheduling results can serve as upstream inputs for supply chain coordination. Delivery windows, replenishment decisions, and transportation batches can then be adjusted according to the actual production rhythm. This structure

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creates an optimization mechanism in which the production side and the supply chain side jointly respond to carbon constraints, supporting both operational efficiency and emission reduction.

3. Experimental methods

3.1. Data sources

The experimental data are constructed from open and collectable sources from 2020 to 2026. Equipment-state data are selected from the UCI AI4I 2020 Predictive Maintenance Dataset, which contains 10,000 industrial equipment records with air temperature, process temperature, rotational speed, torque, tool wear, and machine-failure labels. These fields are used to generate machine load, processing stability, and maintenance-window parameters. CNC process data are selected from the 2026 Multi-Sensor and MTConnect dataset of metal cutting anomaly in milling, which provides acoustic, vibration, current-transformer, MTConnect controller data, and anomaly labels from both laboratory machining and industrial production settings. The smart manufacturing system structure is based on the NIST Smart Manufacturing Systems Test Bed, which supports the setting of MTConnect data streams, equipment-state collection, and manufacturing-system connectivity. Carbon parameters are obtained from UK Government GHG Conversion Factors 2026 and U.S. EPA Supply Chain GHG Emission Factors v1.3 for electricity, fuel, transportation, and supply-chain activity conversion. Orders, process routes, supply-chain nodes, and transportation distances are then constructed as controlled simulation instances within the 2020–2026 data range.

3.2. Optimization model construction

The optimization model integrates equipment processing status, order delivery requirements, and supply-chain node decisions into one constraint system. Equipment-state data are used to estimate processing time and feasible maintenance windows. MTConnect machining data are used to identify abnormal processing states, while carbon emission factors convert electricity, transportation, and inventory activities into comparable tCO_2e indicators [10]. The objective function simultaneously considers production cost, maximum makespan, and total carbon emissions, enabling the algorithm to search non-dominated solutions among cost compression, delivery stability, and emission control, as shown in Formula (1).

$$\min F = (f_1, f_2, f_3) = (C_{total}, C_{max}, E_{total}) \tag{1}$$

In Formula (1), C_{total} denotes total production, inventory, transportation, and delay cost; C_{max} denotes the maximum completion time of all orders; and E_{total} denotes total system carbon emissions. Carbon accounting covers processing electricity, machine idle status, setup change, warehousing, and transportation, and it changes jointly with production batches and transportation batches, as shown in Formula (2).

$$E_{total} = \sum_i \sum_j \sum_m x_{ijm} p_{ijm} e_m + \sum_m I_m e_m + \sum_l q_l d_l \gamma_l + \sum_s H_s e_s \tag{2}$$

In Formula (2), x_{ijm} is the operation-machine assignment variable, p_{ijm} is processing time, e_m is the equipment emission factor per unit time, I_m is machine idle time, q_l, d_l, and γ_l denote transportation quantity, distance, and transportation emission coefficient, while H_s is inventory quantity and e_s is the inventory emission coefficient.

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3.3. Algorithmic solution process

The solution process adopts an improved NSGA-II algorithm. The initial population is generated through the earliest-due-date rule, low-emission machine-priority rule, and supply-chain batch-balancing rule, so that initial solutions satisfy process precedence, machine capacity, inventory limits, and vehicle-capacity constraints. The crossover stage exchanges operation sequences and supply-chain node combinations. The mutation stage adjusts machine selection, production batch size, and transportation batch, while the repair mechanism corrects individuals that violate delivery and capacity constraints [11]. Non-dominated sorting is used to determine the priority relationship among solutions in the three-objective space, as shown in Formula (3).

$$a \prec b \Longleftrightarrow [\forall k \in \{1,2,3\}, f_k(a) \le f_k(b)] \wedge [\exists k, f_k(a) < f_k(b)] \tag{3}$$

In Formula (3), $a \prec b$ means that solution aaa dominates solution b, and f_k denotes the k-th objective function. To prevent the solution set from concentrating in limited local regions, crowding distance is used during selection to maintain Pareto-front diversity, as shown in Formula (4).

$$CD_i = \sum_{k=1}^{3} \frac{f_k(i+1) - f_k(i-1)}{f_k^{max} - f_k^{min}} \tag{4}$$

In Formula (4), CD_i denotes the crowding distance of the i-th solution, while f_k^{max} and f_k^{min} denote the maximum and minimum values of the k-th objective in the current non-dominated layer. The final evaluation uses Hypervolume, Spread, running time, total cost, makespan, and carbon emissions.

4. Results

4.1. Pareto solution performance

The results are obtained from 30 medium-scale controlled simulation instances constructed from open equipment-state data, CNC process data, and carbon emission factors from 2020 to 2026. Each instance contains 40 orders, 8 machines, 4 supply nodes, and 3 transportation modes. Each algorithm is independently executed 30 times, and the mean values are reported. As shown in Table 1, the improved NSGA-II achieves a total cost of RMB 598,600, a maximum makespan of 128.5 hours, and total carbon emissions of 92.4 tCO_2e, outperforming the standard NSGA-II values of RMB 607,400, 132.8 hours, and 99.7 tCO_2e. Its Hypervolume reaches 0.743, and its Spread decreases to 0.286, indicating better convergence and distribution uniformity. Cost-priority scheduling obtains the lowest cost but raises emissions to 111.8 tCO_2e. Emission-priority scheduling reduces emissions, but its delay rate reaches 12.4%, showing that a single-objective strategy cannot maintain both low-carbon performance and delivery stability.

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Table 1. Performance comparison of different algorithms in carbon-constrained production and supply chain coordination optimization

Algorithm	Total Cost (10^4 RMB)	Makespan (h)	Carbon Emissions (tCO_2e)	Delay Rate (%)	Hypervolume	Spread	Runtime (s)
Cost-priority scheduling	54.86	127.4	111.8	9.6	0.612	0.438	18.5
Emission-priority scheduling	65.92	143.1	86.9	12.4	0.586	0.462	17.9
Standard NSGA-II	60.74	132.8	99.7	8.8	0.684	0.351	46.3
Improved NSGA-II	59.86	128.5	92.4	6.7	0.743	0.286	51.8

4.2. Pareto solution performance

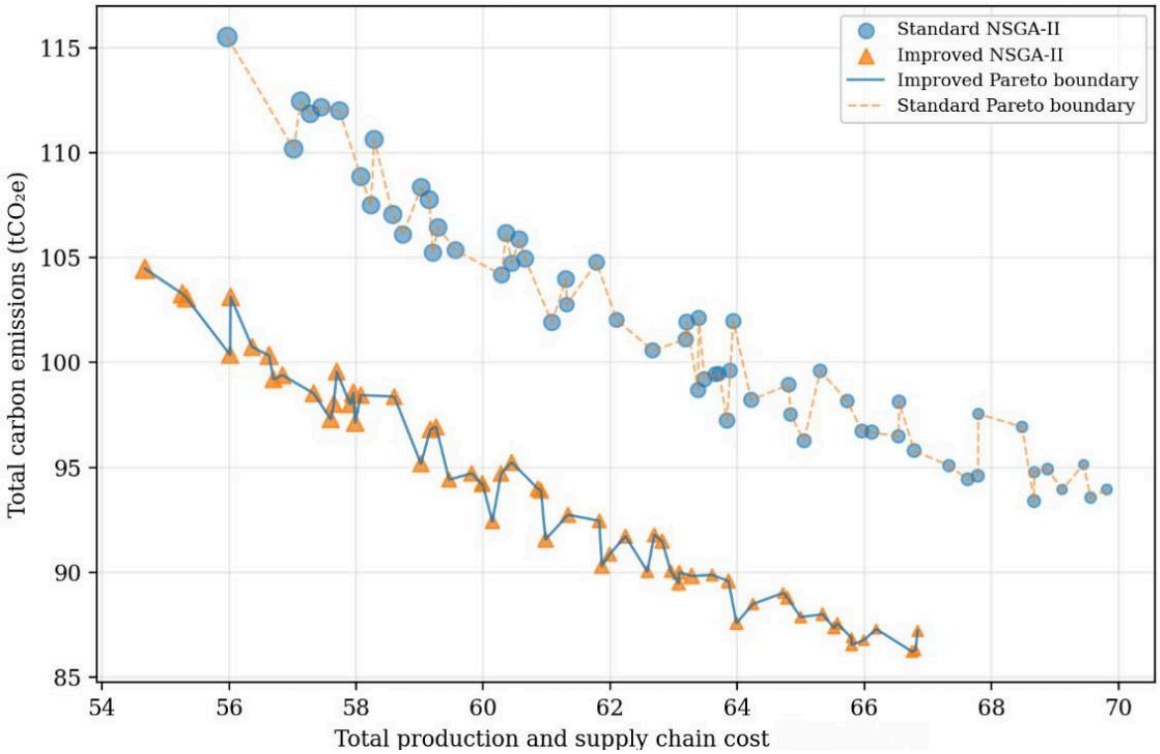

Figure 1. Pareto solution distribution under carbon-constrained coordination optimization

To verify the coordination effect between production and the supply chain, the non-dominated solutions generated by the improved NSGA-II and the standard NSGA-II are further compared across cost, carbon emissions, and delivery delay. As shown in Figure 1, the solution set of the improved NSGA-II moves toward lower cost, lower carbon emissions, and lower delay, indicating that machine selection, operation resequencing, transportation consolidation, and inventory buffering jointly improve system performance. The 60 non-dominated solutions generated by the improved NSGA-II cover a cost range of RMB 549,000–668,000 and an emission range of 86.1–

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104.6 tCO_2e. The balanced region is concentrated at RMB 594,000–620,000, 90.2–96.8 tCO_2e, and a delay rate of 6.1%–7.3%. The standard NSGA-II solutions are more dispersed, and some low-cost solutions are accompanied by higher emissions, showing that the absence of carbon-oriented repair and low-emission initialization weakens coordination stability.

5. Discussion

The experimental results indicate that the advantage of the improved NSGA-II comes from the combined effect of low-emission initialization, delivery-constraint repair, and crowding-distance selection. The cost-priority strategy reduces short-term production cost, but its higher carbon emissions show that equipment energy consumption and transportation consolidation are insufficiently considered. The emission-priority strategy reduces carbon emissions, but its higher delay rate reflects the pressure that single-objective emission reduction places on order fulfillment. The improved NSGA-II forms a more balanced non-dominated solution set among cost, makespan, and emissions, showing that coordinated adjustment of production batches, machine selection, inventory buffering, and transportation batching can reduce the system pressure caused by carbon constraints. The simulation results also show that carbon reduction depends on structural coordination between shop-floor data and supply chain nodes, rather than simple production suppression.

6. Conclusion

A complete technical framework is developed for smart manufacturing driven carbon-constrained production and supply chain coordination optimization, covering data collection, carbon emission accounting, multi-objective modeling, and improved NSGA-II solution. Open equipment-state data, CNC machining data, and carbon emission factors support reproducible experimental scenarios, while the model integrates production cost, maximum makespan, and total carbon emissions into one objective system. The experimental results demonstrate that the improved NSGA-II can generate better Pareto solution sets and provide interpretable trade-off schemes among cost control, delivery stability, and low-carbon operation. This framework offers a feasible path for manufacturing enterprises to conduct low-carbon scheduling, supply chain coordination, and intelligent decision optimization.

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