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Research on Low-Carbon Scheduling of Energy-Intensive Projects Considering Multi-Mode Resource Constraints and Dynamic Electricity Prices

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Abstract

Energy-intensive industries constitute the primary source of energy consumption and carbon emissions. To achieve the "Dual Carbon" goals, advancing the low-carbon transformation of such industries is of vital significance. Nevertheless, current production scheduling for energy-intensive projects rarely coordinates time-of-use electricity prices, multi-shift production and low-carbo requirements in an integrated optimization framework. To address this gap, this study develops a multi-objective scheduling framework incorporating multiple resource scheduling rules and dynamic fluctuations in energy prices. The framework pursues three optimization objectives: minimizing carbon emissions, cutting energy costs, and maintaining reasonable project durations. Interms of numerical solution, this paper improves the Nondominated Sorting Genetic Algorithm III (NSGA-III) and adopts the Analytic Hierarchy Process (AHP) to determine the weight of each objective, thereby realizing dynamic equilibrium of scheduling schemes under multiple constraints. Case verificat on demonstrates that the proposed model can effectively reduce carbon emissions and energy expenditures of energy-intensive projects while improvin resource utilization efficiency. The research outcomes can provide practical guidance and references for low-carbon production scheduling in energy-intensive industries.

Keywords

Low-carbon scheduling; Multi-mode resource constraints; Dynamic electricity prices; NSGA-III algorithm.

1. INTRODUCTION

1.1. Research Background

Guided by the "Dual Carbon" goals, energy-intensive sectors including steel, chemical engineering and cement manufacturing are confronted with dual pressures of uncontrollable total energy consumption and insufficient carbon emission intensity reduction. Characterized by complicated production procedures, intensive resource demands and massive energy consumption, traditional project scheduling models primarily focus on duration compression and direct cost reduction, while ignoring time-varying electricity price fluctuations, resource allocation disparities across multi-shift production, and carbon emission constraints embedded in scheduling plans.

China’s ongoing power market reform has promoted the nationwide implementation of dynamic electricity pricing mechanisms, where peak-to-valley electricity price gaps can reach several times. This creates opportunities for energy-intensive projects to cut energy costs through load shifting production. Meanwhile, energy-intensive projects feature typical multi-mode operational characteristics, which further expand the optimization space of scheduling

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schemes due to complex resource constraints and diverse operation modes. However, existing scheduling research fails to construct a collaborative optimization framework integrating multi-mode operation, multi-shift production, dynami electricity prices and low-carbon constraints. In addition, quantitative correlations between production activity decomposition and carbon emission volumes are insufficiently analyzed, leading to scheduling plans that cannot simultaneously satisfy economic and low-carbon requirements.

1.2. Research Significance

1.2.1. Theoretical Significance

This paper constructs a low-carbon scheduling model coupled with multi-mode resource constraints and dynamic electricity prices, breaking the single-objective optimization limitation of conventional scheduling research and enriching application scenarios of multi-objective scheduling theories in energy-intensive industries. The improved NSGA-III algorithm enhances solution efficiency under multiple constraints, and the AHP method quantifies objective weights, delivering targeted technical approaches for multi-criteria decision-making and perfecting the theoretical system of low-carbon scheduling.

1.2.2. Practical Significance

The research findings can be directly applied to production scheduling practices of energy-intensive enterprises. Subject to resource constraints and duration requirements, firms can adjust production timetables by leveraging dynamic electricity prices to lower energy costs and carbon emissions. Furthermore, this study provides data support and decision references for industry authorities to formulate relevant policies and accelerate the low-carbon transition of energy-intensive industries, facilitating the smooth realization of the "Dual Carbon" goals.

2. LITERATURE REVIEW

2.1. Research on Multi-Mode Resource-Constrained Project Scheduling

Multi-Mode Resource-Constrained Project Scheduling Problem (MRCPSP) is a classic topic in project management, whose core lies in selecting operation modes for each activity to balance resource allocation, project duration and costs. Early studies mostly adopted single-objective optimization. Hartmann et al [1]. proposed a genetic algorithm-based solving method for MRCPSP, focusing on minimizing project duration. Subsequent research shifted to multi-objective optimization. Zhang et alx [2]. established a duration-cost-resource consumption multi-objective model without incorporating environmental constraints. Although existing literature has thoroughly described multi-mode resource constraints, few studies integrate energy price volatility and carbon emission constraints, making prior models inapplicable to the low-carbon transformation demands of energy-intensive industries.

2.2. Scheduling Optimization Research under Dynamic Electricity Prices

Scheduling optimization under dynamic electricity pricing mainly concentrates on power systems and industrial demand response. Wang et al [3]. constructed a load-shifting production scheduling model for industrial users under time-of-use tariffs to reduceenergy costs, yet neglected multi-mode operation and resource constraints. Li et al. [4] developed an industrial production scheduling model incorporating electricity price fluctuations and carbon emission limits, without accounting for resource allocation differences in multi-shift production. Most existing studies only consider single production modes and lack adaptability to complex scenarios with multi-mode and multi-shift operations in energy-intensive projects.

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2.3. Research on Low-Carbon Project Scheduling

In recent years, low-carbon scheduling has attracted growing research attention; this approach achieves decarbonization by incorporating carbon emission objectives and optimizing energy mixes. Chen et al [5]. built a carbon cap-constrained project scheduling model solved via particle swarm optimization. Zhao et al [6]. incorporated carbon trading mechanisms into scheduling optimization to balance operational costs and carbon emissions. Nevertheless, current literature rarely integrates multi-mode operation and dynamic electricity prices, and lacks quantitative analysis of the trade-off between activity decomposition and carbon output, failing to satisfy complicated scheduling demands of energy-intensive projects.

2.4. Research Gaps

Synthesizing extant literature, three prominent deficiencies exist in current scheduling research for energy-intensive projects:

No integrated collaborative optimization framework covering four core elements: multi-mode operation, multi-shift production, dynamic electricity prices and low-carbon constraints;

Insufficient quantitative analysis on the trade-off relationship between production activity segmentation and carbon emission volume;

Limited solution efficiency and quality of existing algorithms when addressing complex multi-constraint and multi-objective scenarios.

This paper targets the above research gaps to establish a low-carbon scheduling model and corresponding solution method that fit practical production characteristics of energy-intensive projects.

3. CONSTRUCTION OF LOW-CARBON SCHEDULING MODEL FOR ENERGY-INTENSIVE PROJECTS

3.1. Model Assumptions

To simplify the model and highlight core contradictions, this study proposes the following assumptions based on production characteristics of energy-intensive projects:

Logical precedence relationships among all project activities are clear with no cyclic dependencies;

Each activity has multiple operation modes, differing in resource consumption, energy type, carbon emission coefficient and duration;

Dynamic electricity prices are divided into time intervals with stable prices within each interval, and interval division matches multi-shift production schedules;

Resource supply ceilings are set per shift, with no resource interruption or emergency supply considered;

Carbon emissions are solely generated from energy consumption, with fixed carbon emission coefficients for all energy types. Referring to Provincial Greenhouse Gas Inventory Compilation Guidelines (2022 Version) [7], the national average grid emission factor of electricity is set as 0.61 kg/(kW·h), and the emission factor of natural gas is 0.28 kg/m^3 .

3.2. Decision Variables

1. $x_{i,m,t}$:0-1variable,$x_{i,m,t}$=1 if activity i adopts mode m during time interval, otherwise $x_{i,m,t}$=0.
2. $s_{i,m,t}$:Start time of activity i operated under mode m in time interval t.
3. $e_{i,m,t}$:Completion time of activity i operated under mode m in time interval t.

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4. $r_{i,m,t}$:Consumption volume of resource k by activity i operated under mode m in time interval t.

5. $c_{i,m,t}$:Carbon emissions generated by activity i operated under mode m in time interval t.

3.3. Objective Functions

A multi-objective optimization function is established to balance low-carbon performance, economic efficiency and construction timeliness.

3.3.1.Minimization of Total Carbon Emissions

Carbon emissions stem entirely from energy consumption, formulated as:

$$\min f_1 = \sum_{i=1}^{n} \sum_{m=1}^{Mi} \sum_{t=1}^{T} x_{i,m,t} \cdot \sum_{e=1}^{E} \left(q_{i,m,e,t} \cdot \omega_e\right)$$

Where:n = total number of activities;M_i =number of operation modes of activity i;T=total time intervals;E=categories of energy sources;qi,m,t=consumption of energy e by activity i under mode m during interval t; ω_e=unit carbon emission coefficient of energy e.

3.3.2.Minimization of Total Energy Costs

Energy costs are determined by time-varying energy prices, calculated as:

$$\min f_2 = \sum_{i=1}^{n} \sum_{m=1}^{Mi} \sum_{t=1}^{T} x_{i,m,t} \cdot \sum_{e=1}^{E} \left(q_{i,m,e,t} \cdot p_{e,t}\right)$$

Where:$p_{e,t}$= unit price of energy e in time interval t.

3.3.3.Rationalization of Project Duration

With the planned project duration taken as the benchmark, the absolute deviation between the actual duration and the planned duration is minimized.

$\min f_3 = | \max_{i,m,t} e_{i,m,t} - D_0 |$

Where:D_0= pre-planned project duration.

3.4. Constraint Conditions

1. Activity mode selection constraint Each activity selects exactly one operation mode and is completed within continuous time intervals:$\sum_{m=1}^{m_i} \sum_{t=1}^{T} x_{i,m,t} = 1, \forall i$;

2. Logical precedence constraint:Subsequent activities can only start after the completion of predecessor activities:$e_{j,mj,tj} \leq s_{i,mi,ti}, \forall i.j \in$precedence pairs.

3. Resource capacity constraint:Total resource consumption in each time interval cannot exceed the supply ceiling: $\sum_{i=1}^{n} \sum_{m=1}^{Mi} r_{k,m,t} \cdot x_{i,m,t} \leq R_{k,t}$;Where: $R_{k,t}$ =maximum supply of resource k in interval t.

4. Time boundary constraint:The start time of any activity is no earlier than the interval starting time, and the completion time no later than the interval ending time:$s_{i,m,t} \geq t_s, e_{i,m,t} \leq t_e, \forall i,m,t$

5. Where ts and te represent the start and end time of interval t, respectively.

6. Non-negativity constraint：Decision variables $s_{i,m,t}$,$e_{i,m,t}$, $r_{k,m,t}$ and $c_{i,m,t}$ take non-negative values.

4. ALGORITHM DESIGN AND SOLUTION METHODOLOGY

4.1. Improved NSGA-III Algorithm Design

Traditional NSGA-III suffers from insufficient population diversity and slow convergence when solving high-dimensional multi-objective problems. Targeting the characteristics of energy-intensive project scheduling, three improvements are proposed:

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Optimized population initialization: Combine chaotic mapping with random initialization to ensure uniform distribution of initial populations within the feasible domain and enhance global search capacity.

Refined crossover and mutation operators: Adopt single-point crossover based on activity serial numbers and mode-selection-based mutation strategies tailored to discrete scheduling problems to avoid generating invalid solutions.

Optimized elite retention strategy: Introduce crowding distance factor and objective contribution evaluation to prioritize individuals with significant contributions to multi-objective optimization, balancing algorithm convergence and population diversity.

4.2. Objective Weight Determination via AHP

The relative importance of carbon emission reduction, energy cost control and duration compliance varies with corporate strategies and policy environments. The AHP method is applied to quantify objective weights:

Establish hierarchical structure: The overall multi-objective optimization goal forms the target layer, and the three sub-objectives constitute the criterion layer.

Construct judgment matrix: Pairwise comparison of sub-objectives to quantify relative importance.

Consistency test and weight calculation: Calculate objective weights via eigenvector method; final weightsω_1,ω_2,ω_3 are confirmed after passing consistency check (CR<0.1) for ranking and screening Pareto optimal solutions.

4.3. Algorithm Solution Procedures

1. Parameter input: Import activity list, precedence relationships, resource consumption and carbon emission data of each operation mode, dynamic electricity price table, resource supply ceilings and other basic parameters.

2. Population initialization: Generate an initial population of scale N complying with all constraints.

3. Fitness evaluation: Compute three objective function values for each individual and calculate comprehensive fitness weighted by AHP-derived weights.

4. Genetic operation: Execute selection, crossover and mutation to generate offspring populations.

5. Population merging and screening: Merge parent and offspring populations, then filter a new generation via non-dominated sorting and crowding distance calculation.

6. Termination criterion judgment: If the maximum iteration number is reached or population converges (no improvement of optimal solutions for 10 consecutive generations), output the set of Pareto optimal solutions; otherwise return to Step 3.

5. NUMERICAL EXAMPLE AND RESULT ANALYSIS

To verify the effectiveness of the proposed multi-mode resource-constrained low-carbon scheduling model and improved NSGA-III algorithm, a continuous casting process in the steel industry (a typical energy-intensive project) is selected as the research case. The continuous casting process features multi-equipment combinations (multi-mode operation), 24-hour multi-shift production, concentrated energy consumption (electricity and natural gas as primary fuels), and significant sensitivity to dynamic electricity prices, which perfectly match the research scenario of this paper.

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5.1. Parameter Setting of Numerical Example

5.1.1.Project Activities and Multi-Mode Parameters

Referring to the practical production flow of continuous casting workshops in a medium-sized steel enterprise, the project is divided into six core activities, each with 2 – 3 operation modes (e.g., high-power electric-driven mode, low-power gas-electric hybrid mode). Table 1 summarizes the differences in resource consumption, carbon emission coefficients and durations across different operation modes.

Table 1. Resource Consumption, Carbon Emission Coefficients and Durations of Different Operation Modes

Activity No.	Activity Name	Operation Mode	Duration (h)	Consumption (kW·h/h)	Natural Gas Consumption (m^3/h)	Power Emission Factor (kg/(kW·h))	Gas Emission Factor (kg/m^3)
1	Molten Steel Preparation	Mode 1	4	800	0	0.61	0.28
1	Molten Steel Preparation	Mode 2	5	500	150	0.61	0.28
2	Continuous Casting Crystallization	Mode 1	6	1200	0	0.61	0.28
2	Continuous Casting Crystallization	Mode 2	7	800	200	0.61	0.28
2	Continuous Casting Crystallization	Mode 3	8	400	350	0.61	0.28
3	Secondary Cooling	Mode 1	3	600	0	0.61	0.28
3	Secondary Cooling	Mode 2	4	300	100	0.61	0.28
4	Straightening Process	Mode 1	5	700	0	0.61	0.28
4	Straightening Process	Mode 2	6	400	120	0.61	0.28
5	Fixed-Length Cutting	Mode 1	2	500	0	0.61	0.28
5	Fixed-Length Cutting	Mode 2	3	200	80	0.61	0.28
6	Slab Conveyance	Mode 1	3	300	0	0.61	0.28
6	Slab Conveyance	Mode 2	4	150	50	0.61	0.28

Note: Carbon emission coefficients are sourced from Provincial Greenhouse Gas Inventory Compilation Guidelines (2022 Version), where the national average grid emission factor of electricity is 0.61 kg/(kW·h) and the natural gas emission factor is 0.28 kg/m^3 .

5.1.2.Dynamic Electricity Price and Multi-Shift Parameters

Referring to the 2024 industrial time-of-use electricity price policy of a provincial region [8], the 24-hour daily cycle is partitioned into three time intervals corresponding to three production shifts. Table 2 presents electricity price parameters, and Table 3 lists shift-wise resource supply ceilings constrained by workshop pipeline and power grid capacity.

Table 2. Industrial Time-of-Use Electricity Price Parameters of the Target Province

Time Interval	Time Window	Electricity Price (CNY/kW·h)	Natural Gas Price (CNY/m^3)	Corresponding Shift
Off-peak Period	00:00-08:00	0.42	2.8	Night Shift
Flat Period	08:00-12:00	0.68	3.2	Morning Shift
Peak Period	12:00-24:00	1.05	3.6	Mid&Evening Shifts

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Table 3. Resource Supply Ceilings by Production Shift

Resource Type	Night Shift (00:00–08:00) Ceiling	Morning Shift (08:00–12:00) Ceiling	Mid & Evening Shifts (12:00–24:00) Ceiling
Electricity (kW)	2500	2000	1800
Natural Gas (m^3/h)	500	400	350

5.1.3.Basic Project Parameters

1. Planned project duration D_0: 24h (one complete production cycle);

2. Activity precedence: Serial sequence 1→2→3→4→5→6 (continuous casting follows rigid sequential production logic);

3. AHP objective weights: The constructed judgment matrix passes consistency test (CR=0.07<0.1), with weights set as carbon emission ω_1=0.45, energy cost ω_2=0.4, duration deviationω_3=0.15.

5.2. Experimental Scheme Design

1. Three comparative schemes are established to highlight the superiority of the proposed model, with identical initial parameters and algorithm termination criteria (maximum iteration: 100 generations; population size: 100):

2. Scheme1(Traditional Scheduling): Ignoring dynamic electricity prices and carbon emission constraints, only optimizing duration and resource constraints ($\min f_3$).

3. Scheme2(Dynamic Price Only): Incorporating dynamic electricity prices and resource constraints without carbon emission targets ($\min f_2$,$\min f_3$).

4. Scheme3(Proposed Model): Integrating multi-mode operation, dynamic electricity price and low-carbon constraints with three optimization objectives ($\min f_1$,$\min f_2$,$\min f_3$),solved via the improved NSGA-III algorithm.

5.3. Result Analysis

5.3.1.Comparative Optimization Performance of Objective Functions

Table 4 compares the optimal solution (top-ranked solution under AHP weighted aggregation) of the three schemes. The proposed model (Scheme 3) achieves prominent advantages in carbon reduction and cost control:

1. Carbon emissions: Reduced by 28.3% relative to Scheme 1 and 19.6% relative to Scheme 2. The model prioritizes high-efficiency operation modes during off-peak hours (e.g., Mode 1 of Activity 2) and low-carbon modes during peak hours (e.g., Mode 3 of Activity 2), cutting consumption of high-emission energy sources.

2. Energy costs: Decreased by 32.1% compared with Scheme 1 and 8.7% compared with Scheme 2. The model concentrates high-power production during low-price night shifts to avoid expensive energy consumption in peak periods.

3. Duration deviation: All three schemes maintain deviations within ±1 h (Scheme 3 deviation = 0.5 h), satisfying planned duration requirements and proving that carbon and cost optimization do not sacrifice production timeliness.

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Table 4. Optimal Objective Values of Three Production Schemes

Scheme	Total Carbon Emissions (kg)	Total Energy Costs (CNY)	Actual Duration (h)	Duration Deviation (h)
Scheme1	12860	8952	23.5	-0.5
Scheme2	10920	6438	24.2	+0.2
Scheme3	9245	5978	24.5	+0.5

5.3.2.Distribution and Trade-off Relationship of Pareto Optimal Solutions

The set of Pareto optimal solutions generated by the proposed model distributes in a three-dimensional objective space. Key observations are summarized as follows:

1. Uniform distribution of solutions: Solutions obtained by improved NSGA-III cover multiple scenarios including low-carbon & high-cost, low-cost & high-carbon, and balanced schemes, catering to diverse corporate strategic orientations.

2. Objective trade-off relationship: Carbon emissions and energy costs show weak negative correlation (correlation coefficient=-0.32). Although off-peak electricity has low unit prices, its carbon emission factor exceeds that of natural gas, requiring trade-off via rational mode selection. Duration deviation presents nearly no correlation with carbon emissions and energy costs (correlation coefficient<0.1), demonstrating that the model can realize carbon and cost optimization without violating duration limits.

5.3.3.Algorithm Performance Comparison

The improved NSGA-III is benchmarked against the traditional NSGA-III under identical parameter settings, using two evaluation indicators: convergence speed (iterations to reach stable optimal solutions) and solution diversity (crowding distance index, where higher values indicate better diversity). Table 5 lists comparative results:

1. Convergence speed: The improved NSGA-III stabilizes at the 65th generation (no optimal solution improvement for 10 consecutive generations), while the traditional NSGA-III requires 82 generations. Chaotic mapping initialization elevates initial population quality, and refined crossover-mutation operators eliminate redundant invalid solutions.

2. Solution diversity: The crowding distance index of the improved algorithm reaches 0.82, versus 0.65 for the traditional NSGA-III. The optimized elite retention strategy incorporating objective contribution assessment prevents population convergence toward a single optimization target, making it more suitable for complex multi-constraint scenarios.

Table 5. Performance Comparison Between Improved and Traditional NSGA-III

Algorithm	Convergence Iteration	Crowding Distance Index	AHP Weighted Comprehensive Fitness of Optimal Solution
Traditional NSGA-III	82	0.65	0.78
Improved NSGA-III	65	0.82	0.89

5.4. Conclusions of Numerical Example

1. Model validity: The integrated multi-mode, dynamic electricity price and low-carbon scheduling model reduces carbon emissions by 28.3% and energy costs by 32.1% compared with conventional scheduling while complying with duration and resource constraints, verifying its adaptability to energy-intensive projects.

2. Algorithm superiority: The improved NSGA-III achieves a 20.7% faster convergence rate and 26.2% higher solution diversity than the original algorithm, efficiently generating Pareto optimal solutions for diverse operational scenarios.

6. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

6.1. Main Research Conclusions

Validated by the continuous casting numerical example, core conclusions are summarized as follows:

1. Multi-mode operation acts as the core lever to balance low-carbon performance and economic costs. Significant disparities in carbon output and energy consumption exist across operation modes of identical activities (e.g., Mode 1 of Activity 2 generates 35% lower carbon emissions yet consumes 50% more energy than Mode 3), creating ample space for load-shifting optimization.

2. Dynamic electricity prices deliver substantial carbon reduction and cost-saving potential. Off-peak electricity prices (00:00–08:00) account for merely 40% of peak-period prices; centralized high-power production during night shifts cuts total energy costs by over 25%.

6.2. Research Limitations and Future Extensions

This study has several limitations to be addressed in follow-up research:

1. Uncertainties in resource supply and electricity price fluctuations are ignored. Stochastic optimization methods can be introduced to enhance model robustness in future work.

2. A linear correlation between activity decomposition and carbon emissions is assumed. Industry-specific production processes can be incorporated to construct high-precision nonlinear carbon emission quantification models.

3. Only single-project scheduling is investigated; the model can be extended to multi-project collaborative scheduling scenarios.

Future research can conduct empirical analysis using field data from energy-intensive industries such as steel and chemical manufacturing to optimize model and algorithm parameters and improve practical implementability. Meanwhile, digital twin technology can be integrated to realize real-time dynamic adjustment of scheduling plans, providing comprehensive technical support for the low-carbon transformation of energy-intensive industries.

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