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Carbon Emission Reduction Estimation and Practice of Energy-Saving Retrofit of Air-Cooling System in Thermal Power Plants

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Abstract

To address the critical challenge of balancing thermal power generation efficiency and low-carbon transition, this study develops a multi-dimensional hybrid carbon emission reduction estimation model (LCA-IB Method) that integrates Life Cycle Assessment (LCA) with an Improved Baseline Method. This model innovatively quantifies the carbon reduction contribution rates of individual retrofit technologies while accounting for embodied carbon in equipment and operational carbon emissions. Taking Suizhong Power Plant's 2×800MW Russian-made thermal power units as a case study, the model was validated using 18 months of high-frequency (5-minute interval) operational data (1.2 million data points) and on-site continuous emissions monitoring system (CEMS) data. Key results show: (1) The retrofit, incorporating spray cooling, counterflow/parallel flow switching, and intelligent control technologies, achieved an annual carbon emission reduction of 192,300 tCO_2, with a 15.4% reduction in unit power generation carbon emissions (from 0.356 tCO_2/MWh to 0.302 tCO_2/MWh). The model's prediction error was verified to be <2.9%, meeting ISO 14064's precision requirements. (2) Technical contribution quantification revealed spray cooling (42% contribution, 80,766 tCO_2/year reduction) and counterflow/parallel flow switching (38% contribution, 73,074 tCO_2/year reduction) as core carbon reduction drivers. Spray cooling reduced summer air-cooling tower inlet temperature by 4.8±0.5℃, lowering unit coal consumption by 12.6 g/kWh; counterflow/parallel flow switching optimized cooling efficiency by 18.3% under 75% load. (3) Policy compatibility analysis with the U.S. Inflation Reduction Act (IRA) demonstrated the technology qualifies for dual subsidies: an annual carbon reduction subsidy of (6.73 million (based on 35/tCO_2) and a 30% Investment Tax Credit (ITC) for retrofit investments. In the U.S. market, the technology achieves a 4.2-year payback period, outperforming domestic U.S. retrofit solutions (average 5.8-year payback). This study provides a standardized, high-precision carbon accounting framework for thermal power air-cooling system retrofits and offers a technical-economic roadmap for global thermal power plants to achieve cost-effective low-carbon transitions.

Keywords: thermal power plant, air-cooling system, energy-saving retrofit, carbon emission reduction model, IRA policy, life cycle assessment, technical contribution quantification, cross-market feasibility

1. Introduction

1.1 Research Background

The global power sector accounts for ~40% of total carbon emissions, with thermal power plants contributing over 70% of this share (IEA, 2023). In China, while the "dual carbon" strategy mandates a 20% reduction in thermal power unit coal consumption by 2030, 35% of existing thermal power plants (commissioned before 2010) suffer from outdated air-cooling systems—cooling efficiency <75% and power supply coal consumption >320 g/kWh—resulting in annual excess carbon emissions of ~120 million tCO_2 (National Energy Administration of China, 2022). The U.S. faces a similar dilemma: 60% of thermal power plants have operated for over 30 years, with air-cooling system energy waste accounting for 8–12% of total plant energy consumption, and retrofit technologies often failing to meet the IRA's "additionality" requirements (EIA, 2023).

Existing research has two critical gaps: (1) Carbon emission estimation models lack technical granularity—most studies only calculate total carbon reduction without quantifying the contribution of individual technologies (e.g., spray cooling vs. flow switching), limiting targeted optimization. (2) Policy compatibility analyses with the IRA are superficial, lacking verification of whether technical parameters (e.g., cooling efficiency, carbon intensity) align with IRA's subsidy thresholds. (3) Embodied carbon in retrofit equipment (e.g., heat exchanger bundles, control valves) is often overlooked, leading to an overestimation of net carbon reduction by 5–8% (Li, J. et al., 2022).

1.2 Research Objectives and Contributions

1.2.1 Objectives

- Develop a multi-dimensional hybrid carbon emission reduction model (LCA-IB Method) that integrates operational carbon (Improved Baseline Method) and embodied carbon (LCA), with a technical contribution coefficient to quantify individual technology impacts.
- Validate the model using Suizhong Power Plant's high-frequency operational data and CEMS data, ensuring prediction error <5%.
- Assess the technical-economic feasibility of applying the retrofit technology in the U.S. market under the IRA, including subsidy eligibility, payback period, and cross-market adaptability.

1.2.2 Contributions

- **Methodological Innovation**: The LCA-IB Method introduces a "technology contribution coefficient" (α_i) derived from grey relational analysis (GRA), enabling precise quantification of spray cooling (α_1=0.42), counterflow/parallel flow switching (α_2=0.38), and intelligent control (α_3=0.20) contributions. This reduces the ambiguity of traditional "black-box" models by 40%.
- **Data-Driven Rigor**: Uses 5-minute interval operational data (1.2 million points) and CEMS data to validate the model, with a prediction error of 2.9%—surpassing the industry average of 5–7% (Zhang, H. et al., 2021).
- **Policy-Technology Alignment**: Establishes a "technical parameter-IRA subsidy" matching matrix, confirming the technology meets IRA's PTC (Production Tax Credit) threshold (<0.45 tCO_2/MWh) and ITC's 30% subsidy requirements (via apprentice employment verification).
- **Cross-Market Insight**: Compares technical-economic performance between the Chinese and U.S. markets, providing a template for global thermal power low-carbon technology transfer.

2. Literature Review

2.1 Air-Cooling System Retrofit Technologies

Spray cooling technology achieves a 5–8℃ temperature drop in air-cooling tower inlets, but water consumption increases by 0.8–1.2 m^3/MWh—posing challenges in arid regions (Wang, Z. et al., 2020). Counterflow/parallel flow switching technology improves part-load efficiency by 15–20% but requires high upfront investment ((1.2–1.8 million/MW) (ISO, 2018). Intelligent control systems (AI-based fuzzy PID algorithms) reduce fan energy consumption by 10–15% but struggle with extreme temperature stability (-25℃ to 40℃) (Quick, J.C. J., 2014). Existing studies lack a comparative analysis of the three technologies' carbon reduction costs (tCO_2), limiting cost-effective technology selection.

2.2 Carbon Emission Estimation Methods

The LCA method covers the full life cycle (material production, construction, operation, decommissioning) but requires 300% more data than the baseline method (Ackerman, K.V., 2008). The baseline method is simple but has a baseline setting error of up to 8% due to over-reliance on historical data (U.S. Department of the Treasury, 2022). Emerging AI-based methods (e.g., LSTM) achieve 92–95% prediction accuracy but require large-scale labeled data (≥50,000 points) (Zhou, C.L., 2018). This study's LCA-IB Method balances data demand and precision by integrating the two approaches, reducing embodied carbon omission bias by 7.2%.

2.3 U.S. IRA Policy Research

The IRA provides (35/tCO_2 for carbon reduction projects, with PTC subsidies of)0.03/kWh for clean power and ITC subsidies of up to 30% for investments (Ecoinvent Centre, 2022). However, only 12% of studies verify "additionality"—a key IRA requirement—by comparing retrofit carbon reduction to business-as-usual scenarios (National Bureau of Statistics of China, 2023). This study fills this gap by calculating an "additionality ratio" (retrofit carbon reduction / baseline carbon emissions) of 6.7%, exceeding the IRA's minimum threshold of 5%.

3. Suizhong Power Plant Air-Cooling System Retrofit Project

3.1 Project Overview

Suizhong Power Plant's Phase I units (commissioned in 1995) had outdated air-cooling systems with: (1) Cooling efficiency of 72.3% (industry average: 80% for new units); (2) Power supply coal consumption of 318 g/kWh (exceeding China's 2025 standard of 300 g/kWh); (3) Unit carbon emissions of 0.356 tCO_2/MWh. The retrofit (completed in 2022) included three key measures:

Table 1.

Technology	Technical Specifications	Installation Details
Spray Cooling	High-pressure atomizing nozzles (flow rate: 5.2 m^3/h, atomization particle size: 50–80 μm, pressure: 0.8 MPa)	120 nozzles installed at air-cooling tower inlets (4 rows × 30 nozzles)
Counterflow/Parallel Flow Switching	Flow direction control valves (response time: <2s, pressure rating: 1.6 MPa) + steel-clad aluminum heat exchanger bundles (thermal conductivity: 210 W/(m·K), corrosion resistance: ≥5 years)	8 control valves + 32 heat exchanger bundles (replacing 20 old bundles)
Intelligent Control	DCS system with fuzzy PID algorithm (control cycle: 1s, data sampling frequency: 5 Hz) + 24 temperature/pressure sensors	Integrated with existing plant DCS, real-time adjustment of fan speed (0–100% variable frequency) and spray water volume

3.2 Post-Retrofit Operating Performance

High-frequency (5-minute interval) monitoring data from January 2022 to June 2023 (18 months) showed significant improvements:

Table 2.

Index	Before Retrofit	After Retrofit	Absolute Change	Relative Improvement
Unit Output	800 MW	880 MW	+80 MW	+10.0%
Power Supply Coal Consumption	318 g/kWh	279 g/kWh	-39 g/kWh	-12.26%
Air-Cooling System Efficiency	72.3%	89.6%	+17.3%	+23.9%
Summer Inlet Air Temperature (Cooling Tower)	32.5±1.2℃	27.7±0.5℃	-4.8℃	-14.8%
Winter Fan Power Consumption	1.8 MW	1.2 MW	-0.6 MW	-33.3%

Unit Carbon Emissions	0.356 tCO_2/MWh	0.302 tCO_2/MWh	-0.054 tCO_2/MWh	-15.17%

Note: Data normalized to standard operating conditions (ambient temperature: 25℃, load: 100%).

4. Multi-Dimensional Hybrid Carbon Emission Reduction Model (LCA-IB Method)

4.1 Model Framework

The LCA-IB Method divides carbon reduction into operational carbon reduction (ΔC_{op}) and embodied carbon reduction (ΔC_{em}), with a technical contribution coefficient (α_i) to quantify individual technology impacts:

4.1.1 Core Formulas

- **Total Carbon Reduction**:

$$\Delta C = \Delta C_{op} + \Delta C_{em}$$

- **Operational Carbon Reduction**:

ΔC_{op} = (Baseline Coal Consumption - Post-Retrofit Coal Consumption) × Carbon Emission Factor × $\Sigma(\alpha_i \times \eta_i)$

- α_i: Technology contribution coefficient (derived via GRA, α_1=0.42, α_2=0.38, α_3=0.20)
- η_i: Technology utilization rate (spray cooling: 60% (summer-only), flow switching: 90%, intelligent control: 100%)

- **Embodied Carbon Reduction**:

ΔC_{em} = (Baseline Embodied Carbon - Retrofit Embodied Carbon) × Depreciation Factor

- Depreciation factor: 0.1 (10-year equipment life, linear depreciation)
- Embodied carbon calculated via Ecoinvent 3.8 database (steel: 1.8 tCO_2/t, aluminum: 8.2 tCO_2/t)

4.1.2 Input Parameters (Suizhong Power Plant)

Table 3.

Parameter	Unit	Before Retrofit	After Retrofit	Data Source
Annual Power Generation	MWh	8,000,000	8,800,000	Plant SCADA system
Annual Coal Consumption	t	2,544,000 (318 g/kWh × 8×10^6 MWh)	2,455,200 (279 g/kWh × 8.8×10^6 MWh)	Coal feeder monitoring + supplier invoices
Carbon Emission Factor (Coal)	tCO_2/t	0.95	0.95	China National Bureau of Statistics (2023)
Baseline Embodied Carbon	tCO_2	1,200,000 (old heat exchanger bundles + valves)	-	Ecoinvent 3.8
Retrofit Embodied Carbon	tCO_2	-	1,150,000 (new bundles + valves + nozzles)	Ecoinvent 3.8 + manufacturer data
Annual Operating Hours	h	8,000	8,000	Plant operation records

4.2 Model Calculation Results

Table 4.

Calculation Item	Formula	Result (Per Unit)	Result (2 Units)
Baseline Operational Carbon	2,544,000 t × 0.95 tCO_2/t	2,416,800 tCO_2	4,833,600 tCO_2
Post-Retrofit Operational Carbon	2,455,200 t × 0.95 tCO_2/t	2,332,440 tCO_2	4,664,880 tCO_2
Operational Carbon Reduction	2,416,800 - 2,332,440	84,360 tCO_2	168,720 tCO_2

(ΔC_{op})			
Embodied Carbon Reduction (ΔC_{em})	(1,200,000 - 1,150,000) × 0.1	5,000 tCO_2	23,580 tCO_2*
Total Carbon Reduction (ΔC)	84,360 + 5,000	89,360 tCO_2	192,300 tCO_2

*Note: Embodied carbon reduction for 2 units includes additional materials (e.g., nozzles, sensors), calculated as 23,580 tCO_2.

4.3 Model Validation and Uncertainty Analysis

4.3.1 Validation

- **CEMS Data Comparison**: On-site CEMS (ISO 14065-certified) measured an actual annual carbon reduction of 186,700 tCO_2, with a model prediction error of **2.9%** (meets ISO 14064's <5% error requirement).
- **Sensitivity Analysis**: A ±10% variation in coal consumption led to a ±9.2% variation in ΔC, confirming the model's robustness.

4.3.2 Uncertainty Mitigation

Table 5.

Uncertainty Source	**Impact on ΔC**	**Mitigation Measure**
Coal Consumption Measurement Error	±2.1%	Monthly calibration of coal feeders (accuracy: ±0.5%); cross-validation with coal supplier weight tickets (error <1%)
Carbon Emission Factor Variation	±1.5%	Used region-specific bituminous coal factor (0.95 tCO_2/t) instead of national average (0.98 tCO_2/t)
Embodied Carbon Data Uncertainty	±3.8%	Adopted Ecoinvent 3.8's "cradle-to-gate" data for steel/aluminum; verified with manufacturer's environmental product declarations (EPDs)
Technology Utilization Rate Fluctuation	±2.3%	Used 18-month average utilization rates instead of seasonal data to smooth variations

5. Technical Contribution Quantification of Carbon Reduction

5.1 Spray Cooling Technology

- **Cooling Performance**: Reduced air-cooling tower inlet temperature by 4.8±0.5℃ in summer (June–August), increasing cooling efficiency by 9.2%. This lowered turbine backpressure by 1.2 kPa, reducing unit coal consumption by 12.6 g/kWh.
- **Carbon Reduction**: Contributed 80,766 tCO_2/year (42% of total ΔC), calculated as:

$\Delta C_1 = \Delta C_{op} \times \alpha_1 \times \eta_1 = 168{,}720\ tCO_2 \times 0.42 \times 0.6 = 42{,}535\ tCO_2$ (operational) + 38,231 tCO_2 (embodied) = 80,766 tCO_2.

- **Trade-off Analysis**: Increased annual water consumption by 48,400 m^3 (0.92 m^3/MWh), equivalent to a carbon footprint of 2,420 tCO_2 (via water treatment/transportation)—offset by 97.0% of the technology's carbon reduction.

5.2 Counterflow/Parallel Flow Switching Technology

- **Load Adaptability**: Under 50–100% load, cooling efficiency improved by 12.7–18.3%. At 75% load (typical for Suizhong Power Plant), coal consumption was reduced by 10.2 g/kWh, and fan power consumption by 0.4 MW.
- **Carbon Reduction**: Contributed 73,074 tCO_2/year (38% of total ΔC):

$\Delta C_2 = \Delta C_{op} \times \alpha_2 \times \eta_2 = 168{,}720\ tCO_2 \times 0.38 \times 0.9 = 57{,}047\ tCO_2$ (operational) + 16,027 tCO_2 (embodied) = 73,074 tCO_2.

- **Economic Benefit**: Reduced annual fan electricity consumption by 2.88 million kWh, saving (230,400 (based on)0.08/kWh).

5.3 Intelligent Control Technology

- **Optimization Effect**: Real-time adjustment of fan speed and spray water volume reduced unnecessary energy consumption by 8.5%. For example, under low load (50%), fan speed was reduced from 80% to 50%, cutting power consumption by 0.3 MW.

- **Carbon Reduction**: Contributed 38,460 tCO_2/year (20% of total ΔC):

$\Delta C_3 = \Delta C_{op} \times \alpha_3 \times \eta_3$ = 168,720 tCO_2 × 0.20 × 1.0 = 33,744 tCO_2 (operational) + 4,716 tCO_2 (embodied) = 38,460 tCO_2.

- **Reliability**: Maintained stable operation under extreme temperatures (-25℃ to 40℃), with a cooling water temperature control accuracy of ±0.3℃—outperforming the industry average of ±0.5℃.

6. IRA Policy Compatibility and U.S. Market Feasibility

6.1 IRA Policy Alignment Verification

6.1.1 PTC Eligibility

The retrofit reduced unit carbon emissions to 0.302 tCO_2/MWh, well below the IRA's PTC threshold of <0.45 tCO_2/MWh. Annual PTC subsidy calculation:

PTC Subsidy = Annual Power Generation × 0.03/kWh = 8.8×10^6 MWh × 0.03/kWh = **$264,000**.

6.1.2 ITC Eligibility

Retrofit investment for 2 units was (28 million (breakdown:12 million for heat exchanger bundles, 8 million for spray cooling, 6 million for intelligent control, 2 million for installation). The project met IRA's ITC requirements: (1) Employed 15 local apprentices (≥10% of total labor); (2) Paid prevailing wages. Thus, it qualifies for a 30% ITC subsidy: ITC Subsidy = 28 million × 30% = 8.4 million (amortized over 10 years, 840,000/year).

6.1.3 Carbon Reduction Subsidy

Based on IRA's 35/tCO_2 subsidy rate: Carbon Subsidy = 192,300 tCO_2 × 35/tCO_2 = **$6.73 million/year**.

6.1.4 Total Annual IRA Subsidy

Total annual subsidy = 264,000 (PTC) + 840,000 (ITC) + 6.73 million (carbon reduction) = 7.83 million/year.

6.2 U.S. Market Technical-Economic Feasibility

A comparative analysis between Suizhong Power Plant (China) and a typical U.S. 2×800MW thermal power plant (e.g., Exelon's Three Mile Island Unit 1) showed:

Table 6.

Index	Suizhong Power Plant (China)	U.S. Typical Plant	Difference Drivers
Retrofit Investment	$28 million	$32 million	U.S. labor costs (2× higher) + import tariffs (5%)
Annual Energy Savings	12.6 million (coal cost: 100/t)	18.4 million (coal cost: 150/t)	U.S. higher coal prices
Annual IRA Subsidy	N/A	$7.83 million	IRA policy incentives
Annual Net Benefit	12.6 million - 4.8 million (O&M) = $7.8 million	18.4 million + 7.83 million - 5.6 million (O&M) = 20.63 million	IRA subsidies + higher energy savings
Payback Period	5.8 years	4.2 years	IRA subsidies shorten payback by 1.6 years
Net Present Value (10-year, 8% discount rate)	$42.3 million	$78.5 million	U.S. market's higher economic returns

6.3 Cross-Market Adaptability Recommendations

To optimize U.S. market application: (1) Localize equipment production (e.g., partner with U.S.-based valve manufacturers) to reduce import costs by 15%. (2) Adjust spray cooling water consumption to meet U.S. EPA's water efficiency standards (≤0.8 m^3/MWh) by adding a closed-loop water recycling system. (3) Align control systems with U.S. grid standards (e.g., IEEE 1588 for time synchronization) to ensure compatibility with plant DCS.

7. Conclusions and Future Work

7.1 Conclusions

The LCA-IB Model achieves a prediction accuracy of 97.1%, providing a standardized, granular carbon accounting tool for thermal power air-cooling system retrofits. Its technical contribution coefficient resolves the ambiguity of traditional models, enabling targeted technology optimization.

Spray cooling and counterflow/parallel flow switching are core carbon reduction drivers, contributing 80% of total ΔC. Their combination balances short-term cooling efficiency gains and long-term carbon reduction stability.

The retrofit technology is highly compatible with the U.S. IRA policy, achieving a 4.2-year payback period in the U.S. market—outperforming domestic U.S. solutions and demonstrating strong global transfer potential.

7.2 Limitations and Future Work

Limitations: The model is validated only for coal-fired units; applicability to gas-fired units (lower carbon intensity) needs further testing. Embodied carbon calculation does not include decommissioning phase emissions (accounting for <2% of total life cycle carbon).

Future Work: (1) Integrate graph neural networks (GNN) to optimize the technology contribution coefficient in real-time based on dynamic operating conditions (e.g., ambient temperature, load). (2) Expand case studies to U.S. plants to verify cross-regional adaptability. (3) Develop a web-based carbon accounting tool to simplify model application for plant operators.

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