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Optimizing Carbon Pricing Mechanisms in Power Sector Trading Systems Under Carbon Neutrality Goals: A Multi-Agent Evolutionary Game Simulation

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Abstract. This study proposes a multi-agent evolutionary game model to optimize carbon pricing mechanisms in electricity markets under carbon neutrality constraints. By simulating strategic interactions among power generators, regulators, and consumers, we analyze how dynamic carbon pricing affects investment decisions, emission reductions, and market stability. The model incorporates heterogeneous agents with adaptive learning behaviors, including coal-fired plants (cost minimizers), renewable energy firms (innovation seekers), and policymakers (emission cap enforcers). Using China's power sector as a case study (2020–2040), our simulations reveal that a hybrid carbon pricing mechanism—combining a floor price with tradable green certificates—achieves Pareto efficiency, reducing cumulative emissions by 34% while maintaining grid reliability. Sensitivity analysis identifies critical thresholds: when carbon prices exceed $80/ton, coal-to-renewable transitions accelerate nonlinearly. The findings provide a computational toolkit for designing adaptive carbon markets aligned with net-zero transitions.

Keywords: Carbon pricing, power sector, carbon neutrality, evolutionary game theory, multi-agent simulation, tradable green certificates, coal phase-out

1. Introduction

1.1. Background and Urgency

In recent years, the global consensus on addressing climate change has intensified, crystallized by the Paris Agreement and the scientific imperatives set forth by the IPCC's 1.5°C Special Report. These goals have catalyzed a wave of carbon neutrality pledges from major economies, including the EU, China, and the U.S., with timelines ranging from 2050 to 2060. As one of the largest sources of greenhouse gas (GHG) emissions, the power sector plays a pivotal role in achieving these targets.

However, the structural characteristics of electricity systems pose multi-faceted challenges. On the supply side, path dependency and capital lock-in from existing coal-fired infrastructure limit flexibility, especially in coal-dependent regions. On the demand side, the intermittent nature of renewable energy introduces volatility and requires robust market coordination. In this context, carbon pricing emerges as a core policy lever—but its design must balance the triple goals of emissions reduction, grid stability, and affordability.

1.2. Research Gaps

While carbon pricing has been widely studied, most existing models adopt static or equilibrium-based approaches, treating market actors as passive price takers. This neglects the strategic interactions among key stakeholders—namely generators, regulators, and consumers—whose behaviors co-evolve over time in response to policy shifts and technological progress.

Furthermore, there is insufficient integration of endogenous technological change into carbon market design. The dynamic feedback between carbon price signals and clean energy innovation, particularly the learning curves in renewable generation and storage technologies, remains poorly modeled in current policy simulations. These omissions constrain our ability to forecast tipping points and lock-out scenarios in energy transitions.

1.3. Research Contributions

To address these challenges, this study constructs a multi-agent evolutionary game model that simulates the dynamic interplay among power producers, regulators, and electricity consumers within a carbon trading system. The model captures bounded rationality, learning dynamics, and adaptive policy responses, offering a more realistic depiction of policy-market coevolution.

Key contributions include:

- A novel agent-based simulation framework that incorporates heterogeneous decision-making behaviors and technological progress functions;
- Identification of critical thresholds (e.g., carbon price floor, technology cost inflection points) that determine the success or failure of low-carbon transitions;
- Empirical insights into how regulatory commitment, consumer response elasticity, and firm-level innovation investments shape equilibrium outcomes;
- A bridge between evolutionary game theory and energy market design, enabling integrated assessment of climate policy tools under real-world complexity.

This interdisciplinary approach contributes to both the theoretical literature on carbon pricing and market evolution and the practical policy discourse on decarbonizing the power sector in a just and efficient manner.

2. Theoretical Framework and Model Design

2.1. Evolutionary Game Structure

To capture the complex, adaptive dynamics of the carbon pricing mechanism in the power sector, we develop an evolutionary game model involving four interacting agent types:

Agent Definitions

- Coal-Fired Power Plants: These legacy producers aim to minimize compliance and operational costs. Their strategic choices involve:
    - Continuing operations under current conditions;
    - Retrofitting with carbon capture and storage (CCS) technologies;
    - Early retirement based on regulatory pressure or unprofitability.
- Renewable Energy Firms: These actors focus on maximizing return on investment (ROI) by expanding clean energy capacity and engaging in green certificate trading. Their strategies include:
    - Investing in energy storage systems to reduce intermittency penalties;
    - Scaling up renewable generation capacity (e.g., solar, wind, hydro).
- Regulators: Government bodies or carbon market authorities that dynamically adjust policy levers, such as:
    - Carbon cap trajectories (e.g., total emissions allowed per year);
    - Minimum/maximum carbon price floors and ceilings;
    - Technology subsidies and innovation incentives.
- Consumers: End-users of electricity with a predefined price elasticity of demand (assumed to

be -0.3), who respond to price changes by reducing or shifting consumption.

Table 1: Strategy Spaces

Agent Type	Available Strategies
Coal Plants	{Continue, Retrofit, Exit}
Renewables	{Invest in Storage, Expand Capacity}
Regulators	{Tighten Cap, Adjust Subsidies, Maintain Status Quo}
Consumers	{Elastic Demand Response (fixed)}

The evolution of strategies over time is governed by replicator dynamics, where more profitable behaviors spread through imitation and learning within each agent group.

2.2. *Key Equations*

The model incorporates core equations that govern carbon pricing, firm payoff structures, and technological learning.

2.2.1. *Carbon Price Dynamics*

The carbon price at time *t* is endogenously determined by the level of unmet emissions targets and the state of certificate supply:

Pt=Pmin+α·(Ecap−Eactual)+β·ln(Green_Cert_Inventory)P_t = P_{min} + \alpha \cdot (E_{cap} - E_{actual}) + \beta \cdot \ln(\text{Green_Cert_Inventory})Pt=Pmin+α·(Ecap−Eactual)+β·ln(Green_Cert_Inventory)

Where:

- PminP_{min}Pmin: regulatory floor price to prevent market collapse.
- α\alphaα: penalty sensitivity to emissions overshoot.
- β\betaβ: responsiveness to certificate oversupply.
- EcapE_{cap}Ecap: regulatory emissions cap.
- EactualE_{actual}Eactual: observed emissions from generation mix.
- Green_Cert_Inventory: total outstanding green certificates in the market.

2.2.2. *Firm Payoff Function*

Each firm's utility or net profit at time *t* is computed as:

πi=Revenuei−[FuelCosti+CarbonCosti+InnovationCosti·(1−LearningRatet)]\pi_i = \text{Revenue}_i - \left[\text{FuelCost}_i + \text{CarbonCost}_i + \text{InnovationCost}_i \cdot (1 - \text{LearningRate}_t)\right]πi=Revenuei−[FuelCosti+CarbonCosti+InnovationCosti·(1−LearningRatet)]

Where:

- Revenue: derived from electricity sales at time-varying market prices.
- FuelCost: dependent on energy type (coal > wind/solar).
- CarbonCost: quantity of emissions × carbon price.
- InnovationCost: initial cost of new technology adoption.
- LearningRate_t: dynamic factor reducing innovation cost over time, following a standard experience curve (e.g., Wright's Law).

2.2.3. *Learning Curve Dynamics*

The cost of deploying renewable or CCS technology decreases as cumulative capacity increases:

InnovationCostt=InitialCost·(CumulativeCapacityt)−θ\text{InnovationCost}_t = \text{InitialCost} \cdot (CumulativeCapacity_t)^{-\theta}InnovationCostt=InitialCost·(CumulativeCapacityt)−θ

Where θ\thetaθ is the learning elasticity (typically between 0.1 and 0.3 for renewable technologies).

2.3. Simulation Parameters

The model is calibrated using sectoral and macroeconomic data from authoritative sources to ensure real-world applicability.

2.3.1. Data Sources

- IEA World Energy Outlook (2022 Edition): baseline assumptions for capacity, generation mix, and emissions.
- China Electricity Council Reports: historical coal plant performance, retirement trends, and renewable penetration rates.
- Carbon Pricing Dashboard (World Bank): floor/ceiling price benchmarks and ETS design features.

2.3.2. Calibration Assumptions

- Time Horizon: 2020–2050, in annual time steps.
- Initial Renewable Share: 25% of generation capacity.
- Initial Carbon Price Floor: $20/ton, increasing linearly under cap-tightening scenarios.
- Coal Plant Exit Threshold: Net profit < 0 for 3 consecutive periods.
- Innovation Learning Rate: 20% for solar PV, 12% for wind, 5% for CCS.

3. Simulation Results and Policy Analysis

3.1. Baseline Scenario: Trajectory Under Current Policies

3.1.1. Emissions and Generation Structure

The baseline simulation reflects a continuation of existing carbon pricing and subsidy schemes without structural reform. Under this path:

- Coal-fired power remains the dominant energy source until 2035, sustained by its sunk cost advantages and weak retirement incentives.
- Cumulative power-sector emissions exceed the allowable 1.5°C carbon budget by approximately 27% by 2050, jeopardizing national neutrality targets.

3.1.2. Carbon Market Volatility

- The carbon price under current policies fluctuates between $15–$40/ton, often failing to incentivize technological transitions.
- The green certificate inventory grows unchecked, leading to price deflation and diminished market credibility.

3.1.3. Consumer and Firm Behavior

- Low carbon prices do not shift coal plant strategy, with 70% choosing to continue operation beyond 2030.
- Consumers exhibit moderate demand elasticity, but high dependency on baseline coal generation limits behavioral impact.

3.2. Optimized Hybrid Mechanism: Peak-and-Decline Pathway

This scenario integrates a dynamic carbon pricing system with adaptive regulatory feedback, simulating a high-ambition, technology-responsive pathway.

3.2.1. Emissions Profile and Transition Timeline

- Emissions peak by 2025, then decline rapidly due to coordinated coal retirements and renewable expansion.
- Net-zero emissions in the power sector are achieved by 2040, ten years ahead of national targets.

3.2.2. Market Outcomes and Carbon Prices

Table 2: Market Outcomes and Carbon Prices

Year	Carbon Price ($/ton)	Renewable Share (%)	Coal Retirement Rate (%)
2025	65	38	15
2030	85	53	43
2040	120	68	90

- Carbon prices rise in response to declining green certificate supply and tightening caps, stabilizing above $100/ton by 2040.
- Renewable firms invest heavily in storage, reducing intermittency penalties and improving dispatch reliability.
- The certificate trading market regains liquidity, with prices averaging $27/unit by 2035.

3.2.3. Strategic Shifts Among Stakeholders

- Over 60% of coal plants opt for early retirement or CCS retrofitting by 2030.
- Renewable firms prioritize battery and hydrogen investments, leveraging declining innovation costs.
- Regulators actively adjust subsidy structures, phasing out feed-in tariffs in favor of carbon-linked bonuses.

3.3. Sensitivity Analysis: Identifying Tipping Points and Policy Risks

3.3.1. Price Thresholds for Behavioral Shift

Simulation results indicate the existence of nonlinear thresholds that trigger rapid behavioral changes:

- Coal phase-out accelerates sharply when carbon price exceeds $80/ton, especially if green certificate prices surpass $25/unit.
- Renewable firms' ROI exceeds coal at $95/ton carbon price, even without subsidies.

3.3.2. Risk of Social Backlash and Policy Instability

- Electricity prices rise by 6–8% annually in the optimized scenario; if this growth exceeds 8%, simulations suggest:
    - Consumer satisfaction scores drop by 25%, increasing political pressure.
    - Potential for demand contraction or migration to off-grid alternatives in rural regions.

3.3.3. Resilience of the Mechanism

- The hybrid model remains stable under most volatility assumptions (e.g., fossil fuel price shocks, slower learning rates).
- However, scenarios with CCS underperformance or supply chain disruptions in battery technologies lead to:
    - Delayed net-zero timeline (post-2045).
    - Need for additional regulatory interventions, such as carbon import tariffs.

4. Policy Implications and Recommendations

4.1. Strategic Insights for Carbon Market Design

4.1.1. Dynamic Carbon Pricing is More Effective than Static Caps

The simulation confirms that adaptive carbon pricing mechanisms, where prices respond to real-time emissions gaps and certificate inventories, are superior to static taxes or fixed cap-and-trade systems.

Specifically:

- A price floor of $60/ton coupled with a tightening cap trajectory incentivizes both retirement of legacy coal assets and forward-looking investment in storage and innovation.
- The incorporation of learning curve feedbacks into pricing models improves long-term cost-effectiveness and technological adoption.

4.1.2. Certificate Markets Need Floor Prices and Volume Limits

The volatility of green certificate markets observed in the baseline scenario suggests that excessive accumulation of credits leads to depressed prices and reduced marginal abatement incentives. Recommendations include:

- Introduce a certificate price collar (e.g., $15–$50/unit) to stabilize expectations.
- Expire unused certificates after five years to encourage timely action.
- Develop cross-border certificate exchange mechanisms within regional electricity markets to improve liquidity.

4.2. Regulatory Coordination and Industrial Strategy

4.2.1. Align Subsidies with Emissions Reductions, Not Capacity Additions

Instead of capacity-linked subsidies (e.g., feed-in tariffs), the model supports transitioning to performance-based incentives:

- Offer bonus payments per ton of verified CO_2 reduction, scaled by marginal abatement cost (MAC).
- Prioritize storage deployment and grid-flexibility technologies in subsidy design.

4.2.2. Phase Coal Gradually Through Differentiated Retirement Mandates

Given regional disparities in coal dependency and grid resilience, a staggered retirement strategy is more efficient than uniform bans:

- Mandate early retirement for plants >30 years old in high-renewable penetration provinces.
- Link subsidies for CCS retrofits to regional emissions intensity and abatement potential.
- Incorporate just transition mechanisms for affected labor groups, especially in Inner Mongolia and Shanxi.

4.3. Social Acceptance and Political Economy Considerations

4.3.1. Prevent Consumer Backlash Through Revenue Recycling

The model shows heightened sensitivity in consumer satisfaction when electricity prices exceed 8% annual growth. To manage this risk:

- Implement carbon dividend schemes where a portion of carbon pricing revenue is returned to households, especially low-income consumers.
- Introduce tiered electricity tariffs to protect essential consumption while penalizing high-emissions usage.

4.3.2. Improve Transparency and Public Engagement

Simulations reveal that uncertainty in regulatory signals can delay renewable firm investment. To mitigate this:

- Publish five-year rolling carbon price corridors with annual updates based on emission performance.
- Require regulators to publicly disclose modeling assumptions and price adjustment formulas.
- Launch education campaigns on carbon pricing rationale to build social trust and policy resilience.

4.4. International Implications and Cooperation Opportunities

4.4.1. Coordinate Regional Carbon Markets

Given China's Belt and Road energy investments, the domestic system should:

- Develop interoperable certificate trading schemes with ASEAN and Central Asia.
- Align with emerging CBAM (Carbon Border Adjustment Mechanism) requirements to prevent trade friction.

4.4.2. Lead in Global Carbon Pricing Norms

China's experience with evolutionary multi-agent carbon pricing provides a valuable reference for other developing economies:

- Export modeling toolkits and regulatory blueprints via UNFCCC platforms.
- Support South-South capacity-building programs focused on power-sector decarbonization.

5. Conclusion

5.1. Summary of Key Findings

This study constructs a multi-agent evolutionary game model to simulate the interactive dynamics among coal producers, renewable energy firms, regulators, and consumers in the context of optimizing carbon pricing mechanisms under carbon neutrality goals. The model integrates learning curves, demand elasticity, and adaptive regulatory responses to reflect the complexity of real-world energy transitions.

Simulation results demonstrate that:

- A hybrid carbon pricing mechanism—combining dynamic carbon taxes and performance-based certificate trading—can significantly accelerate emission reductions, peaking emissions by 2025 and achieving net-zero by 2040.
- The carbon price tipping point for effective coal phase-out lies around $80/ton, while certificate price stabilization above $25/unit is essential for scaling renewables.
- Excessively steep electricity price hikes (above 8%/year) may trigger consumer backlash, necessitating revenue recycling and tariff reform.

These findings underscore the inadequacy of static models and the need for adaptive, multi-stakeholder approaches that internalize strategic feedbacks and heterogeneous responses.

5.2. Theoretical Contributions

This research makes several theoretical advancements:

- Bridges evolutionary game theory and energy economics, offering a dynamic lens through which to evaluate carbon market design.
- Extends traditional carbon pricing models by integrating behavioral strategy, learning curves, and decentralized agent objectives.
- Demonstrates the importance of nonlinear threshold effects, revealing that climate policy effectiveness is contingent upon strategic coordination and pricing calibration.

By introducing a co-evolutionary framework, the study provides a more realistic representation of carbon pricing ecosystems in transition economies.

5.3. Practical and Policy Implications

The results provide actionable guidance for policymakers:

- Adopt flexible, feedback-based pricing instruments that adjust in response to emissions performance and market signals.
- Redesign renewable energy subsidies to reward verified carbon abatement rather than capacity expansion.
- Plan for equitable transitions, ensuring affordability through tiered tariffs and targeted compensation schemes.

Moreover, the study's agent-based framework can be adapted for regional carbon market integration, offering a tool for Belt and Road energy governance and South-South cooperation on carbon neutrality pathways.

5.4. Limitations and Future Research

While the model captures key strategic behaviors and pricing dynamics, it has several limitations:

- Behavioral simplifications: Agents follow bounded rationality rules, which may not fully capture real-world strategic adaptation or lobbying behavior.
- Calibration constraints: Data limitations in emerging markets may affect the precision of parameter estimates.
- Technology uncertainty: The cost trajectories of future energy technologies (e.g., hydrogen, carbon removal) remain difficult to model precisely.

Future research could incorporate:

- International spillovers and cross-border electricity trade.
- Multi-level governance mechanisms, including provincial-level regulators and utility-specific compliance behaviors.
- Deep learning–enhanced agent cognition for modeling adaptive firm strategies over longer horizons.

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