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A Bidirectional Coupling Study on Carbon Emission Forecasting and Energy Planning for Zero-Carbon Industrial Parks: A Case Study of a Chemical Park in Northern China

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Abstract. Industrial parks are a major source of carbon emissions in China, and their zero-carbon transition is critical for achieving the dual-carbon goals. However, existing carbon emission forecasting models of parks commonly suffer from a lack of interpretability, making it difficult to establish clear links between predictions and specific mitigation measures. This paper develops a top-down carbon emission forecasting model based on an extended Kaya identity, decomposing park carbon emissions into five macro-level parameters: park area, land use type, output value per unit area, energy intensity, and carbon intensity. A chemical park in Northern China is selected as an empirical case for validation. The results demonstrate that the proposed model exhibits strong interpretability and policy alignment, providing clear decision-making support for zero-carbon energy planning in industrial parks.

1 Introduction

At the 75th session of the United Nations General Assembly in 2020, China proposed to peak its carbon emissions in 2030 and achieve carbon neutrality by 2060. It marks that the peak of carbon emissions and the achievement of carbon neutrality coming to be a major national strategy [1]. As the core unit that aggregates intensive industrial activities, industrial parks play a significant role in facilitating the manufacturing industry and economic–social development [2]. Massive resource and energy consumption, together with intensive production processes, leads to abundant CO2 emissions. It makes industrial parks a key focal point for China's energy conservation and emission reduction efforts [3-6].

In June 2025, the National Development and Reform Commission (NDRC), the Ministry of Industry and Information Technology (MIIT), and the National Energy Administration (NEA) jointly issued the "Notice on Carrying out the Construction of Zero-Carbon Parks." This notice explicitly supports qualified regions in taking the lead in establishing a number of zero-carbon parks and publishes the basic construction conditions, an indicator system.

To achieve the goal of zero-carbon parks, the primary task is to accurately assess the current state of energy consumption and carbon emissions, and to conduct forward-looking carbon emission forecasts [7-8]. Carbon emission accounting helps parks identify major emission sources, while forecasting provides quantitative support for decomposing emission reduction targets and determining peak carbon pathways [9]. Together, they form the technical foundation for zero-carbon park planning.

However, carbon emission forecasting at the park scale currently faces significant methodological defections. On the one hand, traditional top-down models, often based on macroeconomic data, struggle to capture the emission details and heterogeneity of the meso-scale level of an industrial park [10]. More critically, existing forecasting models, especially those based on machine learning, commonly suffer from a lack of interpretability. Although these models can output predictions, they cannot easily reveal the key drivers of emission changes. This leads to a weak logical connection between the formulation of key mitigation tasks and the prediction results, thereby undermining the practical value of these models for guiding low-carbon planning in parks.

To address these issues, this paper constructs a top-down carbon emission forecasting model based on an extended Kaya identity. Selecting a chemical park in Northern China as an empirical subject, and targeting zero-carbon park completion before 2030. This research establishes a baseline scenario and a near-zero carbon scenario, and proposes key tasks and measures to achieve near-zero carbon goals, aiming to provide a methodological reference and practical guidance for the zero-carbon planning of similar chemical parks.

2 Methods

2.1 Total Carbon Emission Calculation

The carbon emission accounting in this paper follows the "Zero-Carbon Park Carbon Emission Accounting Method (Trial)" appended to the "Notice on Carrying out

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the Construction of Zero-Carbon Parks."[11] The accounting boundary encompasses the sum of direct and indirect carbon emissions from energy activities E_{EA}, and industrial processes E_{IP} within the park's geographic boundary over a calendar year.

$$E=E_{EA}+E_{IP} \tag{1}$$

Carbon emissions from energy activities comprise three parts: emissions from fossil fuels E_{FF}, emissions from energy processing and conversion processes E_{PC}, and indirect emissions embedded in the net import of electricity and heat E_{EH}.

$$E_{EA} = E_{FF} +E_{PC}+E_{EH} \tag{2}$$

Emissions from fossil fuels used as fuel E_{FF}, calculated using the activity data AD_i and emission factor EF_i. Emissions from energy processing and conversion processes E_{PC}, which are calculated based on the carbon balance principle, that is, the difference in carbon content between the input energy and the output energy. Indirect emissions embedded in the net import of electricity and heat E_{EH}, are calculated as the difference between the emissions embedded in the intake volume and the output volume of electricity and heat, respectively, and then summing these two results.

$$E_{EF} =\sum AD_i\times EF_i \tag{3}$$

$$E_{PC} =AD_i\times EF_i - AD_j\times EF_j \tag{4}$$

$$E_{EH} =E_{EI}-E_{EO}+E_{HI}-E_{HO} \tag{5}$$

The emission factor for grid electricity is based on the national fossil fuel power emission factor (0.8325 kg CO_2/kWh). For renewable electricity supplied via direct green power connection or green certificate trading, the emission factor is set to zero. The emission factor for heat can use the default value (0.11 tCO_2/GJ), while the emission factor for non-fossil heat is set to zero.

Industrial process carbon emissions cover major products such as cement clinker, lime, synthetic ammonia (anhydrous ammonia), methanol, primary aluminum (electrolytic aluminum), crude steel, ferroalloys, industrial silicon, and calcium carbide. Industrial process carbon emissions E_{IP} calculated using the Product Output AD_p and emission factor per unit of product EF_p.

$$E_{IP} =\sum AD_p\times EF_p \tag{6}$$

2.2 Carbon Emission Forecasting

The conventional Kaya identity is suitable for large-scale applications (e.g., nations, provinces) but has limitations when applied at the park scale [12-13]. To address this, this research extends and adapts the original Kaya identity in two ways [14-15].

First, based on land use attributes, the park is divided into industrial land, residential land, and service land, broadening the original identity's framework to better capture the functional heterogeneity of industrial parks.

Second, the original variables are replaced to better suit park-level characteristics. Given that population data has low correlation with park carbon emissions, whereas land area better reflects industrial scale, population is replaced by park area. Furthermore, since output value data is more readily obtainable than gross domestic product (GDP) at the park level, GDP is replaced by gross industrial output value.

Through these adaptations, a top-down forecasting method based on the extended Kaya identity is constructed, decomposing the influence factors of park carbon emissions into park area, land type (industrial and non-industrial), economic, energy intensity, and carbon intensity.

$$E' = E'_{ind}+ E'_{non-ind} \tag{7}$$

$$E'_{ind} = A\times r\times g_{ind}\times e_{ind}\times CI_{ind} \tag{8}$$

$$E'_{non-ind}= A\times s\times e_{non-ind}\times CI_{non-ind} \tag{9}$$

Where the subscript E' denotes the carbon emission forecast value; E'_{ind} and $E'_{non-ind}$ are carbon emissions from industrial land and non-industrial land, respectively; A is total park area; r is proportion of operational industrial land; g_{ind} is output value per unit area of industrial land; e_{ind} is energy consumption per unit output of industrial land; CI_{ind} is carbon emissions per unit of energy consumption on industrial land; s is proportion of non-industrial land; $e_{non-ind}$ is energy consumption per area of non-industrial land; $CI_{non-ind}$ is carbon emissions per unit of energy consumption on non-industrial land.

2.3. Data Sources

The data for this study are derived from three categories:

- Basic data of 2022-2024, including total park area, proportion of operational land, industrial output value, and energy consumption by fuel type, were obtained from the park's management committee, the Municipal Development and Reform Commission, and the Municipal Statistics Bureau, supplemented by field survey data.
- Future projections for output growth rate, land development progress, and industry introduction plans were set based on field survey data and the park's development master plan.
- Emission factors and standard coal conversion coefficients were adopted from the "Zero-Carbon Park Carbon Emission Accounting Method (Trial)" and the "China Energy Statistical Yearbook."

3 ANALYSIS AND CALCULATION

3.1. Park Overview

This research selects a chemical park in Northern China as the empirical subject. It has a planned total area of approximately 20 km², with a built-up area of about 5 km². The park's leading industry is fine chemicals, focusing on sub-sectors like chemical raw materials, chemical product manufacturing, and pharmaceutical manufacturing. By 2024, the park housed over 50 enterprises, achieving an annual industrial output value exceeding 5 billion CNY.

Regarding energy infrastructure, the park currently sources its electricity entirely from the public grid, with no on-site renewable power generation facilities. A centralized heating project has not yet been completed. Instead, enterprises rely on decentralized boilers (coal-fired, gas-fired, and biomass-fired) to provide heat for production processes. This infrastructure profile results in high indirect carbon emissions from grid electricity consumption and significant direct emissions from fossil fuel combustion, highlighting the urgent need for a transition towards a cleaner and more centralized energy supply system.

3.2. Energy Consumption and Carbon Emission Profile

From 2022 to 2024, driven by rapid industrial expansion, the park's total energy consumption showed significant growth. Total energy consumption exceeded 100,000 tce in 2024, a three-year increase of approximately 114% (Figure 1). The energy mix is dominated by electricity and raw coal, with a notable acceleration in electrification over the past three years (Figure 2).

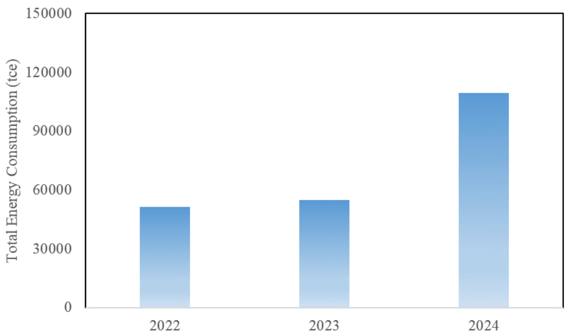

Fig. 1. Total Energy Consumption of the park in 2022-2024

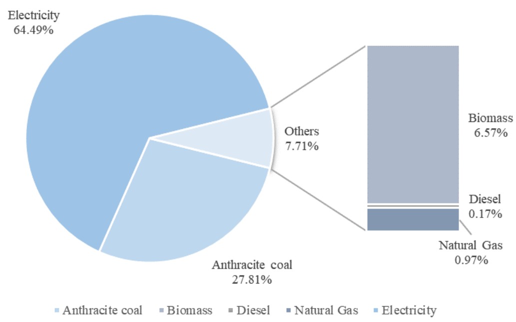

Fig. 2. Energy Consumption Structure of the park in 2024

Consistent with energy trends, total carbon emissions continued to rise, exceeding 300,000 tCO_2 in 2024, a 146% increase from 2022. Regarding the emission structure, indirect emissions from net electricity import are the primary source, accounting for about 62% (Figure 3). Emissions from industrial processes represent only about 1%, mainly from by-product reactions in formaldehyde production and the use of carbonates as desulfurizing agents.

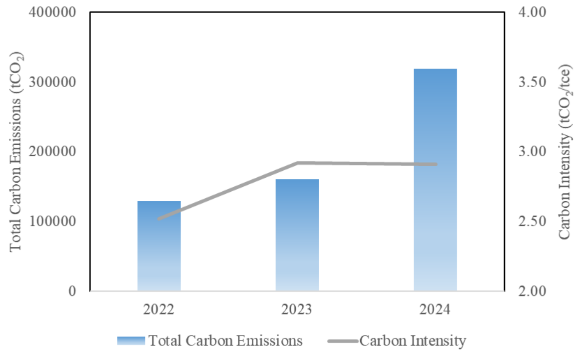

Fig. 3. Carbon emission and carbon intensity of the park in 2022-2024

3.3. Carbon Emission Forecasting

The park consists exclusively of industrial land with no residential or commercial service land uses. Therefore, carbon emissions from non-industrial land are not applicable, and the forecasting focuses solely on emissions from industrial land.

The Baseline Scenario assumes the park continues its traditional, extensive development model, accepting the transfer of energy-intensive industries for short-term economic growth. It continues its current energy structure without substantive clean energy substitution or efficiency improvements. The key parameters for the prediction are presented in Table 1. Under this scenario, total energy consumption would rise rapidly from ~130,000 tce in 2024 to ~840,000 tce in 2030. Total carbon emissions would climb from ~310,000 tCO_2 in 2024 to ~1,850,000 tCO_2 in 2030, an average annual growth rate of ~35% and a 500% increase from the base year. Energy intensity per unit of output remains high, and carbon intensity per unit of energy only decreases slightly from 2.35 to 2.20 tCO_2/tce, showing no decoupling and making peak carbon targets unattainable.

The Near-Zero Carbon Scenario assumes the park implements strict industrial access and stock optimization policies, raising equipment efficiency requirements for incoming projects. The energy system prioritizes clean energy, maximizes renewable energy integration, and promotes electrification and efficiency improvements across buildings, transport, and industry [16-17]. The key parameters for the prediction are presented in Table 2. This scenario targets meeting national zero-carbon park standards by 2030. Here, total energy consumption grows to ~680,000 tce due to industrial growth. However, emissions peak in 2025 (~470,000 tCO_2) before declining to ~140,000 tCO_2 by 2030, a 92% reduction compared to the baseline scenario. Carbon intensity per unit of energy drops sharply from 2.35 to 0.20 tCO_2/tce (a 91% reduction), achieving a substantive decoupling of economic growth from carbon emissions.

The comparison of the two scenario results is shown in Figure 4. Under the baseline scenario, the park's carbon emissions increase year by year, reaching over 1.8 million tCO_2 by 2030. Under the near-zero carbon scenario, emissions peak in 2027 and then decline annually, dropping to approximately 130,000 tCO_2 by 2030.

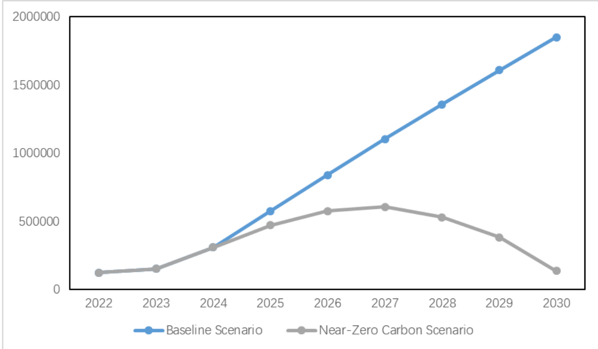

Fig. 4. Carbon emission prediction trend from 2025-2030 under the baseline scenario and the near-zero carbon scenario

Table 1. Carbon emission forecasting under the baseline scenario

Year		2025	2026	2027	2028	2029	2030
Park Area (ha)		2014	2014	2014	2014	2014	2014
Proportion of Operational Industrial Land (%)		28.20	32.50	36.90	41.30	45.60	50.00
Output Value (million CNY)		11752.75	17402.20	23051.65	28701.10	34350.55	40000.00
Output Value Per Unit Area (million CNY /ha)		20.69	26.59	31.02	34.51	37.40	39.72
Energy Consumption Per Unit Output (tce/ million CNY)		21	21	21	21	21	21
Carbon Intensity (tCO_2/tce)		2.33	2.30	2.28	2.25	2.23	2.20
Total Energy Consumption (tce)		247101.7	365068.1	484082.0	603202.5	720835.9	840001.1
Total Carbon Emission (tCO_2)		575746.9	839656.5	1103706.9	1357205.6	1607464.1	1848002.5
Energy Structure	Coal	23.90%	23.90%	23.90%	23.90%	23.90%	23.90%
	Oil	0.10%	0.10%	0.10%	0.10%	0.10%	0.10%
	Gas	9.90%	9.90%	9.90%	9.90%	9.90%	9.90%
	Electricity	60.50%	60.50%	60.50%	60.50%	60.50%	60.50%
	Green Electricity	1.03%	2.00%	3.03%	4.05%	5.02%	6.05%
	Heat	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Biomass	5.50%	5.50%	5.50%	5.50%	5.50%	5.50%

Table 2. Carbon emission forecasting under the near-zero carbon scenario

Year		2025	2026	2027	2028	2029	2030
Park Area (ha)		2014	2014	2014	2014	2014	2014
Proportion of Operational Industrial Land (%)		26.50%	29.20%	31.90%	34.60%	37.30%	40.00%
Output Value (million CNY)		10752.75	15402.20	20051.65	24701.10	29350.55	34000.00
Output Value Per Unit Area (million CNY /ha)		20.15	26.19	31.21	35.45	39.07	42.20
Energy Consumption Per Unit Output (tce/ million CNY)		21	21	21	20	20	20
Carbon Intensity (tCO_2/tce)		2.09	1.78	1.44	1.07	0.65	0.2
Total Energy Consumption (tce)		225807.8	323446.2	421084.7	494022.0	587011.0	680000.0
Total Carbon Emission (tCO_2)		471938.2	575734.2	606361.9	528603.5	381557.2	136000.0
Energy Structure	Coal	16.00%	12.00%	8.00%	4.00%	0.00%	0.00%
	Oil	0.10%	0.10%	0.00%	0.00%	0.00%	0.00%
	Gas	7.60%	6.40%	5.30%	4.10%	3.00%	3.00%
	Electricity	70.00%	74.80%	79.50%	84.30%	89.00%	89.00%
	Green Electricity	21.70%	34.78%	49.29%	65.33%	82.77%	82.77%
	Heat	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Biomass	6.40%	6.80%	7.20%	7.60%	8.00%	8.00%

3.4. Integrated Energy Supply Plan

3.4.1 Bidirectional Iterative Feedback Mechanism

To establish a true bidirectional coupling between the forecasting model and the energy supply plan, an iterative feedback mechanism is implemented. The process begins with the forecasting model generating initial parameter targets based on the near-zero carbon scenario. An initial energy supply plan is then formulated accordingly. If resource constraints or technical limitations render the initial plan infeasible, the planning results are fed back to the forecasting model, which adjusts the relevant parameters. This iteration continues until both the carbon emission targets and the energy supply constraints are satisfied.

The iterative process for this case study proceeded as follows:

Based on the forecast results, the park's annual electricity demand is 1.7 billion kWh and its heat demand is approximately 3.5 million GJ by 2030. Following a cost-priority principle, it is initially assumed that the entire heat demand will be met by centralized biomass heating, requiring a biomass heating capacity of approximately 3.5 million GJ. Concurrently, based on the electricity load forecast, two 300 MW wind power projects are preliminarily planned, providing approximately 1.7 billion kWh of green electricity annually. However, further assessment reveals that the total available biomass resources around the park can only support approximately 1.5 million GJ of heating capacity, rendering the initial plan infeasible due to resource constraints.

The biomass resource constraint (1.5 million GJ) is fed back to the forecasting model. The remaining heat deficit (2.0 million GJ) must be covered by electric boilers, which increases electricity demand by approximately 0.5 billion kWh, raising the park's total electricity demand. To meet this increased electricity demand, the wind power capacity is expanded from 600 MW to 800 MW. Recalculated using the forecasting model, carbon emissions remain below 140,000 tCO_2, satisfying the near-zero carbon target. The iteration thus terminates.

3.4.2 Finalized Energy Supply Plan

Through this bidirectional iterative feedback mechanism, a dynamic coupling relationship is established between the forecasting model and the energy supply plan, ensuring that the final energy supply plan satisfies both carbon emission constraints and resource feasibility.

Leveraging abundant local wind resources, the plan includes two 400 MW wind power projects with direct green power connection. Assuming 2,900 annual utilization hours, they would generate 2.32 billion kWh/year, fully covering the park's 2030 electricity demand of approximately 2.2 billion kWh. A biomass cogeneration plant (2×90 t/h boilers, 2×20 MW turbines) is planned, providing approximately 1.5 million GJ of heat and 250 million kWh/year of electricity. Electric boilers supplies an additional 2 million GJ of heat. To manage the high proportion of variable wind power, a 200 MW/800 MWh energy storage project and a 200 MW/800 MWh grid-forming standalone storage station are planned to smooth output fluctuations and reduce curtailment.

4. Conclusion and recommendations

4.1. Research Conclusion

This research constructed a top-down carbon emission forecasting model based on an extended Kaya identity for a chemical park in Northern China and developed an integrated energy supply plan based on the forecast results. The main conclusions are:

The top-down forecasting model demonstrates strong interpretability and policy alignment. By decomposing park carbon emissions into five macro-level parameters—park area, operational land ratio, output per unit area, energy intensity, and carbon intensity—each with a clear economic meaning and direct link to specific energy planning measures, this method addresses the interpretability flaw of "black-box" models. This creates a clear logical chain linking forecast results to energy supply plans. For example, the target of achieving >93% green electricity share by 2030 directly drove the planning of the two 400 MW wind projects; the target of reducing carbon intensity per unit energy to 0.20 tCO_2/tce directly determined the scale of energy storage and the clean heating plan.

Northern industrial parks possess the resource base to accommodate the transfer of energy-intensive industries from Southern China. The case study park, located in a region rich in wind and biomass resources, can leverage these endowments. The proposed integrated plan (direct green power, biomass cogeneration, waste heat recovery, storage) can meet the new energy demand from industrial transfers while achieving a 92% reduction in carbon emissions and a 91% reduction in carbon intensity per unit energy by 2030 compared to the baseline. This demonstrates that Northern industrial parks are well-positioned to host energy-intensive industries from the South, creating a replicable model for coordinating industrial relocation with zero-carbon transition nationwide.

4.2. Recommendations

While this study has advanced carbon forecasting and energy planning for industrial parks, several avenues for future research remain. The forecasting model employed here is primarily top-down, focusing on macro-level parameters. This allows for rapid assessment of land development and economic growth targets but does not incorporate bottom-up, granular factors related to specific industrial sectors, production processes, or end-use equipment.

Future research should focus on coupling top-down and bottom-up methods. This could involve establishing a systematic bidirectional coupling mechanism, where macro-level targets and constraints set by a top-down model are dynamically iterated with detailed simulations of production activities and mitigation potentials from a bottom-up model. Such an integrated approach would significantly improve forecast accuracy and decision-support capabilities.

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