# Economic analysis and impact assessment of electricity supply and demand-side emission reductions in China under carbon neutrality goals

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## Abstract

The power sector is one of the largest carbon emitters in China, and faces non-linear cost impacts from different emission reduction measures across regions with varying electricity demand characteristics. In this study we analyze the effects and cost-efficiency of supply-side and demand-side emission reduction pathways by classifying Chinese provinces into four categories. This is accomplished through integration of the NEMO (Next Energy Modeling System for Optimization) and the LEAP (Low Emissions Analysis Platform), i.e., LEAP-NEMO. Applying this method, our results show that urbanization will likely drive stable growth in residential electricity demand, while industrial development will vary regionally. Resource-rich regions require wind and solar energy as foundational methods to decarbonize their mix of electricity sources, whereas areas with limited natural resources need nuclear energy and alternative energy generation technologies to mitigate supply gaps. Furthermore, we find that delaying the emission peak year raises marginal carbon reduction costs and the cumulative cost per unit of carbon abatement. A rate of 1.5% reduction in energy intensity is the most cost-effective for the majority of regions.

**Keywords:** Power systems; LEAP-NEMO; Clean energy transition; Energy consumption

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## Highlights

- ✧ Regions in China are categorized based on electricity supply and demand characteristics
- ✧ The distribution of natural resources across regions is considered in the analysis
- ✧ Carbon emission constraints are applied in the modeling of carbon neutrality goals
- ✧ Energy intensity sensitivity is used as an assessment metric for emission reduction

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# 1. Introduction

Greenhouse gas emissions have contributed to global warming, resulting in a global surface temperature increase of 1.1 ℃ above pre-industrial levels during the period of 2011-2020 (IPCC, 2023). Human-induced climate change has caused widespread adverse effects on food and water security, human health, economic systems, and societal structures, resulting in significant losses and damages to both natural ecosystems and human communities. As one of the largest contributors to $CO_2$ emissions, China has pledged to stop increasing its carbon emissions by 2030 and achieve carbon neutrality by 2060 (Li et al., 2022). The electricity sector is a major contributor to carbon emissions in China, being responsible for over 50% of the country's total coal consumption (China Electricity Council, 2021). Specifically, coal-fired power generation alone comprises approximately 43% of China's total $CO_2$ emissions (Yu et al., 2021). This highlights the need for sustainable alternatives in the electricity generation sector to mitigate environmental impacts. The National Development and Reform Commission (NDRC, 2022) proposed accelerating the green and low-carbon transition of the Chinese energy sector. The objective of the "14th Five-Year Plan for a Modern Energy System" is to establish a new type of power system by optimizing the electrical grid through the integration of supply- and demand-side measures. Reforms on the supply side promote the development of renewable energy industries (Elsisi and Abdelfattah, 2020; Yap et al., 2020; Wang et al., 2023; Guo et al., 2023), while demand-side management aims to minimize energy dissipation (Besagni et al., 2020). Both strategies are fundamental for achieving carbon neutrality in the power sector. However, determining the optimal integration of these control measures to reduce $CO_2$ emissions in the power system remains a significant challenge.

Prevailing supply-side research methodologies are increasingly adopting more sophisticated and flexible approaches. This evolution has broadened the analytical

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scope, shifting from a sole focus on electrical power equilibrium to consideration of carbon emission constraints. The main objective of most studies has been to achieve optimal flexibility while minimizing costs within these limitations (Cai et al., 2022; Handayani et al., 2022, 2023). For instance, Awopone et al. (2017) utilized the OSeMOSYS (Open Source Energy Modelling System) in conjunction with the LEAP (Low Emissions Analysis Platform) to examine the least-cost development of a system under a no-policy-change scenario, specifically exploring optimal energy generation strategies for Ghana from 2010 to 2040. Furthermore, Shrestha et al. (2019) employed the HOMER (Hybrid Optimization Model for Electric Renewables) to establish various electricity supply models that meet the dynamic power demands of remote areas, and conducted an analysis focusing on energy costs. They found that one of the main reasons for high electricity generation costs was the surplus of power generated during periods of demand. Also, Ma et al. (2021) proposed a novel model and optimal dispatch for combined heat and power with a power-to-gas (P2G) and carbon capture system. In addition, Wang et al. (2020) adopted a multiscale framework to optimize wind farm layouts without altering electricity demand. However, the above studies have not accounted for the constraints of renewable energy resources in different regions. Meanwhile, the Next Energy Modeling System for Optimization (NEMO) stands out as capable of representing such multiple objective constraints.

The primary approach of demand-side research has been to forecast electricity consumption through the synergistic optimization of various low-carbon power technologies and emission reduction strategies (Ming et al., 2024; Sheikhi et al., 2016). For example, Zhou et al. (2023) proposed a novel hierarchy for electricity demand influencers based on a $CO_2$ emission intensity constraint within the industrial sector, and forecasted electricity demand under various policy constraint scenarios. Moreover, Rao et al. (2024) adopted an optimal economic framework for electricity demand forecasting, calibrating historical GDP statistics with a nighttime light dataset.

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Later, they developed an error correction model based on electricity data to predict electricity consumption trends in the Pearl River Delta region in China under different carbon emission scenarios. In another study, Wu et al. (2021) analyzed the energy demand and carbon emissions in the Yangtze River Delta region in China from 2020 to 2050 under different energy transition scenarios.

Recent studies have explored the synergistic coupling effects between supply and demand in power systems (Zhou et al., 2023). Existing literature has extensively focused on energy supply and demand optimization for individual regions or countries, utilizing a variety of methods. For instance, Liu et al. (2022) comprehensively accounted for the spatiotemporal variations of wind and solar power generation in China, instantaneous electricity demand across various societal sectors, land use, government policies, and renewable energy development strategies. They applied a MILP (Mixed-Integer Linear Programming) model to optimize the configuration of wind and solar systems within each grid, including the location and installed capacity of wind and photovoltaic power plants, and evaluated the economic costs and environmental benefits of different solutions. In addition, Jia et al. (2022) established a dynamic multi-objective optimization model, optimizing the power generation structure to align with future development scenarios in China. This approach explored the optimal pathways for carbon emissions, economic growth, and energy consumption within the context of differing scenarios. Moreover, Yang et al. (2023) constructed a novel integrated two-stage emissions reduction model, emphasizing joint emissions reduction from both the demand and supply sides. However, the studies above were primarily based on localized optimization or short-time-scale models, and did not systematically analyze the variability and feasibility of coordinated strategies across regions with varying electricity supply and demand characteristics. In contrast to previous studies, we adopt the integrated LEAP-NEMO framework, which enables systematic modeling of energy system dynamics across extended temporal scales. In terms of policy evaluation, we explore the independent

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optimization of demand-side and supply-side measures, and further analyze their synergistic effects in different scenarios. In this way, the similarities and differences between different types of regions in achieving the lowest cost emission reduction pathways are revealed.

To this end, we categorize 31 provinces and cities in China into four representative regions based on their electricity supply and demand profiles, enabling a regionally variable analysis. We assess the effectiveness and economic feasibility of various emission reduction strategies on both the supply and demand sides within these regions, providing insights that may aid policy promoting China's carbon neutrality goals. The novelty of this study lies in three main aspects: i) developing a regional classification framework based on electricity supply and demand features to analyze the impact of heterogeneity on emission pathways; ii) proposing integrated supply-demand optimization methods for cost-effective emissions reductions; iii) assessing the impact of different peak carbon emission timelines on the cost of achieving net-zero carbon emissions. The remainder of the paper is organized as follows: Section 2 introduces the methodology, including subject categorization, the employed model framework, and the calculation principles. This section also covers the settings of various scenarios and the sources of input data for the model. Section 3 involves investigation of changes in power generation structure, shifts in sector-specific consumption, and carbon reduction costs, as well as a sensitivity analysis of energy intensity. Finally, strategic recommendations for achieving carbon neutrality in China are proposed in Section 4.

# 2. Region classification and methodology

## 2.1. Region classification

Based on median values of electricity generation and demand data, we classified the 31 provincial-level administrative regions in China into four distinct categories, as illustrated in Fig. 1. Note that LH stands for the low generation and high demand region, HH stands for the high generation and high demand region, LL stands for the low generation and low demand region, and HL stands for the high generation and

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low demand region. Shandong stands out as the province with the highest electricity supply and demand in China, while Tibet is the region with the lowest. Detailed electricity generation and demand data for each province are given in Table S1.

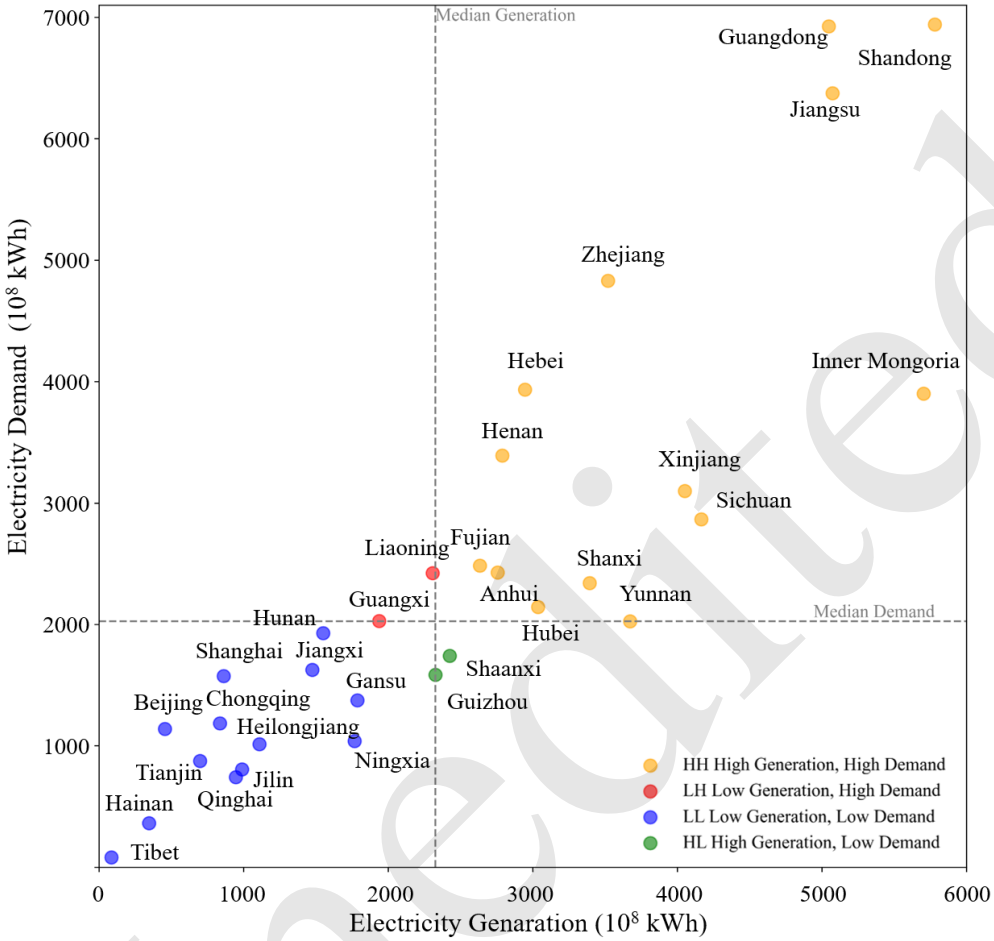


**Fig. 1** Classification of regions according to electricity generation and demand

Fig. 2 presents the geographical distribution of the four studied regions. From the perspective of regional economy and electricity demand, high demand regions (HH and LH) are predominantly concentrated in the economically developed eastern coastal provinces (e.g., Guangdong, Jiangsu, Zhejiang) and certain inland core cities (e.g., Sichuan). These areas are characterized by dense industrial clusters, high population density, and strong economic activity, leading to substantial electricity consumption. In contrast, low demand regions (HL and LL) are primarily distributed in the relatively underdeveloped northwestern and northeastern regions, where economic output and population density are comparatively lower. Regarding resource endowment and power generation capacity, high generation regions (HH and HL),

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such as Inner Mongolia and Shanxi, leverage abundant coal resources and large-scale thermal power installations to achieve high electricity output. Meanwhile, southwestern provinces like Yunnan and Sichuan have capitalized on their rich hydropower resources to become hubs for clean energy generation. Conversely, some core provinces (e.g., Beijing and Shanghai), which are constrained by limited natural resources and/or stringent environmental policies, exhibit lower local power generation capacity and thus heavily depend on external electricity transmission to meet demand.

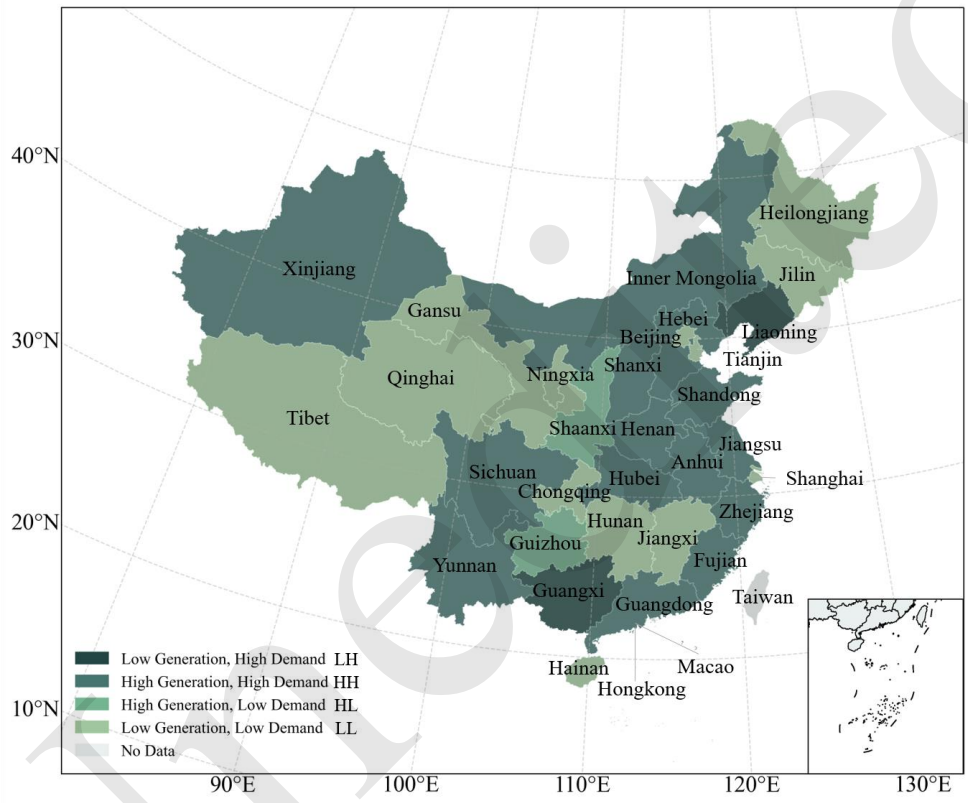


**Fig. 2** Geographical distribution of the four Chinese regions classified by electricity characteristics

## 2.2 Model framework

This study employs LEAP-NEMO, which integrates the open-source energy system optimization tool NEMO (Next Energy Modeling System for Optimization) into the original LEAP (Low Emissions Analysis Platform) framework. The calculation of LEAP encompasses end-use demand analysis, energy transformation calculations, transmission loss analysis, environmental emission impact estimations,

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as well as cost-benefit analysis (Heaps, 2022). An explanation of the processes involved in LEAP can be found in Fig. S1. The modeling framework and key inputs of LEAP-NEMO used in this study are illustrated in Fig. 3. The LEAP model serves as the foundation of this research, and is primarily focused on describing three core parameters of the energy system: electricity generation, energy transformation, and end-use energy demand. The end-use energy demand encompasses multiple industries and sectors, including agriculture, industry, construction, TSAP (Transportation, Storage, and Postal), WRTHC (Wholesale and Retail, Trade, Hotel, and Catering Services), residential services, and so on. On the other hand, electricity generation focuses on aspects such as energy load shape, process efficiency, capacity credit, maximum availability, and equipment lifetime. Based on these parameters, we use LEAP to construct energy models for the four different types of regions.

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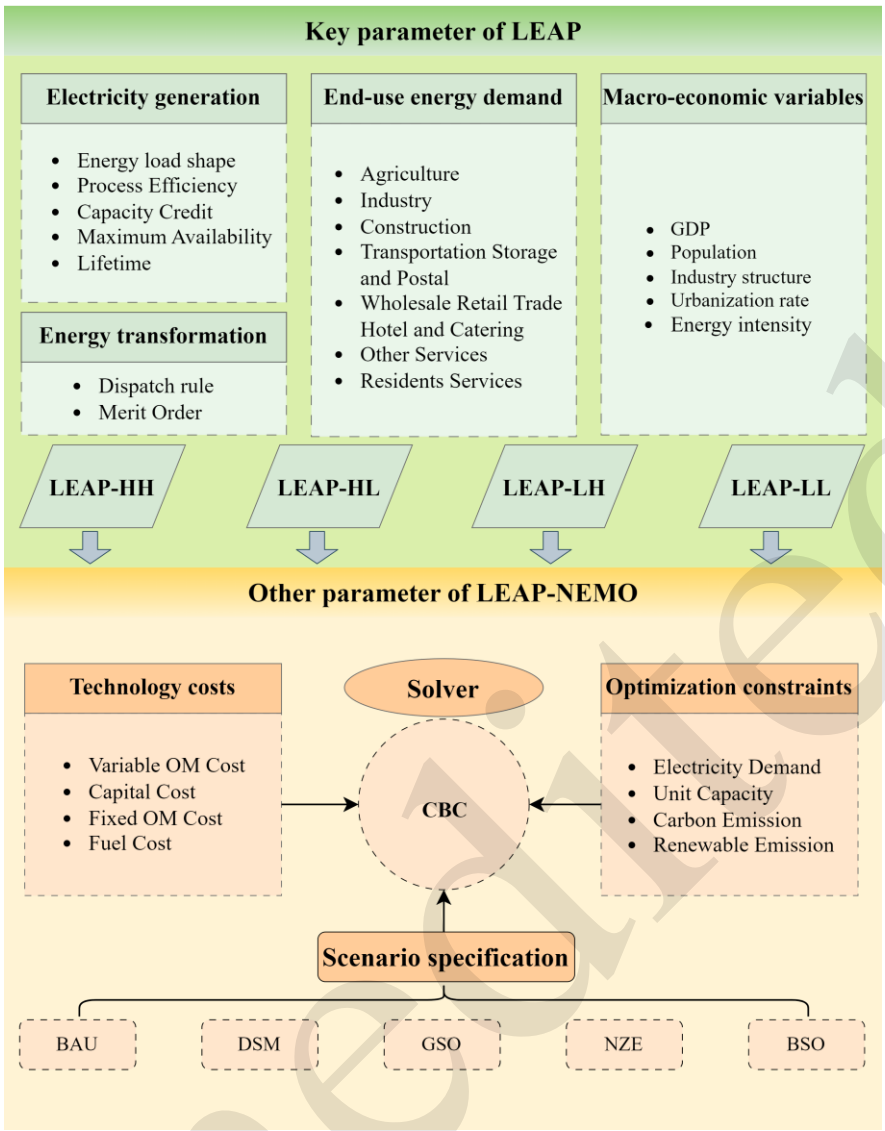


**Fig. 3** The modeling framework and key inputs of LEAP-NEMO

The NEMO module is integrated into the LEAP model to enable advanced optimization analysis of the energy system. LEAP-NEMO aims to minimize the total social cost of the system. The required inputs for technical costs include Variable OM (Operation and Maintenance) Cost, Capital Cost, Fixed OM Cost, and Fuel Cost. The optimization process is constrained by several factors, including electricity demand, unit capacity, carbon emissions, and renewable energy emissions. The model defines multiple future scenarios to evaluate carbon emission pathways and their associated mitigation costs under various supply- and demand-side emission reduction strategies. To determine the planning and optimization of the power generation structure, NEMO integrates multiple solvers, such as CBC (Coin-or Branch and Cut), CPLEX (IBM ILOG CPLEX Optimizer), and DLPK (Dual Linear Programming Kit), which provide efficient computational support for the optimization of the energy system.

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## 2.3. Calculation principles

### 2.3.1 Population projection

A survival transition matrix was constructed based on the actual population status of the statistical region (Wang, 2018):

$$nP_{t_2}(x+n) = nP_{t_1}(x) \times nL(x+n) / nL(x) \tag{1}$$

where $x$ ranges from 0 to 100 years old, $nP_{t1}(x)$ represents the number of people aged [$x$, $x$+$n$] at time $t_1$, and $nP_{t2}(x+n)$ is the number of people aged [$x$+$n$, $x$+2$n$] at time $t_2$. $nL(x)$ is the number of person-years lived by those exactly aged [$x$, $x$+$n$] in the cohort, and $nL(x+n)$ represents the number of person-years lived by those exactly aged [$x$+$n$, $x$+2$n$] in the cohort.

The fertility model is established based on the survival transition matrix:

$$P_{t_2}(0) = L(0)/2 \times \sum[nP_{ft_1}(x) \times nF(x) + nP_{ft_1}(x) \times nF(x+n) \times nL(x+n) / nL(x)] \tag{2}$$

Here, $P_{t2}(0)$ represents the number of people aged 0 at time $t_2$, and $nP_{ft1}(x)$ is the number of women aged [$x$, $x$+$n$] at time $t_1$, with $x$ ranging from [15, 49]. $nF(x)$ and $nF(x+n)$ represent the fertility rates of women of childbearing age between ages [$x$, $x$+$n$] and [$x$+$n$, $x$+$2n$], respectively.

The total population at $t_2$ is:

$$TP_{t_2} = \sum nP_{t_2}(x) \tag{3}$$

where $nP_{t2}(x)$ represents the number of individuals aged [$x$, $x$+$n$] at time $t_2$.

### 2.3.2 The cost of electricity generation

The method for calculating the total cost $TC$ of electricity generation is presented as follows (Cai et al., 2022):

$$TC = \sum_{j}^{n} (fc_j \times Ca_j + foc_j \times Ca_j + Vc_j \times P_j + E_j) \tag{4}$$

where $fc_j$ denotes the capital cost of power technology $j$. $foc_j$ is the fixed O&M cost, $Ca_j$ is the installed capacity, and $Vc_j$ is the variable cost. $P_j$ represents the power generation and $E_j$ represents the fuel cost.

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### 2.3.3 Marginal cost for carbon emission reduction

The marginal cost of carbon reduction $C_{MA}$ is defined as the ratio of the additional cost $\Delta C$ to the amount of carbon reduction $\Delta R$ incurred from implementing emission reduction technologies, relative to a baseline scenario (Schäfer et al., 2016). The specific formula for this quantity is:

$$C_{MA} = \Delta C / \Delta R \tag{5}$$

The marginal cost growth rate for carbon reduction *CR* refers to the rate of increase in the marginal cost of carbon reduction by a specified year. Its expression is:

$$CR = \left(Ev / Sv\right)^{\frac{1}{n}} - 1 \tag{6}$$

where *Ev* and *Sv* respectively represent the marginal cost of carbon reduction at the specified end year and start year, and *n* denotes the difference in years.

The total cost per unit of carbon reduction $TC_{ucr}$ refers to the cumulative marginal cost of carbon reduction over a given period of time. Its specific formula is:

$$TC_{ucr} = \int_t C_{MA}(t) \cdot dt \tag{7}$$

### 2.3.4 Model optimization constraints

To solve the MILP problems in the model, we selected the CBC solver. CBC employs a Branch-and-Bound algorithm as its core framework (Wolsey, 2020). As such, it systematically explores all possible solution candidates but uses branching to subdivide the problem domain, progressively narrowing the search range and using upper and lower bounds to exclude areas that cannot contain the optimal solution. We utilize the heuristic BestBound branching strategy, along with activating the strong cutting plane strategy during the solution process in the CBC solver. These algorithmic choices are designed to improve computational efficiency and effectively address the complexities of the optimization problem. The optimization objective function is as follows:

The terminal electricity demand *SD* is the sum of the actual electricity demands of various industries, which can be expressed as:

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$$SD = \sum_i AL_i \times EI_i \tag{8}$$

where $AL_i$ represents the activity levels of electricity consumption in various sectors, and $EI_i$ represents the energy intensity of the corresponding activity.

The first type of constraint is the electricity demand, which is that the power transformation $PG$ (i.e., the power supply) needs to meet the terminal electricity demand $SD$:

$$PG = \sum_j pg_j = \sum_j IC_j \times CC_j \times MA_j \geqslant SD + \sum_j SL_j \tag{9}$$

$$SL_j = pg_j \times l_j \tag{10}$$

$$CC_j \times MA_j \leqslant CF_j \tag{11}$$

Here, $pg_j$ represents the actual power supplies of different types, $IC_j$ represents the installed capacity, $CC_j$ denotes the capacity credit, $MA_j$ refers to the maximum availability, $SL_j$ indicates the transmission losses for various types of power generation, $l_j$ is the corresponding transmission loss rate, and $CF_j$ refers to the upper limit of the operating rate.

The second type is the unit capacity constraint, which means that the total installed capacity of the region should meet the annual maximum load demand of the power system, in order to ensure safe and stable operation of the system.

$$\sum_j IC_j \times (1 + RM) \geqslant LD \tag{12}$$

In this expression, $RM$ refers to the reserve margin, and $LD$ is the annual maximum load demand.

The third type is an emission constraint, wherein the $CO_2$ emissions of the power system need to reach net-zero by 2060, while also meeting the desired carbon emission peak.

$$\begin{cases} GHG_{2060} = 0 & (13) \\ GHG_{2030} \geqslant GHG_y, y \in [2020, 2060] & (14) \end{cases}$$

The fourth type is the renewable energy constraint. The renewable resources consumed by the generating units cannot exceed the upper limit of the local region's

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resource potential $RE_{max}$. Its expression is as follows:

$$RE_j \leqslant RE_{j,\max} \tag{15}$$

### 2.3.5 Energy intensity sensitivity analysis

Sensitivity analysis is used to study how uncertainty in a model's outputs is apportioned to different sources of uncertainty in its inputs (Saltelli, 2002). In dealing with problems involving multiple input variables, sensitivity analysis helps reveal the strengths and correlations between inputs and outputs (Saltelli et al., 2007). We use the elasticity of cost increase concerning the rate of reduction in energy intensity as a measure of the sensitivity *SA*. The formula is as follows:

$$SA = \Delta C / \Delta EI \tag{16}$$

where $\Delta EI$ represents the rate of energy intensity reduction adopted in other scenarios, relative to the baseline scenario.

## 2.4. Scenario setting and description

In addition to the BAU (business as usual) scenario, we introduce four distinct scenarios categorized into two main categories: single-factor control on either the supply or demand side, and coupled control. On the demand side, single-factor control is exemplified by the DSM (demand-side management) scenario. For the supply side, single-factor control is represented by two scenarios: the GSO (generation sector optimization) scenario and the NZE (net-zero emission) scenario. The scenario involving coupled control of supply and demand is primarily the BSO (both side optimization) scenario.

### 2.4.1 Business as usual scenario

The data used for electricity demand modeling primarily originates from the 2020 Statistical Yearbook of the 31 provinces and cities in China (National Bureau of Statistics of China, 2020) and the Seventh National Population Census (National Bureau of Statistics of China, 2021a). In the industrial sector, GDP is used to represent the activity level, while electricity consumption per GDP indicates the

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energy intensity. In the residential sector, population is used to represent the energy activity level, and per capita electricity consumption is used for energy intensity. Based on the industrial activity levels and elasticity coefficients of various provinces from 2010 to 2020, the development of the industrial sector can be reasonably extrapolated.

In terms of electricity supply modeling, the construction of installed capacity is based on regional electricity generation data from the 2020 China Electric Power Yearbook (National Bureau of Statistics of China, 2021b). Future electricity structure projections are referenced from the Study on China's 2030 Energy and Electricity Development Plan and 2060 Outlook (Global Energy Interconnection Development and Cooperation Organization, 2021). The costs of different power generation technologies have been detailed in Table S2, primarily referencing Wang et al. (2023) and Zhou et al. (2023). Data on regional natural resource potential is sourced from the Energy Research Institute (2022), and the electricity load curves of the four regions are shown in Fig. S2. The parameters for the elasticity coefficients of the industrial activity levels in the four regions are provided in Table 1.

**Table 1** Elasticity coefficient parameters of industry activity levels

| Industry | LH | HH | LL | HL |
|---|---|---|---|---|
| Agriculture | 1.82% | 2.50% | 2.47% | 2.25% |
| Industry | 2.21% | 2.84% | 1.91% | 1.73% |
| Construction | 2.31% | 5.36% | 3.17% | 4.98% |
| TSAP | 1.40% | 4.60% | 2.24% | 2.20% |
| WRTHC | 2.77% | 5.25% | 4.90% | 3.57% |
| Other Services | 1.24% | 8.69% | 6.51% | 5.34% |

Higher elasticity coefficients indicate a sector's increased sensitivity to energy activity levels. In the four regions, the construction sector and the WRTHC sector generally exhibit higher elasticity coefficients. Apart from the LH region, the elasticity coefficients for other industries in the regions consistently exceed 5%.

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### 2.4.2 Demand side management scenario

The DSM scenario mainly focuses on adjusting the energy intensity of various industries and livelihood-related areas in the four regions. Historical data shows that the global average annual reduction rate of energy intensity is approximately 1.2% (Goldemberg and Siqueira Prado, 2013). Ming et al. (2024) set a 2% reduction for high-energy-consuming industries and a 0.5% reduction rate for low-energy-consuming industries in Zhejiang Province. Based on these references, we adopt a 1.5% energy intensity reduction rate. Note that the parameter settings for the electricity transformation are consistent with those of the BAU scenario. Table 2 shows the initial energy intensity settings for different industries in the four regions.

**Table 2** Initial energy intensity parameters in the four regions ($10^{-3}$ kilowatt-hours/RMB)

| Industry | LH | HH | LL | HL |
|---|---|---|---|---|
| Agriculture | 10.76 | 29.65 | 14.37 | 9.96 |
| Industry | 227.51 | 163.08 | 140.06 | 154.48 |
| Construction | 7.88 | 13.85 | 13.12 | 14.90 |
| TSAP | 24.41 | 41.64 | 58.46 | 63.54 |
| WRTHC | 39.2 | 27.34 | 38.65 | 59.91 |
| Other Services | 31.5 | 21.52 | 16.54 | 15.44 |

### 2.4.3 Generation sector optimization and net-zero emission scenario

When exploring the impact of supply-side emission reduction, two scenarios are considered: the GSO scenario and the NZE scenario. The GSO scenario utilizes the LEAP-NEMO for optimizing the power generation mix towards a minimum cost objective, considering actual resource constraints without carbon emission constraints, while maintaining constant energy intensity on the demand side. The distinction between the NZE and the GSO is the additional carbon emission constraint in the NZE scenario. Specifically, the NZE scenario stipulates that the power sector should reach its peak $CO_2$ emissions in 2030, 2040, and 2050, and achieve net-zero $CO_2$ emissions by 2060. The power generation structures of the four regions in 2020 are

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analyzed in greater detail in Table 3.

**Table 3** Power generation structures of the four regions in 2020 (China Electricity Council, 2020)

| Power generation | LH | HH | LL | HL |
|---|---|---|---|---|
| Coal | 57% | 57.2% | 54.0% | 57.6% |
| Wind | 15.6% | 12.2% | 15.3% | 9.9% |
| Solar | 5.8% | 10.6% | 15.2% | 14.5% |
| Nuclear | 2.1% | 3.0% | 15.2% | - |
| Hydro | 19.6% | 17.0% | 38.65 | 18% |

### 2.4.4 Both side optimization scenario

The BSO scenario, which encompasses modifications on both the demand and supply sides, tests the optimal rate of energy intensity reduction (set at 1%, 1.5%, and 2%) for different regions. Moreover, it incorporates optimization of the minimum cost on the generation side under carbon emission constraints. A summary of parameter adjustments across the different scenarios is presented in Table 4.

**Table 4** Comparison of parameter settings for four special scenarios in the BAU scenario

| Scenario | Energy intensity reduction rate | Minimum cost optimization | Carbon emission constraint | Peak year |
|---|---|---|---|---|
| DSM | 1.5% | off | - | 2030 |
| GSO | 0% | on | - | 2030 |
| NZE | 1.5% | on | net-zero in 2060 | 2030~2050 |
| BSO | 1.0%~2.0% | on | net-zero in 2060 | 2030 |

## 3. Results and discussion

### 3.1 Proportion of electricity consumption in demand-side industries

We begin with a demand-side analysis of the BAU scenario, as shown in Fig. 4. The inner part of the ring highlights industries experiencing a reduction in electricity consumption share, while the outer portion indicates those with an increased

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proportion. The continued growth in electricity consumption share of the agricultural sectors within both the HH and LL regions indicates persistent potential for modernization in these areas. For the HH region, the rising share of agricultural sectors likely stems from expanding electrification demands in urban agriculture. Priority should be given to optimizing time-of-use electricity price adaptability for facility-based agricultural systems. On the other hand, a systematic assessment of the levelized cost of electricity for photovoltaic-integrated irrigation systems is recommended for the LL region. The marginal variations observed in electricity consumption within the LH and HL regions suggest an approaching saturation point in the developmental trajectory of this sector. The industrial sector in the LH region is expected to decline, which may require intervention such as establishing a coordinated industrial relocation compensation fund to prevent deindustrialization. In contrast, industrialization in the remaining three regions is expected to progress. In terms of residential electricity consumption, a consistent rise across all regions underscores China's ongoing urbanization efforts. The construction sector in the HL region experiences a significant decline in electricity consumption share, while it remains relatively stable in other regions, indicating that no significant structural changes occur. The share of the TSAP sector marginally increased in the LH and LL regions, which stands in contrast to a universal decline in the WRTHC sector across all regions, reflecting a downturn in this sector within China. Other services in the LH region see a minor uptick in electricity consumption share, yet they still follow the overall national downward trend.

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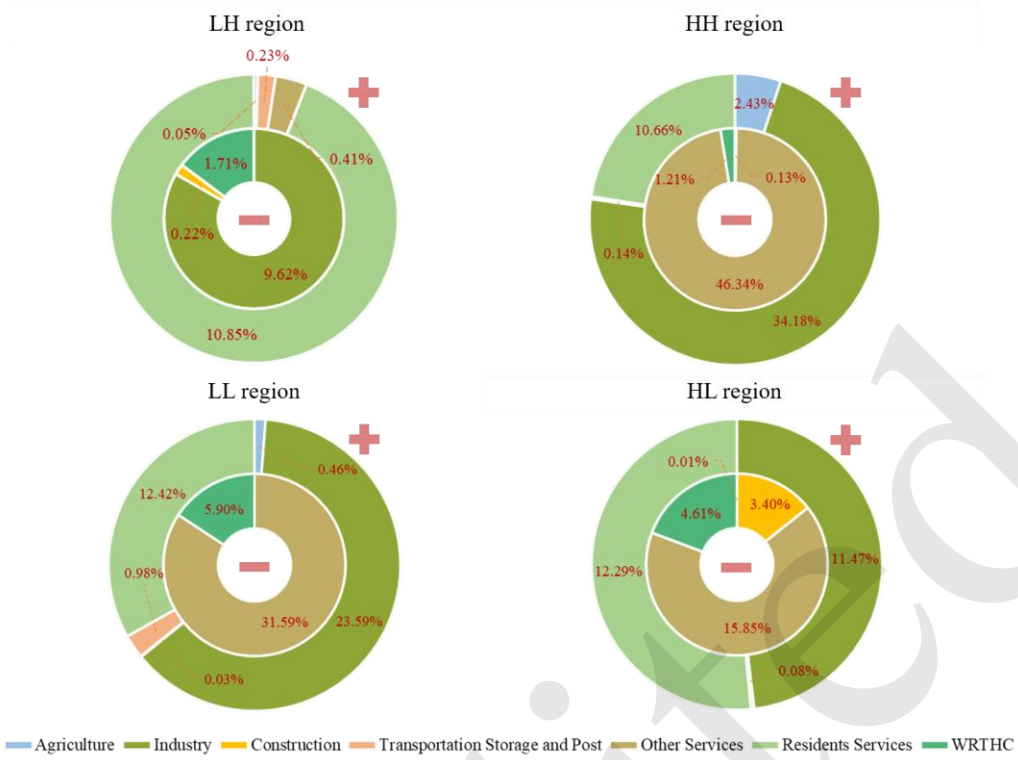


**Fig. 4** Changes in electricity consumption share by demand-side industries from 2020 to 2060 in the four regions (the inner ring indicates a decrease, and the outer ring indicates an increase)

## 3.2 Changes in power generation structure

Fig. 5 displays the decadal changes in the power generation structure from 2020 to 2060. From the perspective of the dominant regional power generation methods, wind energy exhibits the highest rate of expansion in the LH region, whereas solar photovoltaic generation spearheads growth in the other regions. Analyzing the changes in the proportion of various power generation methods, wind power sees its largest proportional increase in the LH region (37.7%), and its smallest in the HL region (21.26%). Solar power experiences the highest proportional growth in the HH region (32.28%), and its lowest in the LH region (22.93%). Nuclear energy's share increases the most in the HL region (8.05%), while LL sees a minimal increase (0.77%). Hydropower's share expands most significantly in the HL region (22.94%), whereas the HH region records the smallest increase (8.03%). Furthermore, studies have revealed that low generation regions generally suffer from scarce wind and solar energy resources. Thus to meet future electricity demands, these areas may require targeted development of nuclear and hydropower

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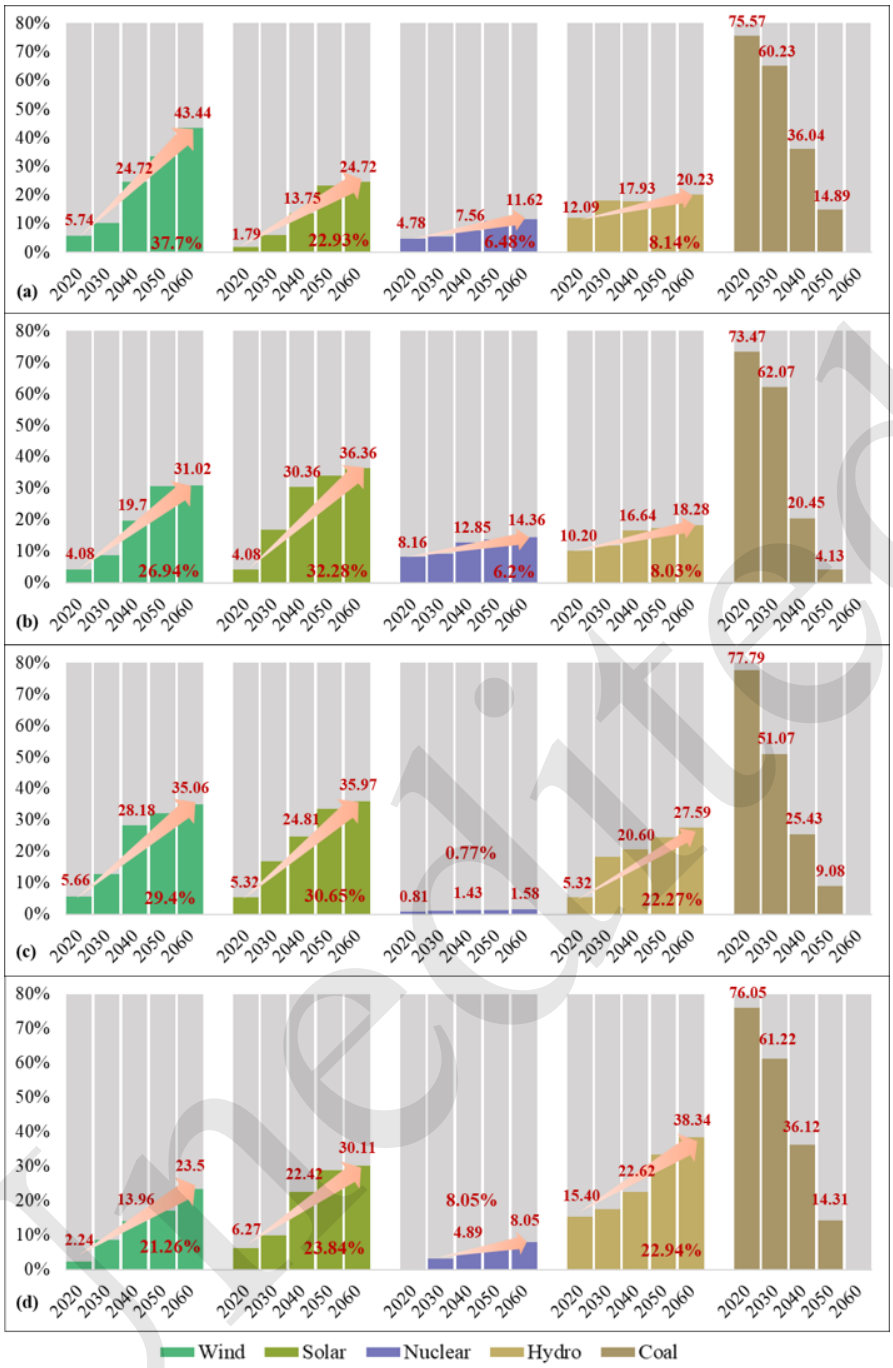


**Fig. 5** Changes in the power generation structure of the four regions from 2020 to 2060 in (a) the LH region; (b) HH region; (c) LL region; (d) HL region

infrastructure. However, it should be noted that the central and southern regions exhibit limited potential for new hydropower development. Consequently, future development strategies in these areas should focus on capacity expansion and efficiency improvements at existing hydropower stations, rather than pursuing new construction projects. Moreover, the large-scale deployment of renewable energy in

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China faces challenges such as intermittency-related grid integration issues, insufficient long-distance transmission capacity, land-use and ecological constraints, and financing barriers. To overcome these issues, policy measures such as grid modernization, electricity market reforms, financial incentives, and coordinated land-energy planning are essential for supporting a balanced and low-carbon power system.

## 3.3. Marginal cost of carbon emission reduction in different peak years

The primary difference between GSO and NZE is that the GSO scenario excludes carbon emission restrictions, while the NZE scenario explicitly accounts for them. Consequently, the cost difference between these scenarios relative to the total carbon reduction achieved serves as an indicator of the marginal cost of carbon mitigation. The NZE scenario establishes three sub-scenarios for different peak years in the power sector, facilitating an exploration of the impact of different peak years on the marginal cost of carbon reduction.

Fig. 6 displays the marginal costs and cost growth rates of carbon reduction in the four regions under different peak years. The bar graph illustrates the growth rate of the cost per unit of carbon reduction, revealing that the growth rate increases with the delay of the peak year across all types of regions. This may be attributed to the necessity for more expensive technologies and targeted policy measures to achieve large-scale reductions in emissions within a compressed timeline. The curve delineates the annual marginal cost of carbon reduction, indicating that the marginal costs for the four distinct regions descend in the following order in 2060: HL, LH, LL, and HH. This order is consistent with the cost growth rate values across the same peak years for each region. The HL region exhibits the highest marginal costs and cost growth rates, which likely stem from Shaanxi's overdependence on thermal power and delayed deployment of alternative energy sources. This results in insufficient early-stage technological substitution, which may cause later-stage reliance on

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premium decarbonization solutions like carbon capture. Conversely, it should be noted that the HH region may have achieved path optimization through a high proportion of clean energy penetration, and later relied more on grid flexibility than novel emission reduction technologies.

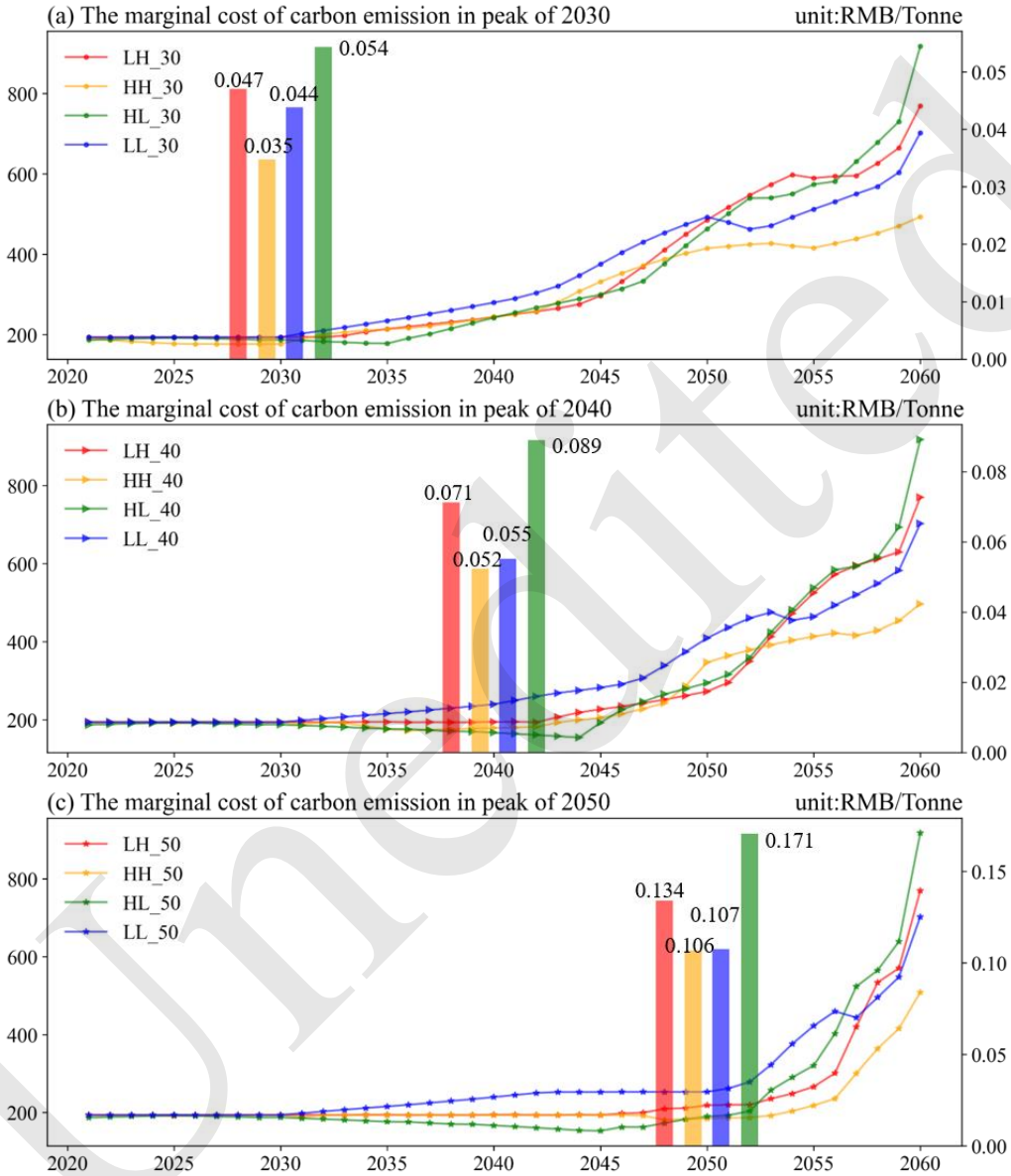


**Fig. 6** Marginal cost and cost growth rate of carbon reduction under different peak years (the left longitudinal axis represents the marginal cost of carbon emission for each year, and the right longitudinal axis represents cost growth rates of carbon reduction)

Furthermore, Fig. 7 illustrates the total cost per unit of carbon reduction across different peak years. By 2060, the cumulative total cost increases with the deferral of the peak year. Additionally, this trend may obscure certain implicit costs: for instance,

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delayed peaking leads to an accumulation of carbon emissions between 2030 and 2050, potentially exacerbating the frequency of extreme climate events and elevating ecological restoration expenditures. Regardless of the peak year, the cumulative cost per unit of carbon reduction by 2060 for the four regions ranks from highest to lowest as follows: LL, LH, HL, and HH. The LL region exhibits the highest costs due to its dual structural constraints: core cities (e.g., Beijing, Shanghai, Chongqing) face spatial limitations and elevated costs for cross-regional green power allocation, perpetuating their partial reliance on high-carbon energy inputs, while peripheral provinces (e.g., Gansu, Qinghai, Ningxia) suffer from inadequate fiscal investment and outdated power grid infrastructure, resulting in an insufficient renewable energy development rate. This bifurcated system sustains the elevated decarbonization expenditures across the LL region.

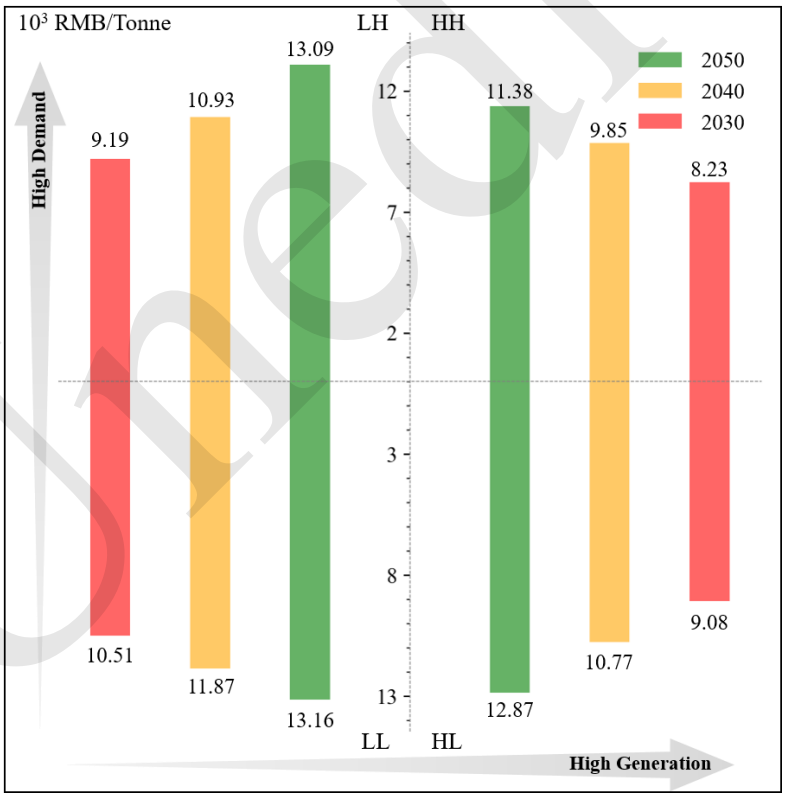


**Fig. 7** Cumulative cost per unit of carbon reduction under different peak years (the first quadrant represents the LH region, the second quadrant represents the HH region, the third is the LL region, and the fourth is the HL region)

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## 3.4 Energy intensity and cost change sensitivity analysis

Here, a sensitivity analysis is conducted on the rate of reduction in energy intensity and the changes in generation costs across different regions. In Fig. 8, the horizontal axis represents time in years, and the vertical axis represents the rate of reduction in energy intensity. The numbers within the heatmap indicate the cost sensitivity values corresponding to specific years and rates of energy intensity reduction.

Our analysis reveals a trend of increasing sensitivity across all regions over time, indicating that the financial impacts of reducing energy intensity are expected to grow significantly by 2060. Regional analysis reveals that the LH, HH, and HL regions exhibit maximal sensitivity at a 1.5% rate of reduction in energy intensity, suggesting optimal economic outcomes at this rate. The LL region reaches its economic optimum when the energy intensity reduction rate escalates to 2%. It is therefore recommended that the LL region set a reduction target that exceeds the national average energy intensity reduction rate. Furthermore, assuming an optimal rate of energy intensity reduction, high energy generation regions are expected to realize their maximum benefits by 2050. Thus, these regions might consider accelerating their efforts to reduce energy intensity. On the other hand, regions with low energy generation are advised to maintain their current reduction pace until 2060, in order to obtain the maximum economic advantage.

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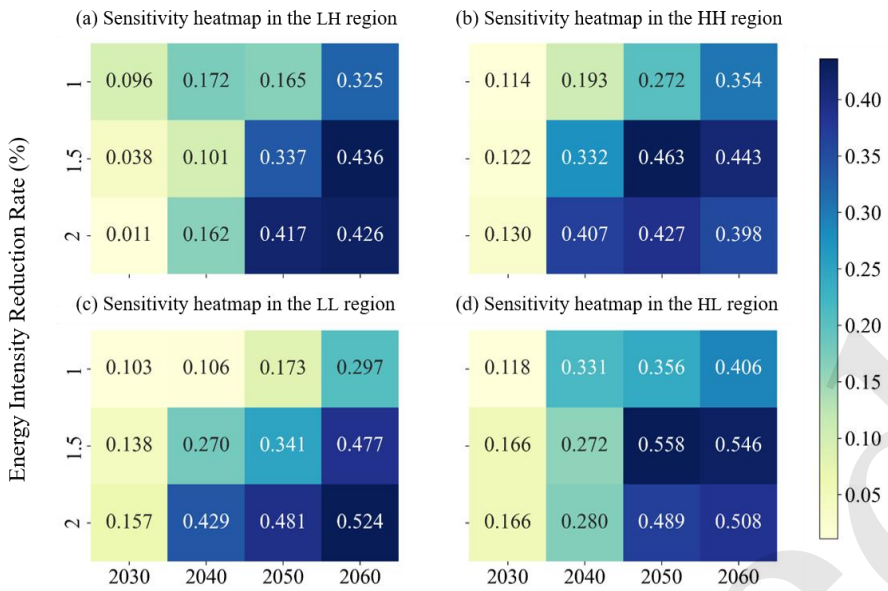


**Fig. 8** Sensitivity heatmap of energy intensity and cost changes from 2020 to 2060 in (a) the LH region; (b) HH region; (c) LL region; (d) HL region

## 4. Conclusions

This study evaluated the future impact of carbon emission reduction efforts in China across supply and demand within regions with different electricity characteristics under carbon neutrality goals, and provided targeted policy recommendations. We categorized provinces into four distinct regions by their electricity characteristics and formulated scenarios including BAU, DSM, GSO, NZE, and BSO. We assessed future shifts in industries' electricity consumption, adaptations in power generation mixes, the marginal cost of carbon reduction across varying peak years, and the interplay between energy intensity and cost dynamics. Our analysis integrated natural resource constraints, providing a more realistic assessment of future development. We evaluated how varying peak year timings affect carbon reduction costs, and determined optimal energy intensity reduction rates for the different regions.

From an industrial development standpoint, industries within the LH region may encounter transformative pressures or declines, necessitating the strategic development of emerging economic drivers and industrial restructuring to prevent deindustrialization. Conversely, the industrialization efforts in the remaining three

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regions are ongoing, emphasizing the need to integrate technological innovations to promote clean industrial growth. Moreover, urbanization is expected to steadily increase residential electricity demand across all regions, and so a sustainable electricity supply will be required to meet this demand.

Renewable energy development plays a pivotal role in the structural transformation of China's electricity sector, as the accelerated adoption of wind and solar energy aligns with international objectives for sustainable development and the transition to clean energy. Considering the differences in resource conditions across regions, energy strategies should be tailored to local circumstances. In resource-constrained areas, priority should be given to nuclear power and other established energy generation methods in order to address electricity supply shortages.

Postponing the peak year of carbon emissions increases the short-term marginal cost of carbon reduction and cumulative unit costs. Moreover, achieving a carbon peak as early as possible is economically and technologically prudent for avoiding compounding costs from climate extremes and ecological restoration work. The regional heterogeneity in marginal costs and cost growth rates across power system typologies requires tailored strategies. Specifically, the HL region – which exhibits both high marginal costs and rapid cost escalation – requires enhanced national policy support and prioritized investment.

The impact of energy intensity reduction rates varies across regions, necessitating strategic adjustments that are fitted to regional disparities. Specifically, the LH, HH, and HL regions should focus on achieving cost optimization with an energy intensity reduction rate of 1.5%, while the LL region would likely benefit from a 2% reduction rate. Additionally, regions with high energy generation should aim to sustain their energy intensity reduction rate beyond 2050, requiring proactive development and implementation of adaptable strategies. In contrast, low energy generation regions will need continued policy support to maintain their reduction

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rates.

Although this study provides an in-depth analysis of optimization pathways and strategies for supply- and demand-side emissions reductions, a few limitations still exist. First, while our assumptions are based on relevant policy documents, the long-term forecast may be somewhat conservative, as it does not fully account for potential technological breakthroughs and rapid policy adjustments. Second, our study primarily involved macro-level analysis and did not fully consider regional differences or fine temporal resolution. There are significant variations in electricity demand, resource endowment, and economic development across different regions. Thus a goal for future research is to optimize the results at a more granular level, particularly by incorporating regional differentiation factors and higher-resolution models. Moreover, expanding the scope to include sectoral interactions and assessing the implications of emerging technologies (such as energy storage, carbon capture, and smart grid innovations) would offer a more comprehensive understanding of the power system's shift towards carbon neutrality.

## Acknowledgments

This work was supported by the Fundamental Research Funds for the Central Universities under Grant No. 226-2024-00017, the National Natural Science Foundation of China under Grant No. 52206281, and the Zhejiang Provincial Natural Science Foundation of China under Grant No. LY24E060002. Numerical computations were performed on the Hefei Advanced Computing Center.

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