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Original Research

High-Resolution Dynamic Accounting of Power Carbon Emission Factors and Green Power Deduction Mechanism – A Case Study of the North Hebei Power Grid

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Abstract

Accurate and dynamic accounting of power carbon emission factors (PCEFs) is essential for supporting low-carbon transition and ensuring the integrity of green power markets. Traditional static and province-level approaches compress spatiotemporal variations into annual averages, which obscures renewable energy volatility, cross-regional power flows, and the environmental attributes of traded green power. This study develops a high-resolution, time- and zone-specific PCEF model that integrates unit-level generation data, hourly granularity, interregional transmission, and a green power deduction mechanism to prevent double counting. Using the North Hebei power grid as the primary case, characterized by over 80% renewable capacity and large-scale clean power exports, the model demonstrates significant improvements in capturing intra-day and seasonal dynamics of carbon intensity. Results show that the mixed PCEF with hybrid power and regional exchange in North Hebei (0.5069 tCO_2/MWh) is notably lower than the fossil-fuel baseline (0.7899 tCO_2/MWh), while the deduction of green power trading raises the retained local factor to 0.6488 tCO_2/MWh. Comparative analysis with Jiangsu Province, a region dominated by fossil power but with high external clean power inflows, validates the model's robustness across diverse energy structures. The findings highlight three key contributions: (1) improving spatiotemporal resolution of PCEF calculations, (2) clarifying carbon responsibility allocation in cross-regional flows, and (3) enhancing the credibility of green power trading mechanisms. This research provides methodological and empirical evidence to guide the development of unified carbon accounting standards, optimize power trading, and support policy design for equitable and effective decarbonization in China's power sector and beyond.

Keywords: power carbon emission factor, dynamic carbon accounting, green power deduction, cross-regional carbon flow, North Hebei power grid

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Introduction

The sustained growth of global energy demand is driving profound transformations in power system structures [1]. By 2040, traditional fossil fuel power generation is projected to phase out of the market, with power systems achieving net-zero emissions and accounting for nearly 50% of global energy consumption [2]. The International Energy Agency's (IEA) "Power Report 2025" highlights that renewable energy's share in global power supply continues to rise, expected to meet 95% of global power demand growth between 2025-2027 [3]. The "Renewable Energy Report 2024" further forecasts that newly installed renewable energy capacity worldwide will exceed 5,500 GW from 2024 to 2030 – nearly triple the 2017-2023 figure [4]. This trend indicates that future power systems will heavily rely on intermittent renewable energy sources like wind and solar. However, the fluctuating output and regional disparities of renewables result in significant spatiotemporal heterogeneity in carbon emissions. For instance, monthly output fluctuations for photovoltaic and wind power in Germany reach 16.13% and 20.95% respectively [5], demonstrating that traditional static methods struggle to accurately capture the temporal and spatial dynamics of carbon emissions. To achieve low-carbon energy transition, it is imperative to establish a dynamic accounting system that reflects spatiotemporal variations in carbon emissions, providing real-time data support for comprehensive low-carbon management across the entire energy chain.

In international research, carbon emission accounting for time-segmented and zone-divided power has made significant progress [6]. A Stanford University team proposed linking environmental quality with grid power flows, using regional average and marginal carbon emission factors to reveal spatial distribution patterns and system marginal response characteristics of hourly-level carbon emissions. The University of California, Davis, extended this approach by conducting empirical verification of hourly-level carbon factor calculation methods at the building level. Meanwhile, Denmark's ENTO Laboratory in Europe developed a dynamic monitoring system for hourly-level carbon factors by tracking power flows from generation to consumption based on physical system characteristics, analyzing the coupling relationship between carbon flow and current. These studies demonstrate that high temporal and spatial resolution carbon accounting is crucial for accurately identifying emission sources and formulating precise reduction strategies. However, existing methodologies still face limitations: most research focuses on localized areas or specific scenarios, lacking a comprehensive dynamic accounting framework that integrates renewable energy volatility, cross-regional power flows, and green power trading.

China's power system is currently at a critical stage of energy structure transformation. Since the proposal of the "carbon peaking and carbon neutrality" goals in 2020, China has accelerated the establishment of a carbon emission statistical accounting system, successively issuing the "Carbon Emission Statistical Accounting System Construction Plan" (2022) and the "Work Plan for Improving the Carbon Emission Statistical Accounting System" (2024) [7, 8], which explicitly require the establishment of a comprehensive carbon emission accounting framework. The power industry is the largest single sector in terms of carbon emissions, accounting for approximately 40% of the nation's total emissions [9]. Academician Shu Yinbiao of the Chinese Academy of Engineering pointed out that renewable energy exhibits significant daily output fluctuations. The probability of renewable sources like wind and solar power reaching their installed capacity is virtually zero, while the probability of exceeding 50% of installed capacity is less than 10%. By 2060, the daily peak power output fluctuations from renewable energy are projected to exceed 1.6 billion kilowatts, accounting for 40% of the nation's peak load [10]. Traditional annual or provincial static accounting methods have become inadequate to meet the demands of high-proportion renewable energy systems for precise carbon emission management. Static accounting methods typically compress dynamic carbon emissions into annual averages, masking real-time fluctuations in power generation structures and the impact of cross-regional power transmission on carbon emissions. This leads to distorted carbon emission responsibility measurement and affects the precise implementation of emission reduction policies.

Currently, China's power carbon emission accounting system faces three structural contradictions. First, traditional static accounting fails to capture hourly-level dynamic changes. Taking Sichuan hydropower as an example, the average power carbon factor from July to October was 0.07 $kgCO_2/kWh$, but the lowest period recorded only 0.025 $kgCO_2/kWh$, representing 21% of the annual average. Spatially, provincial averages obscure regional differences – Lianyungang recorded 0.171 $kgCO_2/kWh$ while Yangzhou recorded 0.473 $kgCO_2/kWh$ [11]. This indicates significant discrepancies in corporate and regional carbon accounting. Second, green power trading conflicts with carbon accounting, leading to "double counting" issues. The green certificate mechanism allows enterprises to count renewable energy attributes toward their carbon reduction credits, yet the current carbon accounting system still employs location-based static emission factors without dynamic adjustments. This results in identical emission reductions being double-counted at both power generation and consumption ends. Third, cross-provincial power transactions face ambiguous carbon emission responsibility boundaries. During interprovincial transmission, power undergoes mixed flows that make it impossible to trace specific energy sources or carbon intensity. The lack of real-time power flow-based dynamic accounting tools and cross-regional data sharing mechanisms leads to imprecise delineation of carbon responsibility, distorted regional carbon data, and undermines the fairness and efficiency of the national carbon market [12].

To address these challenges, there is an urgent need to establish a high-resolution dynamic carbon accounting system that covers power flows, enabling the precise calculation of time-specific and region-specific power carbon factors. This requires models to simultaneously account for unit-level output, variations in energy structures, cross-regional power transmission, and green power trading mechanisms, thereby aligning carbon emission responsibilities with actual power flows. Such systems would support equitable implementation of emission reduction policies and green power trading. Current research predominantly focuses on single-factor or localized scenarios, lacking comprehensive spatiotemporal dynamic accounting methods. Notably, there remains a gap in cross-regional carbon flow tracking and environmental attribute deduction for green power.

To address the aforementioned research gaps, this paper proposes a time-space characteristic-based model for calculating time-sharing and zonal power carbon factors. The model's innovations include: First, establishing a high-resolution calculation framework with power units as the smallest computational unit, enabling hourly and zonal-level dynamic accounting of power carbon factors, thereby overcoming the limitations of traditional annual or provincial static calculations. Second, clarifying environmental rights by explicitly deducting green power trading volumes during factor calculations to prevent double-counting of zero-emission value and resolve "double-counting" issues. Third, quantifying cross-regional carbon emission transfers by integrating inter-regional power flow with carbon flow tracking, which characterizes the spatiotemporal evolution of carbon emission responsibilities and provides a scientific basis for equitable allocation of regional emission reduction obligations.

This study uses North Hebei as a typical case, where the high proportion of renewable energy and large-scale cross-regional power transmission can fully demonstrate the dynamic characteristics of carbon emissions under high renewable energy ratios. Meanwhile, to highlight the comparative features of regions with high fossil fuel shares, Jiangsu Province is selected as a supplementary case. Jiangsu, with a high proportion of thermal power and a relatively low renewable energy ratio, exhibits more stable carbon emissions. However, under the influence of cross-regional power transmission and green power trading, uncertainty still exists in carbon emission responsibility allocation. By comparing the spatiotemporal distribution of hourly carbon emission factors between the two regions, this study reveals differences in the dynamic characteristics of carbon emissions under different energy structures, thereby verifying the model's applicability and robustness across various energy configurations and regional types.

This study utilizes multi-source empirical data, including power generation output, fuel types, cross-regional transmission, and green power trading, to validate model effectiveness. It analyzes variations in power-carbon factors and cross-regional carbon emission transfer characteristics under different scenarios. The research findings provide theoretical and methodological support for establishing precise carbon accounting systems, optimizing green power trading mechanisms, and advancing regional low-carbon development strategies. The paper is structured as follows: Part II reviews domestic and international research progress. Part III constructs models and methodologies. Part IV conducts case analysis and result discussion. Part V presents conclusions and policy recommendations.

Contributions of this study are as follows: (1) Methodologically, we develop a high-spatiotemporal-resolution power carbon emission factor model at the unit level with hourly and zonal granularity, enabling accurate characterization of renewable variability and intra-day/seasonal dynamics. (2) Mechanistically, we integrate a "green-power deduction" scheme with cross-regional carbon-flow tracing to prevent double-counting of environmental attributes and to clearly delineate mitigation responsibilities between sending and receiving regions. (3) Empirically and in application, we validate the model with a North Hebei case and a Jiangsu comparison, provide reusable data requirements and implementation procedures, and offer actionable evidence and policy insights to support unified accounting standards and coordinated electricity-certificate-carbon market design (Fig. 1).

Literature Review

International Studies

Internationally, research on the Power Carbon Emission Factor (ECIF) has evolved from static average-based accounting toward dynamic assessments with high temporal and spatial resolution. Early studies predominantly relied on annual or monthly averages. For instance, Strachan and Kannan (2008), using the hybrid energy system model MARKAL-Macro, analyzed the pathways for achieving the United Kingdom's long-term carbon reduction targets. Their findings highlighted the power sector as the critical domain for meeting the national goal of a 60% reduction in CO_2 emissions by 2050 [13]. Similarly, Hawkes et al. (2014) introduced the concept of the Long-run Marginal Emission Factor (LR-MEF) to capture variations in long-term carbon emissions associated with structural changes in the power system, and, using the UK as a case study, demonstrated the evolving trajectory of LR-MEF over time [14]. In recent years, research has increasingly shifted toward hourly and even real-time prediction of carbon intensity factors, aiming to support refined management for low-carbon dispatch and demand response. Khan et al. (2018) examined

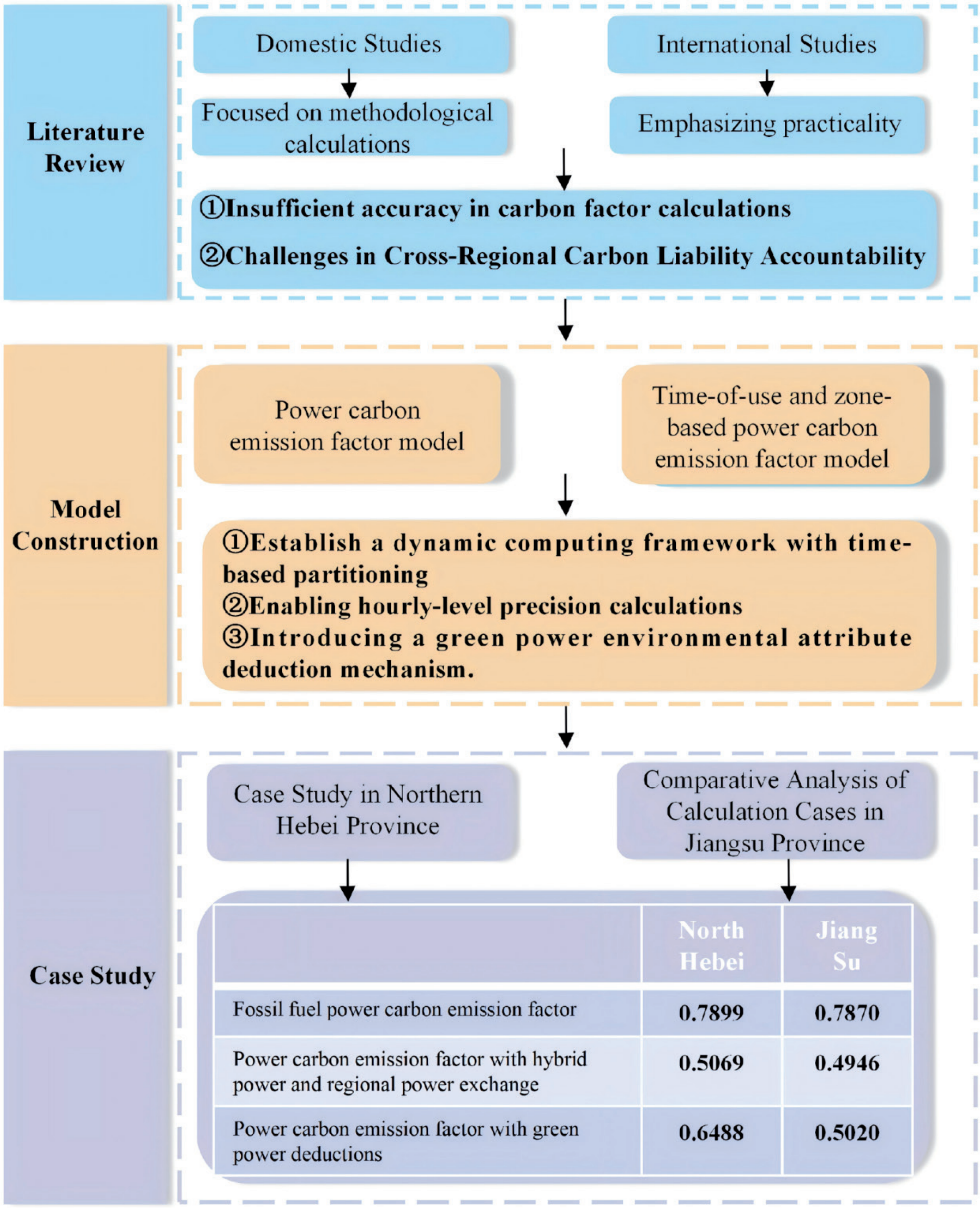

Fig. 1. Research framework.

the temporal variability of carbon intensity within power systems across multiple time scales, finding that intra-day fluctuations were relatively minor, whereas seasonal variations could reach up to ±40% [15]. Lowry et al. (2018) developed a 24-hour forecasting model of carbon intensity, which enabled the identification of high-intensity periods to optimize demand response decisions for building HVAC systems, thereby reducing associated emissions [16]. More recently, Ma et al. (2024) integrated the time-varying carbon intensity of multi-energy systems with user response behaviors, significantly improving the accuracy of emission accounting and enhancing the precision of cross-energy collaborative mitigation assessments [17]. Another important line of research has focused on cross-regional carbon transfer and the allocation of emission responsibilities. Tranberg et al. (2019) proposed a real-time accounting framework for the European power market, enabling precise tracking of carbon responsibility shifts induced by cross-border power exchanges [18]. Scarlat et al. (2022), based on carbon flow measurements of the EU power system from 1990 to 2019, revealed a declining trend in carbon intensity across most member states [19]. Similarly, Duan et al. (2018) constructed an interregional carbon flow network in China, uncovering the pathways of carbon emission transfers as well as the associated control and dependency relationships among regions [20]. At the global scale, Caro et al. (2017) estimated consumption-based emissions for 175 countries during 2008-2012 and reallocated emission responsibilities according to final demand, thereby highlighting the driving role of trade and consumption in transboundary carbon transfers [21].

International scholarship on time- and region-specific power carbon emission factors has evolved into a diversified methodological system, encompassing system optimization modeling, statistical forecasting, power flow tracing, and carbon flow network analysis. In the domain of energy system optimization, Hawkes et al. (2014) developed the dynamic power system optimization model GBPower within the TIMES framework and, through marginal demand experiments, provided the first systematic quantification of the Long-run Marginal Emission Factor (LR-MEF) [14]. With the increasing availability of high-resolution generation data, researchers have advanced dynamic accounting approaches for carbon emissions. For example, Khan et al. (2018) constructed a carbon accounting model based on half-hourly generation data, revealing the true dynamic characteristics of power system emissions at fine temporal resolution [15]. This work underscored the critical importance of high temporal resolution in accurately capturing fluctuations in the power carbon emission factor. In the field of time-series modeling and forecasting, Lowry et al. (2018) employed a Seasonal Autoregressive (Seasonal AR) model to effectively capture the cyclical and trend characteristics of grid carbon intensity, achieving high-accuracy 24-hour forecasts [16]. Within the domain of power flow tracing, Tranberg et al. (2019) developed a real-time consumption-based accounting method grounded in flow-tracing techniques, which provided a more accurate representation of the power carbon emission factor associated with power consumption across European markets [18]. Similarly, Scarlat et al. (2022) extended the conventional life-cycle assessment boundary by integrating the Well-to-Wheel approach, thereby enabling real-time tracking of cross-border power flow carbon intensities [19]. Finally, in regional carbon flow modeling, Duan et al. (2018) combined multi-regional input-output (MRIO) analysis with ecological network analysis (ENA) to establish a multi-region, multi-sector carbon flow framework, systematically tracing and quantifying interregional carbon transfers in China [20].

In terms of deducting environmental attributes of green power, international practice has largely been shaped by the California carbon market. For example, the retirement of allowances has been adopted as a means to deduct the environmental benefits of green power and to avoid double-counting [22]. In addition, when accounting for the carbon emissions of imported power in California, entities that submit Renewable Energy Certificates (RECs) corresponding to the procured volume of "directly delivered" renewable power may apply a zero-emission factor, effectively treating it as zero-carbon power [23]. Moreover, Ma et al. (2024) highlighted the risk that, when corporations rely on RECs, power purchase agreements (PPAs), or on-site renewable generation for self-consumption in Scope 2 accounting, the environmental attributes of green power may not be effectively deducted [24]. Consequently, scholars have recommended the use of residual-mix emission factors instead of average grid emission factors, in order to prevent double-counting of mitigation benefits and to strengthen the environmental integrity of accounting outcomes.

Overall, substantial progress has been made in developing high-resolution methodologies for power carbon emission factor measurement, real-time forecasting models, and cross-regional carbon flow tracing, which have provided critical support for low-carbon dispatch and the allocation of emission responsibilities across regions. However, research and practical exploration remain limited with respect to mechanisms for deducting the environmental attributes of green power and establishing unified cross-regional accounting standards. There is an urgent need to develop a more systematic and operationally robust international accounting framework to avoid double-counting of mitigation benefits and to enhance the comparability of accounting results across different regions.

Domestic Studies

In China, research on the power carbon emission factor has placed greater emphasis on dynamic accounting, cross-regional coordination, and engineering-oriented applications, characterized by close integration with power sector reforms and carbon market mechanisms. In terms of dynamic accounting, studies have focused on deeply coupling the power carbon emission factor with user behavior and market transactions. For example, Li et al. (2022) proposed a novel carbon reduction mechanism for power systems centered on user behavior adjustments and demonstrated its significant mitigation potential at both the system and user levels [25]. Weng et al. (2022) developed a low-carbon economic dispatch model for park-level integrated energy systems that incorporates time-varying power carbon emission factors, aiming to reduce both carbon emissions and operational costs [26]. More recently, Wang et al. (2024) integrated market-based power trading, green power transactions, and energy storage operations into the accounting framework of power carbon emission factors, thereby enhancing the adaptability of factor calculations [27]. In the area of cross-regional collaborative computation, Song et al. (2024) proposed a distributed-architecture-based method for the coordinated calculation of power carbon emission factors across interconnected grids. By applying a block matrix iterative approach, their method improved computational efficiency and enabled accurate estimation of provincial-level carbon emission factors [28]. At the practical application level, research has further explored the engineering value of power carbon emission factors in system operation and dispatch. For instance, Liu (2024) employed dynamic factors as dispatch signals to optimize the operation of energy storage and flexible loads, thereby achieving real-time optimization of system carbon emissions [29]. Meanwhile, Shu (2024) introduced the concept of time- and region-specific power carbon emission factors, offering a new perspective for both policy design and engineering applications [30].

From a methodological perspective, research on the power carbon emission factor in China has gradually developed into a multidimensional technical system, ranging from data-driven modeling and time-segmented refined calculation to full-chain carbon flow tracing. At the data-driven modeling level, Liu proposed the Dynamic Carbon Emission Factor (DCEF) method, which integrates generator characteristics with optimization algorithms to enable low-carbon dispatch [29]. Yang et al. (2023) introduced a Dropout neural network to forecast nodal carbon factors, thereby improving the robustness of prediction outcomes [31]. In terms of time-segmented refined calculation, Weng et al. (2022) dynamically constructed time-varying power carbon emission factor curves based on the ratio of thermal power transmitted through tie-lines to the total power consumption of industrial parks. This approach facilitated time-resolved modeling of carbon emission intensity and provided real-time carbon signals for low-carbon scheduling of storage and load [26]. At the full-chain carbon flow tracing level, Li et al. (2022) established a generation-to-consumption carbon flow tracing model grounded in power flow calculations, enabling accurate computation of nodal-level factors [25]. Similarly, Zhang et al. proposed a comprehensive carbon accounting framework encompassing direct and indirect emissions across generation, transmission, and storage stages, and employed system dynamics to uncover the emission impact mechanisms across different segments [32].

With regard to the deduction of environmental attributes of green power, Chinese policy has explicitly mandated a consumption-based approach grounded in physical power volumes, supplemented by cross-provincial green certificate trading [33]. Building on this framework, Shang et al. (2024) systematically examined the pathways and mechanism design for offsetting green power consumption in the carbon market and proposed three operational methods for deducting green power environmental attributes [34]. More recently, Yang et al. (2025) introduced a provincial-level residual-mix factor (RMF) calculation method that incorporates green power deduction. By excluding intra- and inter-provincial green power transactions from total consumption and calculating carbon intensity only for the "residual power", this method more accurately captures the carbon mitigation value of green power consumption [35].

Overall, domestic research has demonstrated stronger policy relevance and engineering applicability, yet several gaps remain to be addressed. Specifically, further progress is needed in refining temporal granularity (with limited studies at the minute- or hour-level), standardizing mechanisms for green power attribute deduction, and developing real-time decomposition methods for cross-regional carbon transfers.

In summary, international studies on power carbon emission factors have mainly focused on methodological exploration. Their aim is to develop more refined

Table 1. Summary of major research methodologies for power carbon emission factor estimation.

Method	Application	Strengths	Limitations
Data-driven modeling methods	Forecasting variations in grid power carbon emission factors	Hourly-level estimation and forecasting of power carbon emission factors	1) Existing accounting methods mainly emphasize average carbon emissions over longer periods (e.g., daily, monthly, or yearly).
	Improving the accuracy of power carbon emission factor estimation	Hourly-level estimation incorporating renewable energy variability	
	Assessing long-term variations in power carbon emission factors	Long-term estimation of marginal power carbon emission factors over the time dimension	
Carbon flow tracing	Estimating power carbon emission factors under renewable energy fluctuations	Hourly-level estimation of power carbon emission factors with renewable energy fluctuations	
Cooperative game approach	Allocating carbon emission responsibilities	Spatially differentiated estimation of power carbon emission factors	2) They neglect the impact of renewable energy fluctuations on grid carbon emissions during actual operation. 3) Spatial resolution is insufficient to accurately reflect conditions at the local level. 4) Temporal resolution fails to capture short-term variations (at the hourly or even minute scale).
Combined carbon flow tracing and power flow analysis	Dynamic estimation of power carbon emission factors	Dynamic estimation of power carbon emission factors across the system, generation, grid, and demand sides	
	Forecasting node-level power carbon emission factors in power systems	Forecasting node-level variations in power carbon emission factors	
	Measuring power carbon emission factors across provincial grids	Dynamic estimation of power carbon emission factors across interconnected power grids	

and rigorous models for spatiotemporal dynamic estimation, thereby improving both the accuracy and timeliness of emission assessments. In contrast, Chinese research emphasizes integration with policy frameworks and market mechanisms. It highlights practicality and engineering application. By applying dynamic carbon emission factor estimation, these studies assist power and energy systems, as well as generation, grid, and demand-side entities, in optimizing power trading behaviors and formulating effective low-carbon strategies. Table 1 provides a synthesis of the major methodologies, application scenarios, and the corresponding strengths and limitations in existing studies on power carbon emission factor estimation.

Summary and Research Gap

In summary, existing research has provided a solid technical foundation for power carbon emission factor estimation. However, notable gaps remain in spatiotemporal refinement, environmental rights accounting, and cross-regional carbon flow tracing. In particular, current studies in high-renewable power systems have not effectively integrated the unit-level and hourly real-time data with green power deduction mechanisms, leading to insufficient accuracy and limited interpretability of carbon factor calculations. Moreover, carbon responsibility allocation in interprovincial and cross-regional power trading still lacks dynamic and traceable accounting methods. This shortcoming constrains carbon market pricing, equitable cost sharing, and the design of low-carbon dispatch strategies. Accordingly, this paper proposes a spatiotemporally explicit dynamic model for power carbon emission factor estimation, incorporating green power deduction, to improve accounting accuracy, clarify environmental benefits, and enable robust decomposition of carbon flow responsibilities.

Materials and Methods

The parameters and definitions involved in the model described in this paper are shown in Table 2.

Power Carbon Emission Factor Model

The power carbon emission factor, also known as the power carbon dioxide emission factor or grid carbon emission factor, refers to the carbon dioxide emissions generated during the production process due to the use of a unit of power, typically measured in grams of carbon dioxide per kilowatt-hour (kWh). Traditional methods are mostly based on annual or provincial static data, which fail to reflect the real-time dynamic characteristics of the power grid. This study constructed a dynamic calculation framework for time-based and zone-based calculations, enabling refined calculations at the unit level and hourly level, and introduced a green power environmental attribute deduction mechanism.

The main steps in calculating the regional power carbon factor are threefold. The first step is to determine the power generation and direct carbon emissions within the region. The second step is to clarify the net power flow relationships within the regional power grid. The final step is to solve the equation. The specific calculation formula is shown in (1):

$$F_j = \frac{C_j + \sum_n (F_n \times E_{imp,n,j}) + F_{grid,i} \times E_{imp,i,j}}{E_j + \sum_n E_{imp,n,j} + E_{imp,i,j}} \tag{1}$$

In the formula (1), F_j is the carbon emission factor of regional power grid j, C_j is the direct carbon emissions from power generation within region j, E_j is the total power generation from non-fossil energy sources within region j, excluding market-based transactions, $E_{imp,n,j}$ is the net power transmission from province n to region j, F_n is the power carbon emission factor of province n's power grid, $F_{grid,i}$ is the power carbon emission factor of regional power grid i, and $E_{imp,i,j}$ is the net power transmission from regional power grid i to region j. Among them, the formula for direct carbon emissions from power generation is shown in (2):

$$C_j = \sum_m F_m \times D_{m,j} \tag{2}$$

In the formula (2), m denotes the m-th type of energy, $D_{m,j}$ is the energy data for power generation in regional grid j, and F_m is the carbon emission coefficient for the energy type m. The formula for calculating the carbon emission coefficient is shown in (3):

$$F_m = N_m \times C_m \times O_m \times \frac{44}{12} \tag{3}$$

In the formula, N_m is the average lower heating value, C_m is the carbon content, and O_m is the oxidation rate.

Time-of-Use and Zone-based Power Carbon Emission Factor Model

The above-mentioned power carbon emission factor model has limitations in terms of temporal and spatial resolution and its ability to reflect the power structure. Traditional power carbon emission factor models are typically based on national or provincial regions and use static historical data to construct annual power carbon emission factors, which cannot reflect the real-time dynamic changes in grid carbon emissions and power carbon emission factors. At the same time, the calculation only considers total power consumption and does not distinguish between different types of power sources, making it difficult to reflect

Table 2. Parameter settings and definitions.

Parameters	Definition	Unit
F_j	Power carbon emission factor of regional power grid j	tCO_2/MWh
C_j	Direct carbon emissions from power generation within region j	tCO_2
E_j	Total power generation from non-fossil energy sources within region j excluding market-based transactions	MWh
$E_{imp,n,j}$	Net power transmission from province n to region j	MWh
F_n	Power carbon emission factor of province n's power grid	tCO_2/MWh
$D_{m,j}$	Energy data for power generation in regional grid j	t
F_m	Carbon emission coefficient for the energy type m	tCO_2/t
N_m	Average lower heating value	GJ/t
C_m	Carbon content	tC/TJ
O_m	Oxidation rate	%
$E_{j,t}$	Fossil fuel power carbon emission factor in region j during unit period t	tCO_2/MWh
$W_{j,t}$	Total carbon emissions from fossil fuel power generation in region j during unit period t	MWh
r	Power generation unit in region j	/
$F_{r,t}$	Power generation volume of fossil fuel-based unit r during unit time t	MWh
	Carbon emission benchmark value corresponding to thermal power unit r	tCO_2/MWh
$G_{g,t}$	Power generation of renewable energy plant g in region j	MWh
$D_{x,j,t}$	Power input from external region x to region j within unit time t	MWh
X	Total number of regions supplying power to region j	/
d_x	Power carbon emission factor of region x	tCO_2/MWh
$\sum_{x=1}^{X} D_{x,m,t}$	Total amount of power supplied by external regions	MWh
X	Total number of regions supplying power to region j	/
$\sum_{s=1}^{S} O_{s,j,t}$	Total amount of power exported from region j to external regions within unit time t	MWh
$T_{j,t}$	Carbon emission factor with green power deductions	tCO_2/MWh
$U_{j,t}$	Non-fossil energy volume traded in the market	MWh

the impact of the proportion of coal-fired and green power in a region on the power carbon emission factor.

Therefore, based on the benchmark model, we introduced refined temporal and spatial resolutions and constructed a time- and zone-specific power carbon emission factor model from a power plant perspective. The model calculates power generation and carbon emissions based on the type of power plant. On a temporal scale, time can be defined in terms of years, months, weeks, days, hours, and even minutes.

On a spatial scale, based on administrative divisions, it can be divided into national, regional, provincial, municipal, and county levels, with the smallest regional unit defined as a plant or station. Furthermore, the model takes into account interregional power exchanges, fully reflecting the temporal and spatial environmental attributes of regional power, thereby enabling the calculation of power carbon emission factors across all time and space.

(1) Fossil fuel power carbon emission factor model

From the perspective of the power generation unit, the formula for calculating the fossil fuel power carbon emission factor in region j is shown in (4) and (5).

$$E_{j,t} = \frac{W_{j,t}}{\sum_{i \in j} F_{r,t}} \tag{4}$$

$$W_{j,t} = F_{r,t} * \rho_r \tag{5}$$

Among these, $E_{j,t}$ is the fossil fuel power carbon emission factor in region j during unit period t, $W_{j,t}$ is the total carbon emissions from fossil fuel power generation in region j during unit period t, r is the power generation unit in region j, $F_{r,t}$ is the power generation volume of fossil fuel-based unit r during unit time t, and ρ_r represents the carbon emission benchmark value corresponding to thermal power unit r.

The statistical scope of this formula only includes fossil fuel power generation within the region. Fossil fuels are the main source of carbon emissions on the supply side and are applicable for calculating the carbon emission levels of fossil fuel power generation within the region.

(2) Power carbon emission factor with hybrid power and regional power exchange

With the development of green power, the integration of new energy into the grid, and the transfer of carbon emissions associated with interregional power transmission, all of these factors will have an impact on the regional power carbon emission factor. The formula for calculating the power carbon emission factor for different types of power generation units and inter-regional power transmission $K_{j,t}$ is shown in (6).

$$K_{j,t} = \frac{W_{j,t} + \sum_{x=1}^{X}(D_{x,j,t} * d_x) - \sum_{s=1}^{S}(O_{s,j,t} * K_{j,t})}{\sum_{r \in j} F_{r,t} + \sum_{g \in j} G_{g,t} + \sum_{n=1}^{X} D_{x,j,t} - \sum_{s=1}^{S} O_{s,j,t}} \tag{6}$$

$G_{g,t}$ represents the power generation of renewable energy plant g in region j, with renewable energy plants set to have zero carbon emissions. $D_{x,j,t}$ represents the power input from external region x to region j within unit time t, X represents the total number of regions supplying power to region j, d_x represents the power carbon emission factor of region x, and $\sum_{x=1}^{X} D_{x,m,t}$ represents the total amount of power supplied by external regions. S represents the total number of regions to which region j exports power, and $\sum_{s=1}^{S} O_{s,j,t}$ represents the total amount of power exported from region j to external regions within unit time t.

The statistical scope of this formula comprehensively considers the combined power generation of fossil fuel power plants and non-fossil fuel power plants within the region, as well as power transmission between regions. It does not distinguish between thermal and green power, making it more applicable.

(3) Power carbon emission factor with green power deductions

To avoid double-counting the zero-emission value of non-fossil energy, this study introduces a green power deduction mechanism into the integrated model. The formula for the power carbon emission factor with green power deductions is shown in (7).

$$T_{j,t} = \frac{W_{j,t} + \sum_{x=1}^{X}(D_{x,j,t} * d_x) - \sum_{s=1}^{S}(O_{s,j,t} * K_{j,t})}{\sum_{i \in j} F_{r,t} + \sum_{m \in j} G_{g,t} + \sum_{n=1}^{N} D_{x,j,t} - \sum_{s=1}^{S} O_{s,j,t} - U_{j,t}} \tag{7}$$

Among these, $T_{j,t}$ is the carbon emission factor with green power deductions, and $U_{j,t}$ is the non-fossil energy volume traded in the market. The formula further deducts non-fossil energy, better reflecting the environmental attributes of green power. At the same time, it helps resolve the issue of double-counting that companies may face when calculating the zero-emission value of non-fossil energy in Scope 2 calculations and power emission factor calculations.

Data Requirements

The time-of-use and zone-based power carbon emission factor model proposed in this paper can effectively improve the accuracy of power carbon emission factor calculations. In practical applications, the following four types of data are required to support calculations. First, power plant operation data, including the time-of-use output of fossil fuel and renewable energy plants. Second, fuel characteristic parameters, including lower heating value, carbon content, and oxidation rate data. Third, inter-regional power transmission data, including time-of-use power flow direction and losses. Fourth, green power transaction data, including the power volume and time distribution corresponding to green certificates.

After obtaining the relevant data, the carbon emissions of fossil fuel power plants can be calculated based on the model. Based on the time data obtained, the power data, and the carbon emission data within a unit of time t are matched, thereby calculating the power carbon emission factor within a unit of time t.

Results

North Hebei Region and its Power Market-Related Situation

North Hebei power grid covers Zhangjiakou, Chengde, Qinhuangdao, Tangshan, and Langfang in the northern part of Hebei Province[1]. The North Hebei Power Grid is an important power hub for the coordinated development of the Beijing-Tianjin-Hebei region, which is adjacent to Beijing-Tianjin and bears the important tasks of guaranteeing the security of power supply to the capital city of Beijing, serving the economic and social development of the North Hebei region, and serving the development of new energy resources in the country. The North Hebei power grid has its own unique resource endowment and development characteristics. The North Hebei region is rich in wind, solar, and other renewable energy resources, and new energy accounted for a high proportion. As of the end of 2024, the total installed capacity of new energy in the North Hebei Grid reached 71,857,800 kilowatts, with 81.3% of the installed capacity under unified control[2], which is the first provincial power grid in China where the installed capacity of new energy exceeds that of conventional power sources. The North of Hebei region has a high pressure of exporting power and undertakes the task of delivering clean power to Beijing, Tianjin, and other regions.

In terms of power trading, in 2024, the total amount of thermal power trading in the North Hebei power grid was 49.454 billion kWh, with an average price of RMB 418.10/MWh. Settlement of new energy trading power 28.754 billion kWh, the average price of 402.29 yuan/MWh.

Data Sources

Multi-source data for the whole year of 2024 are selected for this study, mainly including:

1) Power generation data: unit-by-type, hour-by-hour power generation (including ≥300 MW coal power units, small units, gangue power, gas units, wind power, and photovoltaic) from the North Hebei Dispatch Centre.

2) Fuel characteristics: the baseline emission factor for 2024 issued by the Ministry of Ecology and Environment[3].

3) Transmission data: hour-by-hour cross-provincial power transmission and transmission losses between Hebei and other regional power grids.

4) Green power trading data: the corresponding power volume of green certificates and their hour-by-hour distribution.

Generating units in northern Hebei can be divided into two categories: fossil energy units and new energy units, among which fossil energy units can be divided into coal-fired units with a rating of more than 300 MW, coal-fired units with a rating of less than 300 MW, coal gangue generating units, and gas-fired units, and different units correspond to different carbon emission benchmarks, according to which the carbon emission benchmarks are measured for the carbon emissions of each fossil energy unit. New energy units include wind power units and photovoltaic units, and the carbon emission of new energy units is 0. The power generation and carbon emission of different types of units are shown in Table 3.

Case Study Results

Based on the above data, the calculation of the power carbon emission factor can be achieved through the process of data input, carbon emission calculation, calculation of the power carbon emission factor, and output of results. The calculation process flowchart is shown in Fig. 2, and the calculation results are shown in Table 4.

According to the calculations in Table 4, the fossil fuel power carbon emission factor in the North Hebei region in 2024 is 0.7899 tCO_2/MWh. This figure is relatively lower than the national average fossil fuel power carbon emission factor of 0.8325 tCO_2/MWh, indicating that the carbon emission levels from fossil fuel power plants in the northern Hebei region are comparatively lower.

The power carbon emission factor with hybrid power and regional power exchange is 0.5069 tCO_2/MWh in the North Hebei region. This figure is lower than the fossil fuel power carbon emission factor for the North Hebei region, as well as the national and provincial average power carbon emission factor in Hebei Province (national level: 0.5366 tCO_2/MWh; Hebei level: 0.7252 tCO_2/MWh). This is primarily attributable to the low-carbon, emission-reducing nature of renewable power, which has led to a reduction in the proportion of thermal power generation following the integration of renewable sources.

As one of the nine major clean energy bases outlined in China's 14th Five-Year Plan, the North Hebei Clean Energy Base region has witnessed rapid and high-quality growth in its new energy sector. Data indicates that by 2023, the installed capacity of new energy sources within the North Hebei power grid exceeded 50 million kilowatts, accounting for 76% of the total installed power generation capacity. New energy generation now constitutes 51% of the region's total power output, making the North Hebei region the first in the nation to establish a power generation system predominantly reliant on new energy sources. The utilization of clean

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[1] The northern Hebei region studied in this paper is the five cities of Zhangjiakou, Chengde, Qinhuangdao, Tangshan and Langfang covered by the northern Hebei power grid.

[2] http://www.north Hebei .sgcc.com.cn/html/main/col19/2014-06/27/20140627161613838605892_1.html.

[3] https://www.mee.gov.cn/zcwj/zcjd/202410/t20241021_1089825.shtml.

Table 3. Unit type and related data.

Type of unit	Power Generation (MWh)	Carbon emissions baseline (tCO_2/MWh)	Corresponding carbon emissions (tCO_2)
Coal-fired units above 300MW class	30090276.2563	0.7822	23536614.0877
Coal-fired units below 300MW class	54196211.8567	0.7944	43053470.6989
Coal gangue generator sets	105416.8000	0.8042	84776.1906
Gas-fired unit	24393.3900	0.3288	8020.5466
Wind turbine	51436261.7490	0	0.0000
Photovoltaic generator sets	30686626.2980	0	0.0000

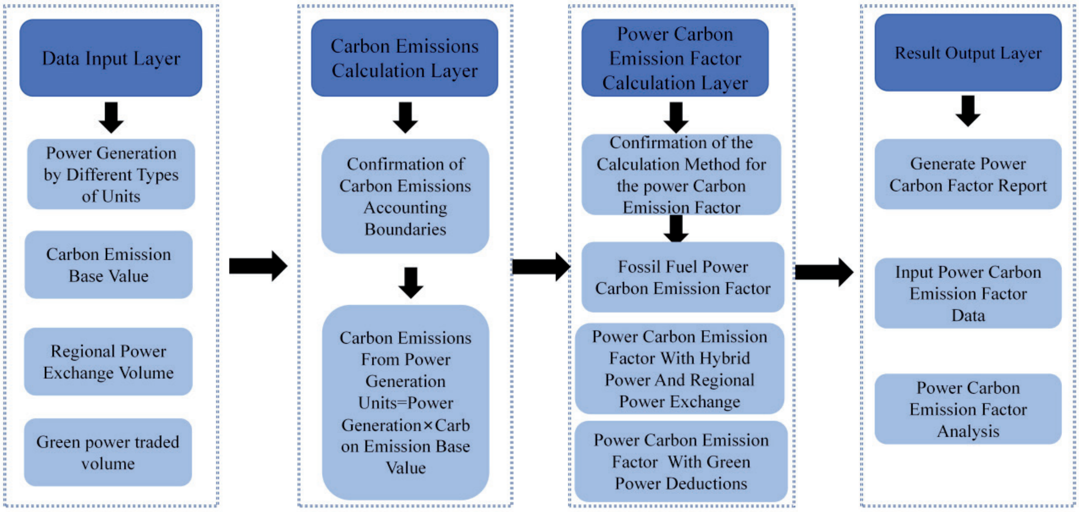

Fig. 2. Calculation process flowchart of the power carbon emission factor.

Table 4. Calculation results for power carbon emission factors of the North Hebei region.

Fossil fuel power carbon emission factor (tCO_2/MWh)	Power carbon emission factor with hybrid power and regional power exchange (tCO_2/MWh)	Power carbon emission factor with green power deductions (tCO_2/MWh)
0.7899	0.5069	0.6488

energy has effectively reduced carbon emissions within the North Hebei power system, leading to a decrease in the power carbon emission factor.

In 2024, the settlement volume of new energy transactions within the North Hebei power grid reached 28.754 billion kilowatt-hours. Based on relevant data and formulas, after deducting non-fossil energy transaction volumes, the power carbon emission factor with green power deductions in the North Hebei region was calculated as 0.6488 tCO_2/MWh. This figure exceeds the national average power carbon emission factor (excluding non-fossil energy volumes traded in the market) (national average level: 0.5856 tCO_2/MWh). This indicates that substantial volumes of low-carbon power are dispatched from North Hebei, resulting in a relatively elevated carbon intensity for locally retained power.

Comparative Analysis – Jiangsu

In order to further verify the reasonableness of the designed time-of-use and zone-based power carbon emission factor, and to form a more systematic and comprehensive analysis conclusion, this paper, on the basis of completing the calculation of the power carbon emission factor of the North Hebei region, selects Jiangsu Province as a comparative case to carry out in-depth analyses. The calculation results are shown in Table 5.

Jiangsu Province is a large economic province and an energy consumer in the eastern part of China. The types of power in Jiangsu Province mainly include coal power, nuclear power, wind power, and other new energy generation. Jiangsu Province is actively promoting the green transformation of its energy

Table 5. Calculation results for power carbon emission factors of Jiangsu Province.

Fossil fuel power carbon emission factor (tCO_2/MWh)	Power carbon emission factor with hybrid power and regional power exchange (tCO_2/MWh)	Power carbon emission factor with green power deductions (tCO_2/MWh)
0.7870	0.4946	0.5020

structure, with new energy installed capacity accounting for about 42% of the total installed power supply in 2024, surpassing coal power and becoming the top power source in Jiangsu. At the same time, Jiangsu Province has a strong power demand, relying on extra-high-voltage transmission channels and the large-scale introduction of clean energy from outside the region. Power from outside the region has become an important power supply guarantee for Jiangsu Province.

According to the calculation results in Table 5, the fossil fuel power carbon emission factor in Jiangsu Province is 0.7870 tCO_2/MWh, which is lower than the national fossil fuel power carbon emission factor (national level: 0.8325 tCO_2/MWh), indicating that the level of carbon emission from fossil energy units in Jiangsu Province is relatively low. In Jiangsu Province, the power carbon emission factor with hybrid power and regional power exchange is 0.4946 tCO_2/MWh, which is lower than the average power carbon emission factor of 0.5978 tCO_2/MWh in Jiangsu Province.

This is mainly due to the development of renewable energy in Jiangsu Province. Jiangsu Province focuses on green and low-carbon development, and the power generation structure within the region is constantly transforming to be cleaner and lower-carbon. Jiangsu Province has a wide variety of new energy sources, and the Tianwan Nuclear Power Station in Jiangsu Province, as one of China's important nuclear power bases, has abundant nuclear power resources. As a stable baseload energy source that produces almost no carbon emissions, nuclear power provides a large amount of low-carbon power to the Jiangsu power grid. In addition, wind power and photovoltaic power generation are developing rapidly in Jiangsu Province, which ranked second among all provinces and cities in the country in terms of the total amount of offshore wind power installed in Jiangsu Province in 2024.

As of May 2025, Jiangsu's new energy installed capacity exceeded 100 million kilowatts, reaching 101 million kilowatts, accounting for 46% of the province's total installed power supply, and becoming the first province in the Yangtze River Delta to "break the 100 million" new energy installed capacity. In the power system, renewable power has thermal power substitutability, and new energy development promotes a power carbon emission factor that is lower than the national level.

In addition, Jiangsu Province, as a large power-using province, in order to meet the demand for power, relies on the Longquan–Zhengping and other large-scale transmission projects, resulting in a large-scale transfer of clean energy into Jiangsu Province every year. The entry of clean energy also reduces the carbon emission factor of Jiangsu Province as a whole. The power carbon emission factor with green power deductions is 0.5020 tCO_2/MWh, and the volume of green power trading in Jiangsu Province in 2024 is 12.657 billion kWh. After deducting the volume of green power trading, the power carbon emission factor of Jiangsu Province increases, but it is still lower than the national average power carbon emission factor (excluding market-traded non-fossil energy) (the national average is 0.5856 tCO_2/MWh).

Through a comparative analysis of the power carbon emission factor in the North Hebei region and Jiangsu Province, although the power carbon emission factor of fossil energy in both regions is lower than the national average, the carbon emission level of fossil energy units in northern Hebei is still relatively high. This indicates that the North Hebei region still needs to further strengthen the low-carbon transformation of coal power units, accelerate the elimination of backward production capacity, and promote the optimisation and upgrading of energy structure.

From the perspective of inter-regional power transmission, the North Hebei region, as a major green power exporting province, produces a large amount of green power for export, which, to a certain extent, reduces the proportion of local green power. However, Jiangsu Province, as a major recipient province of foreign power, effectively replaces local coal power consumption through the introduction of cleaner power from outside the region, which plays a significant role in carbon emission reduction. As a result, Jiangsu Province's power carbon emission factor with hybrid power and regional power exchange is lower than that of the North Hebei region. This result highlights the important role of inter-provincial green power consumption in reducing carbon emissions in the recipient region, and also shows that the Jibei region, as a green power exporting region, needs to coordinate the development of local clean energy and the transition process of coal power while guaranteeing the transmission.

Discussion

The discussion in this study focuses on elucidating the mechanism through which high-resolution dynamic carbon accounting clarifies the allocation of cross-regional carbon responsibilities and green electricity environmental rights. The results demonstrate that the power carbon emission factor model based on high-spatiotemporal-resolution effectively captures the dynamic characteristics of regional power structures, significantly enhancing the accuracy, timeliness, and comparability of carbon accounting outcomes. Recent years have witnessed significant progress in carbon emission accounting based on power carbon emission factors, particularly in “minute-level” real-time carbon measurement and the assessment of cross-provincial indirect emissions [36, 37], which provides valuable perspectives and a foundational support for this research.

Furthermore, the study finds that integrating the “green power deduction” mechanism with cross-regional carbon flow tracing not only effectively avoids the double-counting of environmental attributes [38, 39], but also contributes to a fairer delineation of emission-reduction responsibilities between power-exporting and power-importing regions. Ge (2024) quantitatively revealed the significant impact of inter-regional carbon emission responsibility transfer and green rights circulation on the calculation results of regional grid emission factors [40], providing crucial methodological support for constructing a unified and transparent carbon accounting system in this study. Addressing carbon accounting for green power consumption, Chen (2024) proposed an improved calculation method for grid emission factors that considers green electricity consumption. This method achieves refined carbon emission measurement for end-users by accurately identifying the environmental value of green power [41], thereby laying a solid theoretical foundation for the green power deduction model developed in this paper.

From a methodological perspective, this study finds that when the temporal granularity is coarsened from hourly to day-ahead, the standard deviation of the carbon emission factor increases by more than twofold, and the peak-shaving and valley-filling and emission reduction potential of adjustable loads is overestimated by over 30%. Research by Zhao (2023) and Yang (2024) on the spatiotemporal heterogeneity of power carbon factors [42, 43] further corroborates the necessity of implementing high-precision, high-spatiotemporal-resolution accounting in power systems with a high penetration of renewable energy. In the future, by incorporating minute-level data, high-precision weather forecasts, and blockchain-based traceability verification technologies, the prediction error could potentially be controlled within ±0.02 tCO_2/MWh. This not only offers a replicable and scalable technical framework for other developing countries but also helps avoid the risk of the “low-carbon resource curse” on a global scale [44].

From a policy standpoint, the findings of this study provide a quantitative basis for designing a unified national power carbon accounting system and its coordination mechanism with green power trading. As inter-regional power transmission scales up in China, the associated issue of carbon emission transfer becomes increasingly prominent, making the establishment of standardized accounting methods to clearly define regional emission responsibilities urgent [45]. Case analysis further reveals that in some renewable-rich regions, large-scale cross-provincial power export leads to a discrepancy between the calculated local carbon intensity and their abundant resource endowment. This phenomenon is not isolated; similar characteristics have been observed in studies on “carbon emissions in resource-based cities” and “carbon footprint accounting” by Gou (2025) and Wang (2024), which further validates the universality and explanatory power of the model proposed herein across regions with diverse resource endowments [46, 47]. In summary, this research not only deepens the understanding of the mechanisms behind cross-regional power carbon flow tracing and responsibility allocation but also provides a scientifically feasible pathway for China to refine its carbon emission intensity and total amount control system and to promote the synergistic development of the electricity and carbon markets.

Conclusions

This study focuses on three core issues: the spatiotemporal refinement of power carbon emission factor calculation, the decomposition of cross-regional carbon responsibility, and the attribution of green power environmental rights. It constructs a dynamic model for calculating the hourly and regional power carbon factor and validates the model’s effectiveness using the North Hebei region power grid as a case. The main conclusions are as follows:

The model achieves a breakthrough in high-spatiotemporal-resolution for power carbon emission factor calculation. Compared with the traditional annual/provincial static calculation method, this study takes the power generation unit as the smallest calculation unit and refines the time granularity to the hourly level, which can accurately capture the intra-day dynamic changes in power system carbon emissions. For example, in the North Hebei region, due to the characteristic of wind power generation being “low during the day and high at night”, the hourly power carbon factor at night (average 0.42 tCO_2/MWh) is 17.6% lower than that during the day (0.51 tCO_2/MWh). This difference cannot be reflected in traditional calculations. At the same time, the model has the potential to be extended to the minute level, providing a methodological basis for real-time low-carbon dispatch and significantly improving the refinement level and dynamic response capability of carbon emission calculation [48, 49].

The cross-regional carbon flow tracking mechanism clarifies the spatiotemporal transfer rules of carbon emission responsibility. By quantifying the cross-regional transmission power and corresponding carbon factors between North Hebei and Beijing-Tianjin and other regions, it is found that in 2024, North Hebei’s net clean power transmission exceeded 30 billion MWh, corresponding to a transfer of about 1.5 million tons of CO_2 emissions. This objectively reflects the regional responsibility pattern of "the sending end bears the cost of emission reduction, and the receiving end enjoys the benefits of low carbon". This result solves the problem of "ambiguous responsibility" of cross-regional carbon emissions in traditional calculations, providing a quantitative basis for regional coordinated emission reduction in the Beijing-Tianjin-Hebei region and a replicable calculation logic for the allocation of cross-regional power grid carbon emission responsibilities across the country.

The green power deduction mechanism effectively avoids the risk of "double counting" of carbon emissions. By combining the 2024 green power trading data of 28.754 billion kWh in North Hebei, the model explicitly deducts the non-fossil energy trading power, and the power carbon factor rebounds from the mixed state of 0.5069 tCO_2/MWh to 0.6488 tCO_2/MWh, accurately restoring the actual carbon intensity of the local retained power. This correction process clarifies the principle of the transfer of green power environmental rights with transactions, avoiding the problem of "counting as low-carbon contribution at the generation end and then counting as emission reduction at the consumption end", providing key calculation support for the coordinated operation of the green power market and the carbon market.

The case calculation results verify the driving role of high proportions of new energy in the low-carbonization of the power grid. The new energy installed capacity in the North Hebei power grid accounts for 81.3%, and the wind power and photovoltaic power generation account for 51% of the total power generation, directly driving its power carbon emission factor with hybrid power and regional power exchange (0.5069 tCO_2/MWh) to be lower than the national average (0.5366 tCO_2/MWh) and the average of Hebei Province (0.7252 tCO_2/MWh), fully demonstrating that the large-scale integration of new energy is the core path to reducing the carbon intensity of the power grid. At the same time, the change in the carbon factor after the deduction of green power also reveals the special carbon intensity of "green power transmission regions", providing a reference benchmark for the carbon emission calculation of similar regions.

Policy Recommendations

Based on the research conclusions, the following policy recommendations are proposed to promote precise carbon accounting and low-carbon transformation in the power system:

First, establish a unified national high-resolution power-carbon factor accounting standard system. Clearly define the time granularity to at least the hourly level and spatial boundaries, standardize the calculation methods for cross-regional carbon flows, such as the proportion of carbon allocation for transmission losses and the conversion rules for cross-provincial carbon factors, and unify the carbon emission benchmark values for different types of power generation units, such as coal-fired, gas-fired, and new energy. Ensure the standardization and comparability of data across different regions and power grids, providing a unified accounting basis for the construction of the national carbon market and the decomposition of regional emission reduction targets [48].

Second, improve the green power deduction and cross-regional carbon responsibility coordination adjustment mechanism. Incorporate the dynamic green power deduction rules of this model into the green certificate trading and power trading settlement processes. Require green power purchasers to use the regional power-carbon factor after deducting green power in their Scope 2 carbon accounting, rather than the average factor of the entire network. At the same time, establish a cross-regional carbon emission responsibility "compensation-allocation" mechanism. For regions like North Hebei that export green power, compensation can be provided through central government transfer payments and cross-regional transmission carbon subsidies to address the "passive increase" in local carbon intensity caused by exporting low-carbon power. This avoids the mismatch of emission reduction responsibilities and benefits, and ensures the enthusiasm of regions for emission reduction [49].

Third, promote the open sharing and real-time release of power-carbon factor data. Relying on the dispatching data platforms of State Grid and China Southern Power Grid, build a national power-carbon factor database, integrate multi-source data such as unit output, cross-regional transmission, and green power trading, and achieve real-time updates and queries of carbon factors by time and region on a daily basis. Open enterprise-level and regional-level carbon factor data interfaces to the public, supporting power dispatching institutions in optimizing low-carbon dispatching strategies, enterprises in conducting precise carbon management, and research institutions in deepening technical research. At the same time, strengthen data quality supervision, establish data traceability and error correction mechanisms to ensure the authenticity and authority of the data.

Fourth, integrate carbon factor signals into the power dispatching and demand response system. It is recommended to introduce a "carbon factor optimization objective" in the dispatching of provincial and above power grids. Under the premise of ensuring power supply security, prioritize the dispatching of units and cross-regional transmission channels with lower carbon factors. At the same time, promote the "time-of-use carbon price + time-of-use power price" linkage mechanism, implementing higher power prices during high-carbon periods and lower prices during low-carbon periods for the user side [50]. This will guide industrial and commercial users to adjust their power consumption behavior (such as transferring high-energy-consuming production to the peak wind power period at night), optimize the overall power consumption structure, enhance the capacity for new energy consumption, and achieve the coordinated optimization of economic benefits and low-carbon goals.

Limitations and Future Directions

This study has several limitations. First, due to restricted access to high-spatiotemporal-resolution data on power plant emissions and renewable generation, certain parameters relied on statistical inference or estimation, which may introduce local uncertainties. Second, the proposed power-carbon-certificate coordination framework is built upon static assumptions and does not yet capture the dynamic feedback effects under policy and price linkages [44]. Third, the empirical analysis focuses on North Hebei and Jiangsu, without encompassing provinces with more diverse energy structures. Future research could address these gaps by incorporating real-time monitoring and multi-source data fusion to enhance accuracy, developing dynamic optimization models to characterize multi-market interactions, and extending comparative analyses to national or cross-regional scales to support a unified system for power-sector carbon accounting and coordinated trading.

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Conflict of Interest

The authors declare no conflict of interest.

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