International Journal of Sustainable Energy Planning and Management Vol. 46 2025 41–57

International Journal of
Sustainable Energy Planning and Management

Quantitative Analysis and Carbon Reduction Strategies Based on Spatiotemporal Electricity Carbon Emission Factors

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ABSTRACT.

Different temporal and spatial dimensions of carbon accounting (CA) can yield varying carbon emission results. Fine-grained time- and region-specific carbon emission factor (CEF) accounting for a target power grid can improve both accuracy and interpretability. This paper uses a central China power grid as a case study to examine the calculation methods for CEFs across different temporal and spatial dimensions. It focuses on the differences in CA at substation, administrative, and voltage levels (VLs) across various time periods. First, the paper summarizes the development trends in power grid CEF calculations, highlighting the importance of regional division and time-based accounting. Second, a multidimensional CEF calculation method is proposed based on the coupling mechanism between power generation and carbon emissions, emphasizing the close relationship between carbon emissions and electricity under different generation structures and energy usage patterns. Finally, through quantitative analysis, the paper examines carbon emission variations across different temporal and spatial ranges and discusses the advantages and disadvantages of various partitioning strategies from the perspectives of power generation companies, electricity consumers, and the government. The study provides valuable insights for further research and standardization of CEFs in power grids.

Keywords

Carbon emission factors;
Spatiotemporal;
Substation;
Administrative division;
Voltage level

http://doi.org/10.54337/ijsepm.9789

1. Introduction

As global climate change intensifies, an increasing number of countries and organizations recognize the necessity of reducing, compensating for, or completely offsetting greenhouse gas emissions (particularly carbon dioxide) to achieve the goal of "carbon neutrality." The attainment of carbon neutrality primarily hinges on reducing carbon emissions, with accurate carbon accounting (CA) serving as an essential foundation [1]. The precision of this accounting directly impacts the rationality of carbon reduction policies, the effectiveness of management and operational mechanisms, and ultimately determines whether the carbon neutrality goal can be genuinely realized [2].

To systematically and accurately account for greenhouse gas emissions, the World Resources Institute (WRI) publishes the "Greenhouse Gas Protocol: Corporate Accounting and Reporting Standard," which classifies greenhouse gas emissions from corporate activities into three distinct scopes [3]. Scope 2 Accounting refers to the accounting of indirect carbon emissions from purchased electricity, heat, steam, or cooling. The Scope 2 accounting methodology outlined in the Corporate Standard is widely recognized and adopted as an industry standard. Compared to other accounting methods, Scope 2 Accounting comprehensively considers indirect greenhouse gas emissions, including those from electricity consumption, the

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Received 13.12.2024 | Accepted 03.07.2025 | Published 09.09.2025

List of Abbreviations

AD	*Administrative division*
CI	*Carbon intensity*
CA	*Carbon accounting*
CEF	*Carbon emission factor*
TRG	*Target regional grid*
VL	*Voltage level*

embedded emissions in purchased goods and services, and transportation emissions associated with business activities [4].

The power system is one of the major global sources of greenhouse gas emissions. Accurately calculating the CEF of power grids is crucial for formulating effective carbon reduction policies. However, there is currently no unified standard for calculating CEFs in power grids, either domestically or internationally [5]. The differences in focus between environmental regulatory authorities and the power sector contribute to discrepancies in carbon emission accounting. The environmental regulatory authorities are responsible for monitoring and managing environmental quality, including air pollution and climate change, and are more concerned with carbon emissions across and within industries. This sector seeks to control carbon emissions through the development and enforcement of regulations, standards, and emission permits, with stakeholders such as the public, environmental organizations, and the international community, who are primarily focused on environmental protection. In contrast, the power sector's primary goal is to ensure a stable electricity supply while optimizing the efficiency of energy production and utilization. The power sector tends to adopt measures like technological innovation and energy transition to reduce carbon emissions, such as increasing the share of renewable energy [6], enhancing generation efficiency [7], and promoting clean energy technologies [8]. The stakeholders in the power sector, including energy companies, electricity consumers, and governments, are more concerned with the reliability of energy supply and cost-effectiveness [2].

To measure carbon emissions from different electricity sources and more accurately assess the contribution of the power system to greenhouse gas emissions, many countries, organizations, and institutions have proposed methods for calculating grid CEFs based on the Scope 2 Accounting approach. The grid CEF refers to the amount of carbon dioxide emitted per unit of electricity generated by the grid, typically expressed in gCO_2/kWh [9]. Initially, grid CEFs were primarily used for national-level energy emission estimations, considering only the emissions from traditional power generation methods. However, with the gradual proliferation of renewable energy sources, particularly as solar and wind power generation costs decrease, more countries and organizations have begun incorporating these clean energy sources into their power systems. Consequently, increasing research has introduced the concept of "auxiliary and supplemental power sources" [11] and started to account for the emission factors of different types of renewable energy under varying conditions, driving the evolution of grid CEFs. To address emerging challenges, researchers have begun integrating novel approaches such as those based on nighttime light data for analyzing dynamic spatiotemporal evolution and spatial effects of urban carbon emissions [12] and assessing wind power spatiotemporal footprints toward carbon neutrality [13]. Additionally, city-scale energy consumption and decoupling effects have been explored in multiscale investigations of carbon emission dynamics [14].

The diversity in methodologies highlights the gaps in precision, spatial granularity, and real-time adaptability of current approaches, necessitating a robust spatiotemporal carbon emission accounting framework. While much of the prior work has emphasized either broad regional patterns or specific operational dynamics, there remains a significant need for integrated methodologies that bridge spatial and temporal dimensions at different scales, as well as for standards that address intersectoral differences [6-8].

This study aims to develop a robust spatiotemporal CEF calculation framework tailored to regional power grids and seeks to provide actionable insights for policymakers, power companies, and researchers working toward achieving carbon neutrality in power systems. To achieve this aim, the study is guided by the following research questions:

1. How do different partitioning strategies impact the accuracy and applicability of CEF calculations across spatiotemporal dimensions in a regional power grid?
2. How can spatiotemporal coupling mechanisms between power generation units and carbon emissions improve the precision and adaptability of CEF accounting?

3 What are the advantages and limitations of these strategies from the perspectives of power companies, electricity consumers, and government authorities?
4 What standards and frameworks can be proposed for integrating spatiotemporal CEF calculations into carbon reduction strategies and policy development?

By addressing these questions, this paper takes a regional power grid in central China as a case study to explore the differences in electricity CEF calculations based on various partitioning accounting strategies within different time periods to bridge the methodological gaps in carbon accounting. It further discusses the advantages and disadvantages of these strategies from the perspectives of power companies, electricity consumers, and government authorities, providing a reference for further research and the development of standards for CEFs in China's power grids. The main contributions of this paper are summarized as follows:

1 Review and Gap Analysis: It reviews the current trends of electricity CEFs calculations identifying gaps in precision, spatial granularity, and real-time adaptability. It highlights the importance of incorporating spatiotemporal dynamics into CEF frameworks, addressing Research Question 1.
2 Proposed Methodology: Based on the coupling mechanisms between the electricity generation of different types of power generation units and their carbon emissions, this paper proposes a calculation method for spatiotemporal CEFs. This method analyzes the coupled relationship between temporal carbon emissions and electricity power across multiple spatial dimensions, considering different power structures and energy consumption characteristics, to achieve CEF calculations across various accounting scopes. This contribution directly addresses Research Question 2, improving precision and adaptability in CEF accounting.
3 Quantitative Analysis and Strategy Evaluation: Through quantitative analysis of the differences in CEFs across different accounting scopes within the target regional grid (TRG), the paper explores the pros and cons of different partitioning strategies from the perspectives of power companies, electricity consumers, and government authorities. This addresses Research Question 3, providing insights into the practical applicability of CEF frameworks for stakeholders.
4 Framework Proposal: Based on the findings, the study provides a preliminary framework for integrating spatiotemporal CEF calculations into broader carbon reduction strategies and policy development, addressing Research Question 4.

Section II introduces the current trends in accounting for electricity CEFs. Section III proposes the theoretical method for calculating spatiotemporal CEFs. Section IV describes the calculation results of CEFs in the provincial TRG. Section V provides comparative analysis and carbon reduction strategies and Section VI concludes.

2. Evolution and Trends of Power Grid Carbon Emission Factors

The evolution of CEFs in power grids reflects the growing need for precision and adaptability in CA methodologies. This chapter provides an overview of the current research status, trends, and significance of power grid CEFs, highlighting global advancements, innovative methodologies, and their implications across various accounting scopes and timeframes.

2.1 Research Status and Trends

Globally, a series of standards have been established to guide and regulate corporate carbon audits. At the national and regional levels, the Intergovernmental Panel on Climate Change (IPCC) developed the IPCC Guidelines for National Greenhouse Gas Inventories in 2006 [15]. For corporate and product-level accounting, the WRI and the World Business Council for Sustainable Development released frameworks for greenhouse gas accounting in 2001, 2011, and 2015 [16]. In the U.S., the Infrastructure Investment and Jobs Act of 2021-2022 mandated the Energy Information Administration (EIA) to publish hourly average and marginal CEFs, incorporating CA into green microeconomic infrastructure [18]. This initiative promotes the development of carbon sink markets and enhanced the system of emission reduction responsibilities. In response, EIA has developed a national grid monitoring platform that provides hourly power generation and consumption data at national, state, and balancing area levels [19]. The California Air Resources Board has released hourly carbon emission data related to electric vehicles under the Low Carbon Fuel Standard [20]. Finland's Fingrid system uses real-time generation data and carbon emission coefficients to estimate grid carbon emissions [21], while France's eCO_2mix system dynamically monitors electricity-related carbon emissions, linking them to power generation, load, and energy exchange with neighboring countries [22]. The PJM and UK grid publishes real-time marginal carbon factors and short-term carbon forecasts [23].

In addition to regulatory frameworks, innovative methodologies have emerged in academia. A systematic analysis of city energy systems modeling to address CO_2 emissions at various scales [25], as well as optimization methods for energy communities aiming for full decarbonization [8] emphasize the integration of spatiotemporal dynamics in CA. Dynamic spatiotemporal models, such as those based on nighttime light data [12] and wind power spatiotemporal footprints [13] mentioned before. Stanford University proposed a method for calculating carbon factors hourly within load-balancing areas, using a multi-regional carbon balance equation [26]. The University of Freiburg in Germany has utilized publicly available European grid data to compute hourly carbon factors [27]. The analysis of Vietnam's energy-related carbon emissions using system dynamics [28] further refined spatiotemporal approaches. Similarly, sustainable energy planning for positive energy districts highlights the value of real-time CA [29]. Furthermore, approaches like real-time building energy carbon intensity (CI) tracking and mixed-grid environment GHG emission assessments [30-32] underscore the need for localized, dynamic analysis.

In China, research on time- and region-specific CA for power grids is still in the exploratory phase. Tsinghua University has combined carbon emission analysis with power flow calculations to develop a theoretical framework for carbon flow analysis in power systems [33]. This approach defined key matrices and vectors related to carbon flow, calculating emissions across generation, transmission, and distribution. The method revealed the carbon emission characteristics and distribution across different time and space scales, considering factors such as energy mix, generation efficiency, and electricity trading. Meanwhile, the State Grid Big Data Center and Shanghai Envision Digital have developed a new framework for calculating regional and marginal CI using state estimation and power flow characteristics. This method assessed carbon emissions more accurately and supported emission reduction and energy optimization strategies [2][5]. Another Study has explored the decoupling effects and spatiotemporal dynamics of carbon emissions across China using advanced econometric and geospatial techniques [35]. At the governmental level, various standards and guidelines have been implemented to support enterprise-level carbon audits and the calculation of regional CEFs [36].

Research on grid CEFs is evolving toward more precise, regionally detailed, and real-time accounting methods. To calculate CEFs accurately, researchers are focusing on the fine-grained collection and processing of data across all stages of the power system. This includes gathering comprehensive data on generator parameters [39], fuel supply chains [40], and transmission and distribution networks [41] to enable more precise calculations. To reflect regional variations in electricity-related carbon emissions, grid CEF studies are increasingly being regionalized, accounting for geographical, market, and other influencing factors. By calculating carbon factors for different regions, researchers provide more accurate insights into localized emissions, supporting the formulation of region-specific policies. Additionally, the time-varying nature of grid carbon emissions has prompted a shift toward more dynamic and real-time studies. Real-time monitoring of power system operations and continuous updates to carbon factor calculations allow researchers to better capture temporal variations in carbon emissions. This approach enhances the responsiveness of CA, reflecting changes in power system operation and providing timely data for emissions management and policy-making.

2.2 Research Significance

Different accounting scopes can provide varying levels of carbon emission data, which enhances the accuracy and comparability of assessments. At the substation level, carbon emissions can be precisely quantified for the specific areas served by each substation, providing valuable data for optimizing substation operations and management. At the administrative division (AD) or zonal level, such data enables the formulation of region-specific carbon reduction strategies based on the economic development and energy consumption patterns of each area. Regarding voltage levels (VLs), distinguishing the carbon emissions associated with high, medium, and low voltage grids can aid in optimizing grid structure and operations, thereby reducing losses and emissions across different VLs [42].

Power Companies: can leverage data from different accounting scopes to optimize operations. Detailed carbon emission data allows for the identification of high-emission points, enabling the development of targeted carbon reduction measures such as optimizing grid structure, reducing line losses, and enhancing energy efficiency. Accurate carbon emission data also facilitates better participation in carbon markets, where companies can formulate carbon quota management strategies, achieving both carbon reduction and economic benefits. Calculating CEFs across different accounting scopes increases transparency, making it clearer where and how emissions originate and are distributed. This transparency helps ensure that power consumers fairly share the responsibility for carbon emissions and supports the equitable functioning of carbon trading mechanisms in the market [43].

Power Consumers: can make more environmentally friendly choices based on CEFs calculated across different accounting scopes. This includes guiding consumption behavior: by understanding the carbon emissions of their region or VL, consumers can choose lower-carbon electricity options, such as using power during off-peak times or selecting green energy products. Targeted carbon emission data can also guide consumers to optimize their electricity usage, reducing energy waste and lowering their overall carbon footprint [44].

Governments: need to formulate precise carbon reduction strategies and policies based on carbon emission data from different accounting scopes. By utilizing data on carbon emissions across various regions and VLs, governments can create more targeted policies, such as regional emission reduction targets, differentiated electricity pricing, or incentive measures. Detailed CEF data also helps governments better regulate carbon emissions in the power industry and assess the effectiveness of implemented policies [45].

The significance of multi-time durations accounting for grid CEFs can be summarized as follows:

1. *Reflecting real-time carbon emissions:* The operational state of the power system constantly changes over time, with varying loads, generation structures, and energy consumption levels affecting carbon emissions. Temporal accounting enables dynamic tracking of CI at different time intervals, revealing discrepancies in emissions during peak and off-peak periods. This is crucial for the timely understanding of grid carbon emissions and for implementing more precise carbon reduction measures.
2. *Facilitating low-carbon dispatch optimization:* Temporal accounting provides essential data for low-carbon economic dispatch in power systems. By analyzing the variation of CEFs across time periods, grid operators can prioritize the use of low-carbon and clean energy generation while minimizing reliance on high-carbon generation units. This optimizes the overall carbon emissions of the grid.
3. *Supporting carbon trading and policy formulation:* Time-series accounting provides foundational data for carbon market development and carbon trading pricing. Significant differences in CEFs across different time periods allow governments and power companies to design more accurate carbon trading rules, ensuring that carbon costs are differentiated by time. This aids in policy regulation and carbon market efficiency.

3. Calculation of Spatiotemporal Electricity Carbon Emission Factors

To comprehensively assess electricity carbon emissions, this section introduces a theoretical framework to analyze spatiotemporal emission factors and examines their applicability across various international contexts. By addressing both foundational principles and comparative insights, the discussion aims to bridge the gap between theory and global implementation.

3.1 Theoretical Framework

Carbon emissions in power systems originate from generation plants and propagate through the grid via active power flow, ultimately assigning emission responsibility to end-users based on their consumption. The carbon flow mechanism traces emissions from generators to consumers, linking physical power transfer with carbon accountability.

As shown in the abstract power flow diagram of adjacent regional grids in Fig. 1, each circle can represent a substation or the grid of an AD, and the dashed rectangles represent the grids covered by different VLs. Let the set of adjacent regional grids that input power flow to regional grid $\boldsymbol{n}$ be denoted as $\boldsymbol{x}$, and the set of regional grids that receive power flow output from regional grid $\boldsymbol{n}$ be denoted as $\boldsymbol{y}$. The active power flow from grid $\boldsymbol{i}$ to grid $\boldsymbol{n}$ and from grid $\boldsymbol{n}$ to grid $\boldsymbol{j}$ during period $\boldsymbol{t}$ can be denoted as $P_{i,n}^{t}$ and $P_{n,j}^{t}$, respectively. Assuming that the

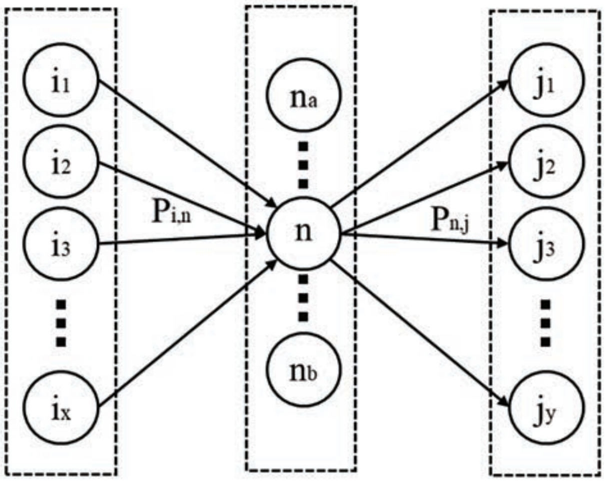

Figure 1: Abstract power flow diagram of adjacent regional grids.

power flow from n to j contains a component from the power flow input by i, denoted as $P_{j,i}^t$, and based on the proportional sharing principle [33], the following formula (1) can be obtained:

$$\frac{P_{j,i}^t}{P_{n,j}^t}=\frac{P_{i,n}^t}{\sum_{i=1}^{x}P_{i,n}^t} \tag{1}$$

If the CEF of the active power flow from line $i \in x$ into n at t is CI_i^t, then the carbon emission CE_j^t of the active power flow $P_{j,i}^t$ in the outgoing branch j is the sum of the contributions of all branches in x to the carbon flow in branch j [33], which can be expressed as formula (2):

$$CE_j^t=\sum_{i=1}^{x}P_{j,i}^t\times CI_i^t. \tag{2}$$

Thus, the CEF CI_j^t of the outgoing branch j can be expressed as formula (3):

$$CI_j^t=\frac{CE_j^t}{P_{n,j}^t}=\frac{\sum_{i=1}^{x}P_{j,i}^t\times CI_i^t}{P_{n,j}^t}. \tag{3}$$

Substituting equation (1) into equation (3) to eliminate $P_{j,i}^t$ can get equation (4):

$$\begin{aligned}CI_j^t&=\frac{\sum_{i=1}^{x}P_{j,i}^t\times CI_i^t}{P_{n,j}^t}=\frac{\sum_{i=1}^{x}P_{n,j}^t\times\frac{P_{i,n}^t}{\sum_{i=1}^{x}P_{i,n}^t}\times CI_i^t}{P_{n,j}^t}\\&=\frac{\sum_{i=1}^{x}P_{i,n}^t\times CI_i^t}{\sum_{i=1}^{x}P_{i,n}^t}=\frac{CE_i^t}{\sum_{i=1}^{x}P_{i,n}^t}=CI_n^t\end{aligned} \tag{4}$$

where CE_i^t is the total carbon emission of the active power flow entering n through branch i during time duration t, and CI_n^t is the CEF of grid n at t. Additionally, considering the total generation and load within the regional grid, we can obtain the power flow carbon emission balance equation for the regional grid n as formula (5):

$$\sum_{i=1}^{x}P_{i,n}^t\times CI_i^t+\sum_{k=1}^{K}P_{gen,k}^t\times CI_{gen,k}^t=\left(\sum_{j=1}^{y}P_{n,j}^t+\sum_{l=1}^{L}P_{load,l,n}^t\right)\times CI_n^t \tag{5}$$

where $P_{i,n}^t$ represents the active power flow into n at t, CI_i^t represents the CEF of the active power flow into n at t (i.e., the CEF of region i); k is the total number of generators in grid n, $P_{gen,k}^t$ represents the generation output of generator k in grid n during the accounting period, and $CI_{gen,k}^t$ represents the CEF reference value for generator k, which can be obtained from the emission baseline values of different generator types published by local carbon emission benchmarks (e.g., Chinese non-green energy power generator carbon emission benchmark values published by Ministry of Ecology and Environment [47,48], U.S. net electricity generation and resulting CO_2 emissions by fuel [49], or electricity carbon emission benchmarking in National Allocation Plans of internal European Commission [50]). $P_{n,j}^t$ represents the active power flow from n to j, and L is the total number of loads in grid n, with $P_{load,l,n}^t$ representing the sub-load l in grid n. CI_n^t is the CEF of grid n. For the grid boundaries n, it is scalable from Chinese regional grids to U.S. balancing authorities or European national systems, while the temporal resolution t is adjustable from 15-minute (one electricity market transaction cycle) to hourly (typical in Western systems).

Based on the above concepts, the direct carbon emission from power generation within regional grid n can be defined as formula (6):

$$CE_{G,n}^t=\sum_{k=1}^{K}P_{gen,k}^t\times CI_{gen,k}^t \tag{6}$$

where $CE_{G,n}^t$ represents the direct CO_2 emissions from power generation in grid n during t. Consequently, the CEF for a power generation grid n can be easily calculated by formula (7):

$$CI_{gen,n}^t=\frac{CE_{G,n}^t}{\sum_{k=1}^{K}P_{gen,k}^t} \tag{7}$$

where $CI^{t}_{gen,n}$ represents the CEF for power generation in grid $\boldsymbol{n}$ during the accounting period. The CEF for a power consumption grid $\boldsymbol{n}$ at $\boldsymbol{t}$, denoted as $CI^{t}_{load,n}$, can be defined directly as formula (8):

$$CI^{t}_{load,n} = \frac{\sum_{l=1}^{L} P^{t}_{load,l} \times CI^{t}_{load,l}}{\sum_{l=1}^{L} P^{t}_{load,l}} \quad (8)$$

where $CI^{t}_{load,n}$ represents the CEF for the load in grid $\boldsymbol{n}$ during the accounting period.

3.2 Comparative Analysis of International Applicability

The methodology's transferability is evidenced through systematic comparison with international standards (Table 1). Three key universal features emerge:

1 *Temporal Granularity*: While the proposed 15-minute resolution exceeds the hourly reporting common in Western systems, the underlying time-discretization in Equations (3)-(5) remains valid across scales. This enables adaptation to grids with varying data availability.

2 *Spatial Scalability*: The general proportional sharing principle (Equation 1) and carbon flow balance (Equation 5) can be independently validated in U.S. balancing authorities [26] and European national grids [51, 52]. The framework accommodates differing regional divisions through adjustable $\boldsymbol{x}$ (input regions) and $\boldsymbol{y}$ (output regions) parameters.

3 *Policy Integration*: the multi-scale approach resolves a critical gap between: EU-style national reporting, U.S. sub-regional markets, and China's provincial hierarchies.

4. Spatiotemporal Carbon Factors of Target Grid

To validate the methodology, a case was implemented in a Chinese provincial grid. The generation, consumption, and external electricity inflow data for the TRG on a typical day are illustrated in Fig. 2, with a sampling period of 15 minutes. The TRG's generation structure is predominantly based on thermal power, particularly coal-fired plants. This composition produces a relatively high CEF for power generation in the TRG. In recent years, the grid has increased its investment in renewable energy sources (e.g., wind, solar) and cleaner transitional fuels (e.g., natural gas), though their overall contribution remains comparatively small. However, during active photovoltaic generation periods (from 7:00 AM to 5:00 PM), the ratio of renewable energy in the TRG shows a noticeable increase. The layout of the grid's power sources is relatively concentrated, with major thermal power plants located near coastal and suburban areas. While this centralized arrangement facilitated energy dispatch and management, it also leads to concentrated pollution emissions. The grid structure is complex, carrying a substantial load for both urban and surrounding areas. Its multi-tiered structure (high, medium, and low voltage) requires refined management to minimize transmission losses and enhance efficiency.

4.1 Substation Electricity Carbon Emission Factor

The substation node CEF refers to the carbon emission intensity associated with the electricity transmitted or processed by a specific substation, calculated as a unit in the power system. This factor reflects the power sources feeding through the substation and their respective carbon emission characteristics, enabling more precise management and optimization of grid carbon emissions. For any substation, the output power must always balance with the input power.

Table 1: Comparison of Carbon Emission Factor Calculations Methods [26, 36-38, 51,52].

Country	Time-Space Division	Regional Interaction
U.S.	Based on hourly generation and load data provided by grid companies, authorized by the U.S. Congress, hourly CEFs for 66 load balancing areas are calculated and published.	Sub-regions ensured minimal power interaction between regions; regional power interactions are not considered in the CEF calculation.
EU	Hourly CEFs are calculated by countries.	Power interactions with neighboring countries are considered.
China	Annual provincial CEFs are calculated and published by Chinese Ministry of Ecology and Environment.	Not considered.
Proposed Framework	Based on the spatial regional division, the grid topology + AD are combined, and 15 minutes is used as the minimum measurement unit to form a series of CEF of different scales.	Grid topology and exchange of power and carbon flow between regional grids are considered, carbon tracking can be achieved.

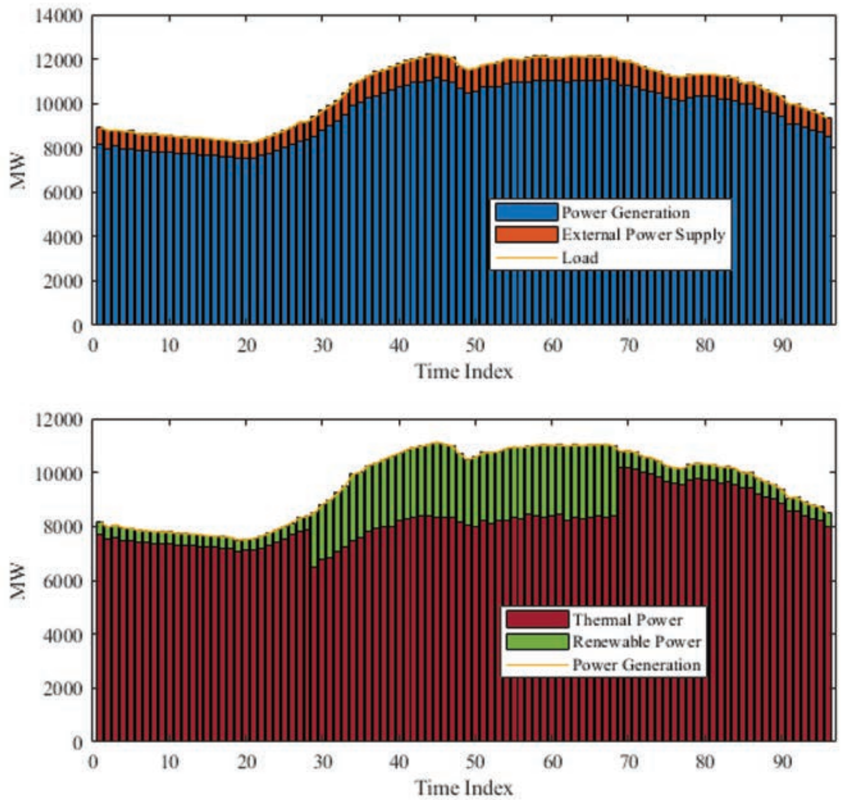

Figure 2: Generation, load consumption, and external power inflow data for the target regional grid on a typical day.

The substation electricity CEF is calculated using the carbon flow balance equation (Equation 5), providing the carbon emission intensity for each substation during the accounting period. As illustrated in Fig. 3, the real-time power generation in the TRG during the accounting period is 10,937 MW, with coal power accounting for 72.6%, wind power for 11.88%, and solar power for 15.48%. The real-time load is 10,848 MW.

In Fig. 3, the nodes represent substations of 500kV and above, along with the topological connections of high-voltage transmission lines between them. The size of the nodes represents the power generation or load of each station, while the node colour indicates the CEF, with colours ranging from red to green signifying high to low CI. Since the substations include connected renewable energy units, the CEFs for all substations are lower than that of a pure coal-fired power plant. The carbon emission benchmark values for various types of non-green energy power generation units from 2021 to 2024, as issued by the Ministry of Ecology and Environment of the People's Republic of China [47, 48], are shown in Table 2. Among them, conventional coal-fired units mainly use thermal coal, lignite, and

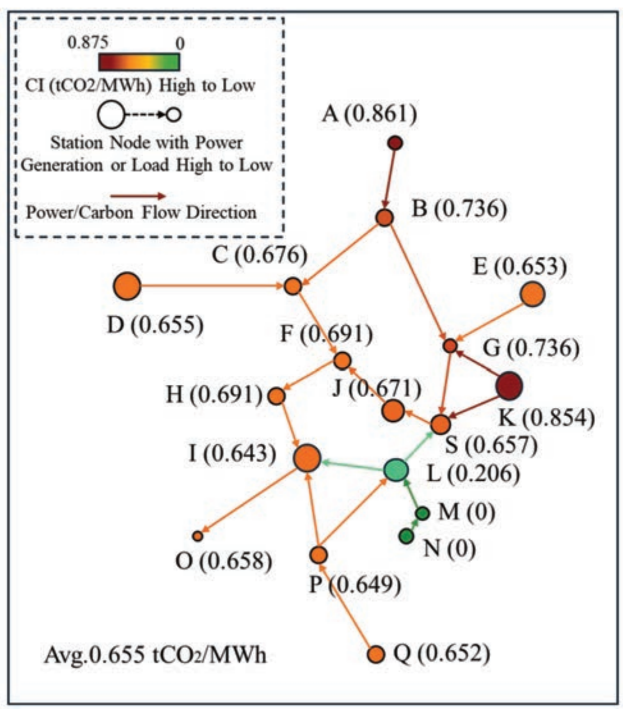

Figure 3: Schematic diagram of carbon emission factors for 500kV substations.

Table 2: Carbon Emission Benchmark Values for Various Types of Non-Green Energy Power Generation Units from 2021 to 2024 [47, 48].

Unit Type	Primary Fuel	Generation Benchmark Value (tCO_2/MWh)			
		2021	2022	2023	2024
Conventional Coal-Fired Units > 300MW	bituminous coal, lignite or anthracite	0.8218	0.8177	0.7950	0.7910
Conventional Coal-Fired Units ≤ 300MW	bituminous coal, lignite or anthracite	0.8773	0.8729	0.8090	0.8049
Unconventional Coal-Fired Units	coal gangue, slime or coal-water slurry	0.9350	0.9303	0.8285	0.8244
Gas-Fired Units	natural gas	0.3920	0.3901	0.3305	0.3288

anthracite as primary fuels, while unconventional coal-fired units primarily utilize coal gangue, coal slime, and coal-water slurry as fuels. Gas-fired units mainly employ natural gas as fuel. The table demonstrates that the carbon emission benchmarks for all types of units have been decreasing annually with the continuous development of power generation technologies. In this case study, the carbon emission benchmark for conventional coal-fired power plants is set at 0.875 tCO_2/MWh, while that for gas-fired units is set at 0.363 tCO_2/MWh. For stations primarily using renewable energy, such as stations L, M, and N, the CEFs were noticeably lower, consistent with the 2024 IPCC benchmarks for clean energy technologies.

Fig. 4 illustrates the time-series variation of the electricity CEFs for several typical 500kV substations. It is evident that the time-series changes in the CEFs for each station were significant. Particularly during periods of active photovoltaic power generation, the CEFs of the 500kV substations decreases due to the increased share of PV generation from both their associated substations and linked PV units. For certain stations, such as A and K, the reduction in CEFs is more pronounced because these stations are located near the coast and have a higher number of associated PV units. Conversely, substations, such as L, M, and N, have consistently lower CEFs, resulting in a lower average CEF (AVG.) for the TRG area than those substations where thermal power dominates generation and consumption. Using the overall regional grid CEF for CA would be unfair to some sub-regions and substations. If the CA is conducted using the average regional grid CEFs published by China's Ministry of Ecology and Environment, the TRG area would have to align with the CEFs of its broader region (the North China grid), and the accounting period is annual. This would obscure the time-series variations shown in the figure.

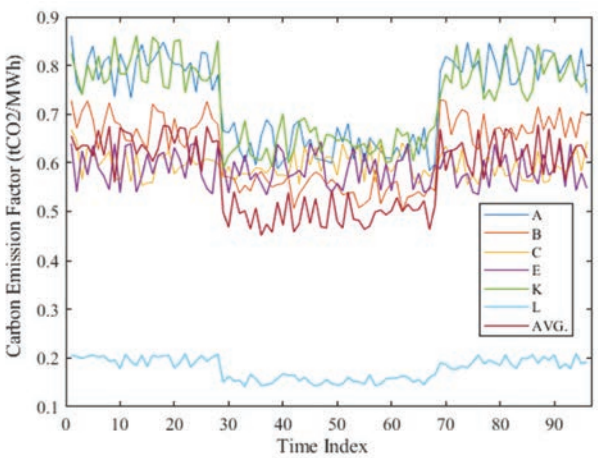

Figure 4: Time-series variation of electricity carbon emission factors for several typical 500kV substations.

4.2 Electricity Carbon Emission Factor by Administrative Division

In China's power system, ADs (e.g., provincial/municipal boundaries) serve as fundamental units for grid operation and carbon accounting, as they align with the State Grid's regional dispatch structure and government-led emission reduction targets. This study focuses on administrative regional grids for China's context. Based on the AD principles provided by the government and power grid companies, the TRG can be divided into sub-regional grids, treating each sub-grid as a node as shown in Fig. 5. By calculating the total generation, total load, total input power, and total output power of the sub-regional grid, and applying Equation (5), the CEF of each sub-regional grid can be determined. Additionally, based on the substation CEFs derived from the above calculations, the CEF of the sub-regional grid can be obtained through a weighted average, as shown in Equation (9). Assuming that the regional power grid $\boldsymbol{n}$ contains $\boldsymbol{K}$ generating units and $\boldsymbol{L}$ loads, the regional average CEF is the sum of the total carbon amount of power generation and the carbon amount of load divided by the total power generation and total load in the region.

$$CI_{avg.,n}^{t} = \frac{\sum_{k=1}^{K} P_{gen,k}^{t} \times CI_{gen,k}^{t} + \sum_{l=1}^{L} P_{load,l}^{t} \times CI_{load,l}^{t}}{\sum_{k=1}^{K} P_{gen,k}^{t} + \sum_{l=1}^{L} P_{load,l}^{t}} \quad (9)$$

Fig. 5 presents the distribution of the CEFs of sub-regional grids based on AD, calculated through weighted averaging. To highlight variations in regional CEFs, the figure marks the renewable energy stations at the 220 kV and 110 kV VLs (new green nodes). Different ADs encompass various substations, with colours representing the magnitude of the regional CEF, ranging from red to green, indicating high to low values. In Region 1, due to the limited presence of renewable energy units, the CEF is relatively high (R1: 0.766 tCO_2/MWh), whereas Region 7, with multiple renewable energy stations, benefits from a significantly higher proportion of green energy in its generation and consumption, leading to a lower regional CEF (R7: 0.290 tCO_2/MWh).

The CEF on the generation side is influenced by the type of fuel and generation efficiency. Coal-fired power plants have the highest CEF, followed by natural gas, while wind, solar, and hydro energy contribute significantly lower emissions. The average CEF for the regional grid is calculated to be 0.655 tCO_2/MWh. The generation CEF depends solely on the amount of electricity generated and the carbon emissions produced. The higher the share of renewable and low-carbon energy in the grid, the lower the region's CEF.

The total carbon emissions input to a transmission station equals the sum of the carbon emissions of its

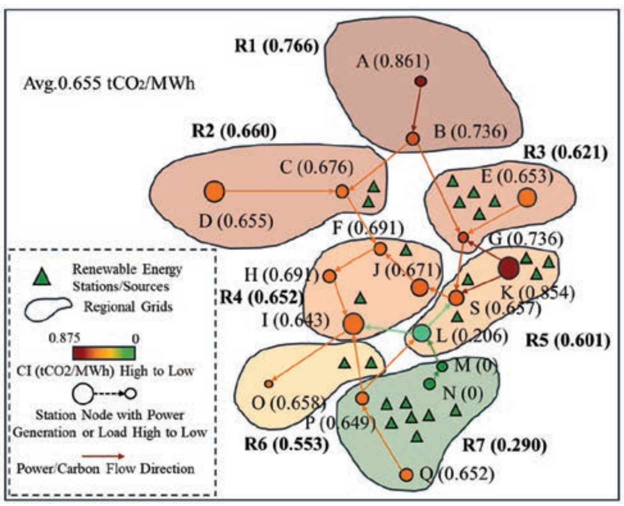

Figure 5: Schematic diagram of carbon emission factors of sub-regional grids based on administrative divisions.

connected input lines, and the substation's CEF is the ratio of its total carbon input to its total active power input. If internal station losses are ignored, this ratio also equals the total output power. In transmission, line losses must be considered, with the carbon factor on the transmission line being equivalent to the carbon factor of the output station.

On the consumption side, the CEF is affected by transmission line losses, load distribution, and the integration of distributed energy resources. The total carbon input to a load station equals the sum of the carbon emissions of its connected input lines, and its CEF is the ratio of its total carbon input to its total active power input or the total active power output of its connected lines and total load. For load stations with distributed generation, the impact of distributed generation must be accounted for, as it offsets the carbon emissions associated with centralized power supply. The consumption-side CEF is further influenced by temporal variations in load profiles, with peak-demand periods often corresponding to higher CEFs due to the reliance on less efficient peaking power plants. Therefore, demand-side management can significantly reduce overall CEFs.

The interaction between generation and consumption dynamics plays a critical role in determining the overall grid CEF. For example, a high share of renewable generation reduces the baseline CEF but may require adjustments in consumption patterns to fully utilize low-carbon power, such as incentivizing consumption during periods of high renewable availability (e.g., sunny or windy days). Similarly, load stations equipped with energy storage systems can mitigate the temporal mismatch between renewable generation and demand, enhancing the overall carbon efficiency of the grid.

Fig.6 illustrates the temporal variations of electricity CEFs across different administrative grid regions. Similar to the substation CEFs, the temporal fluctuations of CEFs within each regional grid are significant throughout the day. The average CEF of the TRG aligns with the general trend observed in most ADs. However, notable differences are observed for regions with a higher proportion of thermal power generation (R1) and wind power generation (R7), where the CEFs deviate considerably from the regional average during each accounting period, though the overall trend remained similar. The temporal curves provides a clear visual representation of the impact of increased renewable energy generation on carbon reduction.

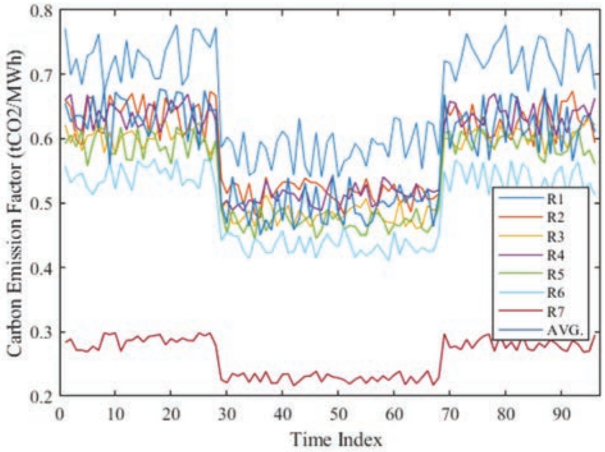

Figure 6: Temporal variations of electricity carbon emission factors across different administrative grid regions.

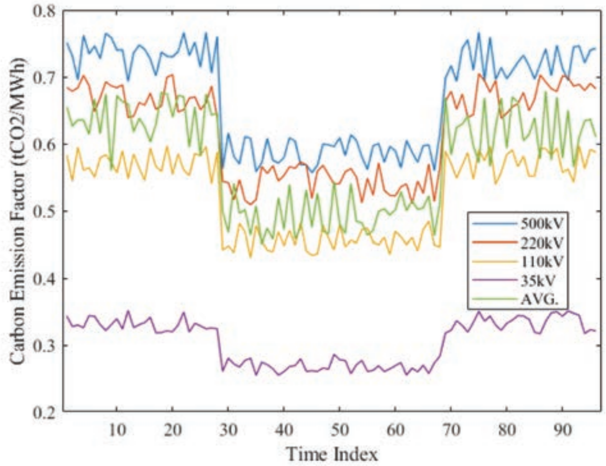

Figure 7: Temporal variations of electricity carbon emission factors across different voltage levels.

4.3 Electricity Carbon Emission Factor by Voltage Level

VL division refers to the classification of a power grid based on its operational voltage ranges (e.g., 500 kV, 220 kV, 110 kV, and 35 kV). This approach facilitates the analysis of carbon emissions across the hierarchical structure of the power network, providing valuable insights into the carbon intensity associated with high-, medium-, and low-voltage grids. By identifying CI disparities across VLs, this method supports grid optimization strategies, improves energy transmission efficiency, and highlights the role of renewable energy integration at different levels.

The TRG can also be divided by VL to calculate the CEF, similar to the method used for calculating CEFs by AD. By calculating the total generation, total load, total input power, and total output power for each VL grid, and applying Equation (5), the CEF of each VL grid can be determined. The weighted average method can also be used for this calculation. Table 3 displays the CEFs of TRG categorized by different VLs. The 220 kV and above grid, dominated by thermal power plants, exhibits a higher CEF, whereas the low-voltage grid, with a high proportion of distributed renewable energy sources, has a significantly lower CEF compared to the high-voltage grid. Since the 35kV grid primarily incorporates wind power units, while the renewable energy units in other VLs are predominantly solar PV, the CEF shows a more significant decline in other VLs during periods of substantial increases in solar power generation, as illustrated in Fig. 7.

In summary, all input parameters in Equations adhere to IPCC-recognized standards, ensuring international reproducibility. The 15-minute resolution provides finer temporal granularity than typical hourly Western reporting, while voltage-level insights offer transferable knowledge for grids with distributed renewables (e.g., Germany's 380/220kV transition). The methodology's spatial scope can be adapted to local needs - from U.S. balancing areas to European national grids - by adjusting the n boundary definitions in Equations.

5. Comparative Analysis

In CA for the power sector, different spatiotemporal dimensions of calculation for the substation level, the AD level, and the VL have distinct advantages and disadvantages for utilities, consumers, and government

Table 3: Carbon Emission Factors by Voltage Levels.

Voltage Level	Emission Factor (tCO_2/MWh)	Green Power Proportion	Thermal Power Proportion
500 kV	0.741	31.18%	68.82%
220 kV	0.682	37.32%	62.68%
110 kV	0.577	42.33%	57.67%
35 kV	0.339	62.59%	37.41%

authorities. These methods influence the fairness of carbon emission data and subsequent policy formulation and implementation. Fairness in carbon accounting refers to the equitable allocation of emission responsibilities and benefits among stakeholders, ensuring that each entity contributes to carbon reduction efforts in proportion to their emissions and capabilities. This principle encompasses three dimensions: responsibility proportionality, stakeholder equity, and temporal and spatial consistency. Fairness requires high-emission sources to bear larger reduction obligations, transparent data to enable equitable decision-making, and accurate representation of variations across different regions and time periods. As such, fairness serves not only as an ethical guideline but also as a critical criterion for evaluating carbon accounting methodologies and their implications for policy and practice.

In this context, the fairness implications of spatiotemporal carbon accounting methods are evident. Substation accounting is precise but complex, AD accounting supports policy making but lacks granularity, and VL accounting is technically targeted but overlooks regional variations. The time-series accounting of grid CEFs not only enhances the accuracy of carbon emission calculations but also provides a scientific basis for optimizing power system dispatch, formulating carbon trading policies, and developing emission reduction strategies. However, it imposes high requirements on grid structure and data precision. Fairness evaluations require localized management when there are significant disparities in CI, ensuring that high-emission sources face appropriate reduction pressures and responsibilities [47].

1 *Substation Carbon Accounting:* Substations serve as nodes, directly reflecting localized power flow and carbon emissions, enabling identification of high-emission points. Utilities can use substation-specific CI data to optimize power dispatch, reduce line losses, and enhance energy efficiency at the substation level. Both utilities and power consumers can take targeted emission reduction measures based on specific substation carbon profiles. However, as the number of substations increases, the complexity of calculation and management also rises, requiring utilities to handle large amounts of granular data. Some substations may have particularly high or low carbon intensities due to their function or service area, potentially misrepresenting the overall regional CI. While substation-level accounting provides detailed local information, it may result in perceived unfairness for individual substations handling high loads or sourcing from carbon-intensive power. Balancing localized management with system-wide optimization is therefore necessary.

2 *Administrative Division Carbon Accounting:* Accounting at the AD level provides direct data support for government policy making, facilitating the implementation and assessment of regional carbon reduction strategies. It allows for holistic coordination, aligning power production and consumption with the region's economic development, energy structure, and reduction goals. However, substations within a region may draw from different power sources and handle varied loads, meaning an average CEF may not capture intra-regional differences. Broad-based accounting may obscure high-emission sources, hindering precise carbon management and blurring carbon responsibility. While regional accounting balances local and overall differences, it may allow high-emission points to be masked by lower regional carbon levels, potentially making it difficult for utilities and consumers to assume clear carbon responsibilities.

3 *Voltage Level Carbon Accounting:* VL accounting (e.g., 500kV, 220kV) reflects carbon emissions across high, medium, and low-voltage grids, highlighting the structural layers of the power network. This approach helps optimize grid structure and reduce energy losses. Utilities can adjust transmission and distribution strategies based on voltage-level CI profiles to optimize grid operation. While this method captures differences between VLs, it overlooks regional variations within the same voltage class, resulting in muted CI disparities. Carbon emissions between high- and low-voltage grids can differ significantly, and a unified accounting approach may mask local issues. Voltage-level accounting emphasizes the technical aspects of grid losses and efficiency but may not fully reflect uneven carbon emissions within a region, potentially compromising fairness.

4 *Addressing Carbon Factors Disparities:* In cases where certain substations have high carbon factors, but the broader region has a lower

overall intensity, this imbalance often arises from uneven power supply structures. High-emission substations should be accounted for separately to avoid masking localized issues within broader regional accounting. Combining substation-level accounting with targeted governance of high-emission sources can achieve more precise management. Governments can impose stricter reduction targets on high-emission substations within a region or use carbon trading mechanisms to require these substations to purchase additional carbon allowances. Encouraging and supporting technological upgrades or the adoption of low-carbon energy sources for high-emission substations, alongside the introduction of compensatory mechanisms (e.g., carbon capture technologies, green power procurement), can further mitigate carbon emissions in these cases.

The comparative analysis of spatiotemporal electricity CEF accounting methods reveals their diverse policy implications. Substation-level accounting supports localized carbon reduction policies, enabling targeted management of high-emission nodes through stricter reduction targets or technological upgrades. Local authorities could incentivize the adoption of low-carbon technologies via subsidies, grants, or carbon credits specifically targeting high-emission substations. Administrative region-level accounting facilitates regional carbon trading systems and proportional reduction targets aligned with economic and energy goals. Governments could introduce region-specific carbon trading systems or enforce reduction targets proportional to regional carbon intensity. Policies may also include infrastructure investment for energy efficiency improvements tailored to the regional context. Voltage-level accounting informs technical optimization policies for grid operations. Utility companies could be mandated to adopt best practices for grid structure optimization, supported by regulatory policies that standardize efficiency benchmarks at different voltage levels. Time-series analysis underpins dynamic carbon management strategies. Time-series CEF data could inform real-time power dispatch strategies and peak load management policies, encouraging the use of cleaner energy during high-carbon periods and incentivizing off-peak power consumption. Complementary measures could include public reporting of various level emissions to enhance transparency and accountability. The identified policies aim to ensure fairness and precision in carbon accounting, fostering effective implementation of carbon neutrality initiatives at both local and regional levels.

6. Conclusion and Discussion

This study aimed to develop a robust spatiotemporal CEF calculation framework tailored to regional power grids, addressing the gaps in precision, spatial granularity, and real-time adaptability identified in existing methodologies. Guided by the research questions, the study investigated how different partitioning strategies impact the accuracy and applicability of CEF calculations, explored their advantages and limitations, and proposed standards for integrating spatiotemporal CEF calculations into carbon reduction strategies and policy development. Based on a power grid in central China, this study investigated the differences in CEF calculations under various zonal accounting strategies. The comparative analysis revealed that substation-level accounting enables precise emission hotspot identification but requires complex data management, while AD methods facilitate policy implementation at the cost of masking local disparities. Voltage-level accounting proved effective for grid loss optimization but failed to address spatial inequities in emission distribution. It analyzed the advantages and disadvantages of these accounting methods from the perspectives of power companies, electricity consumers, and government authorities. The study demonstrated that different accounting scopes provide various levels of carbon emission data, accurately reflecting the temporal carbon emission characteristics of substations, ADs, and VLs. This contributed to improving the precision and comparability of CA. The proposed CEF calculation method integrated the carbon emission characteristics of generation units and regional energy usage within different periods, enabling the analysis of the coupling between carbon and electricity across multiple spatiotemporal dimensions. The findings offered valuable insights and support for the further development of CEF standards in China’s power grid, with significant practical implications.

Due to the dominance of coal-fired power, the carbon factor of generation in the TRG area is relatively high. Coal combustion produces substantial CO_2, placing the region’s power system among the highest emitters nationally. As China advances its carbon peak and neutrality goals, this power grid faces immense pressure to reduce emissions. The local government has introduced several measures, such as phasing out outdated capacities, improving energy efficiency, and promoting clean energy. However, achieving substantial emission reductions will require time and technological advancements. The area is one of China's first carbon trading pilot regions, and the power sector has gradually begun participating in carbon market trading. Power companies must manage carbon quotas based on emission levels and actively explore low-carbon generation technologies to minimize carbon costs.

The local government is also pushing forward policies to encourage renewable energy development and improve energy efficiency, such as supporting distributed solar power, wind energy projects, and substituting some coal-fired plants with natural gas. In the future, the TRG is expected to gradually increase the share of clean energy, reducing the role of coal in its generation mix. This transition will not only lower carbon emissions but also improve local air quality and the environment. To address the carbon challenge, the grid may increasingly rely on technological innovations, including enhancing the efficiency of thermal power units, developing carbon capture and storage technologies [55], and expanding the use of energy storage. Additionally, the grid will strengthen power cooperation with neighbouring provinces, optimizing the allocation of electricity resources through cross-regional power dispatch and transmission, thus reducing overall CI.

The presented methodology offers a practical and adaptable framework for spatiotemporal electricity CEF calculations, driven by the growing demand for precise and transparent carbon accounting. From the perspective of driving factors for adopting the presented methodology and its potential applications in practice, the framework is capable of meeting the requirements of:

1 *Increasing Demand for Precise Carbon Accounting*: Governments, utilities, and corporations are facing mounting pressures to meet carbon neutrality goals. Traditional CEF methods lack the granularity to provide actionable insights, particularly at the local or temporal level. The methodology enables precise, spatiotemporally detailed carbon accounting, aligning with stricter reporting and compliance standards, such as those under international agreements (e.g., Paris Agreement) and national carbon trading systems.

2 *Facilitation of Tailored Policy Formulation and Implementation*: Policymakers require robust data to design equitable and effective carbon reduction policies. The presented methodology provides insights at various levels—substation, administrative region, and voltage level—offering a comprehensive framework for policy development. Decision-makers can use the methodology to identify high-carbon areas, implement region-specific reduction targets, or establish carbon trading mechanisms. For instance, detailed data allows for stricter regulations on high-emission nodes while incentivizing cleaner energy practices.

3 *Support for Utility Companies' Operational Optimization*: Utilities are increasingly tasked with integrating renewable energy sources and improving grid efficiency. The methodology highlights carbon intensity disparities across different voltage levels and regions, helping utilities make informed decisions. The results can optimize power dispatch, reduce transmission losses, and prioritize renewable energy integration, leading to operational cost savings and reduced carbon footprints.

4 *Enhancement of Consumer and Stakeholder Engagement*: As consumers and stakeholders demand more transparency, the methodology offers a way to provide detailed and trustworthy carbon accounting at a granular level. The transparency achieved through the methodology fosters public trust and accountability. Utilities and governments can communicate their efforts more effectively, encouraging consumer behavior changes, such as adopting off-peak consumption patterns or investing in green technologies.

5 *Adaptability to Emerging Carbon Market Mechanisms*: As carbon trading markets evolve, participants need more detailed carbon intensity data to maximize their financial and environmental performance. The methodology provides the granularity needed for dynamic carbon pricing, helping utilities and industries to strategically participate in carbon trading or offset mechanisms.

While the spatiotemporal CEF accounting methodology offers significant advancements, it is not without limitations. The reliance on high-resolution data, computational intensity, and trade-offs between granularity and fairness represent key challenges. Additionally, the methodology's context-dependent applicability and limited integration with broader economic models may restrict its versatility in certain scenarios. Addressing these limitations through data standardization, computational innovations, hybrid accounting strategies, contextual customization, and cross-sectoral integration would enhance its robustness and applicability. These considerations highlight the need for ongoing research and collaboration to optimize the presented approach for diverse practical settings.

Acknowledgments

This work is supported by Technology Project of State Grid Tianjin Electric Power Company (2024-06): "Research on hierarchical partition dynamic calculation and panoramic monitoring technology of electric power carbon emission and its application." The authors also would like to express their sincere gratitude to State Grid Tianjin Power Economics and Technology Research Institute for providing valuable data support, and to Shanghai Envision Digital Co., Ltd. for offering the experimental and testing environment. Special thanks to Ms. Tingting Liu for her contributions to the software front-end display, and to Mr. Ming Duan for his excellent project management and coordination efforts.

Author Contributions: Z.Tian: conceptualization, supervision, resources, project administration; Y.Gao: supervision, resources, validation, project administration, J.Wu: writing—review and editing, project administration, validation; Y.Tang: conceptualization, methodology, formal analysis, writing—original draft, writing—editing; G.Liu: conceptualization, validation; J.Yun: resources, project administration. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: We have no conflicts of interest to disclose. All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

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