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Review

Time-Sharing and Zonal Electricity Carbon Emission Factor: Research Progress, Key Challenges, and Future Prospects

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Abstract

Traditional regional or annual average electricity carbon emission factors struggle to accurately reflect the temporal and spatial variations in carbon emissions associated with electricity consumption, making it difficult to support refined low-carbon management needs such as demand-side response, green electricity trading, and carbon footprint accounting. The Time-Sharing and Zonal Electricity Carbon Emission Factor (TSZ-ECF), a key metric that dynamically characterizes the marginal carbon emission intensity per unit of electricity consumption across different time periods and grid nodes (or regions), has garnered widespread attention in academia and industry in recent years. This paper systematically reviews the theoretical foundations of TSZ-ECF, mainstream accounting methods, their advantages and disadvantages, and applicable scenarios. It focuses on analyzing the application value and practical progress of TSZ-ECF in areas such as electricity market mechanism design, user-side carbon management, grid planning and operation, and policy formulation. Finally, the paper delves into the key challenges faced in current research and outlines future research directions for TSZ-ECF. This review aims to provide researchers and practitioners in related fields with a comprehensive overview of the current state of research, promoting the advancement of TSZ-ECF theory, methodologies, and applications to support the low-carbon transition of power systems and the achievement of "Carbon Neutrality and Carbon Peaking" goals.

Keywords: electricity carbon emission factor, time-sharing zoning, electricity carbon emission, decarbonization of the power sector, dynamic electro-carbon factor

Introduction

Against the backdrop of global warming, in December 2015, the Paris Agreement set a hard target to limit the global average temperature increase to within 2ºC above pre-industrial levels and strive to keep it within 1.5ºC [1]. To better achieve this goal, China issued the "Carbon Peaking" and "Carbon Neutrality" plan (referred to as "Carbon Neutrality and Carbon Peaking") in October 2021. All industries across the country have begun to systematically promote the transformation of their industrial structures, striving

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to achieve a comprehensive green transition as soon as possible [2]. In the power industry, in 2024, carbon emissions from the power sector accounted for 45% of the country's total emissions [3]. Therefore, successful emission reduction in the power industry is crucial for the early realization of the "Carbon Neutrality and Carbon Peaking" goals. Against this background, China's power industry covers extensive fields and needs to accurately measure and control carbon emissions. There are shortcomings in this process that must be addressed in a targeted manner. Under current conditions, this has become an urgent problem for the industry to solve.

There have been some studies on the methods and indicators for calculating carbon emissions, and the electricity-carbon factor is one of the key indicators [4]. The electricity carbon factor, also known as the power carbon dioxide emission factor or grid carbon emission factor, refers to the carbon dioxide emissions caused by the use of a unit of electricity during the production process of a product. The traditional calculation method mainly adopts the traditional grid carbon emission factor method with a regional overall unit and a time span of years. For instance, internationally, Australia [5] and the United Kingdom [6] calculate the average carbon emission factor on an annual basis. In addition, some Chinese researchers have systematically sorted out and summarized the development status and calculation methods of the average electricity-carbon factor of domestic and foreign power grids, and optimized the calculation methods and management models of the electricity-carbon factor from the practical application level [7].

However, during the process of using the traditional method for calculating power grid emission factors, it was found that this method has a low update frequency and precision, a large spatial span, and is difficult to reflect the dynamic changes and regional differences of carbon emissions in the power system. Therefore, in order to precisely calculate the carbon emissions of each region, it is necessary to calculate the power emission factors by time periods and regions.

For the time-sharing and zoned problem, reference [8] analyses the carbon mechanism of every grid-side link. An optimised grid-side accounting method is proposed. The new method cuts model complexity and boosts data-update frequency. Reference [9] considered the multi-period coupled MCI (Marginal Carbon Intensity) theory and proposed and verified an adaptive fast calculation method for MCI uncertainty analysis; reference [10] proposed a carbon-green certificate mutual recognition mechanism based on MCI, which solved the incentive problem; reference [11] built a hierarchical, zoned, and decoupled model. It calculates province-wide grid-supply carbon factors. The model gives each sub-region its own targeted factor. Reference [12] combines the carbon emission flow theory and proposes a carbon emission calculation method for each link in the entire process of the power system, which can more accurately reflect the changes in carbon emissions of the power system. Reference [13], based on the typical spatio-temporal fusion characteristics of power grid energy flow, proposed an hourly power grid carbon emission factor prediction model based on the T-Graphormer graph neural network, and the prediction effect has been significantly improved. To address the issue of data sensitivity, reference [14] adopts a distributed architecture for cross-grid collaborative calculation of power carbon emission factors, enabling each company to accurately calculate the regional power carbon emission factors of each province simply by exchanging the calculation results of the factors. Among the current methods for calculating the electro-carbon factor in China, reference [15] proposed a calculation method for the carbon emission flow of the power system based on the power flow distribution matrix, successfully achieving accurate tracking and source tracing of the carbon emission flow of the power system. Reference [16] proposed a carbon flow analysis method based on graph theory, which improved the deficiencies of existing methods in the distribution of carbon flow networks and path traceability. Based on the theory of carbon emission flow analysis in power systems. Reference [17] proposed a carbon measurement method for the entire process of power systems. Reference [18] proposed a carbon flow tracking method for power systems based on a complex power distribution matrix, which can accurately calculate the real-time carbon emission distribution of the power system.

In the field of international research, multiple institutions and scholars have proposed different calculation methods for carbon emission factors. Based on the time granularity, the EU strengthens the fairness of cross-border carbon accounting through the CBAM mechanism and produces relevant reports every quarter [19]. The United States proposed the carbon balance equation, which better considers the power transmission between regions and the changes in carbon emissions at different times [20]. Japan, on the other hand, calculates the carbon emission factors for specific regions and times based on the power generation and emission factors of different power generation types, combined with regional power demand [21]. The time granularity of both is at the hour level.

Through literature research, it can be found that the research focuses on Time-Sharing and Zonal Carbon Emission Factor at home and abroad are different: the core objective internationally is to improve the calculation accuracy to reflect the spatio-temporal differences, while in China, more emphasis is placed on precisely calculating and analyzing carbon emission factors in combination with the unique characteristics of China's power system operation and energy structure. Therefore, this article summarizes the research progress in regions such as the United States, the United Kingdom, and the European Union, elaborates on the development trends within China, and analyzes their respective advantages and disadvantages. The aim

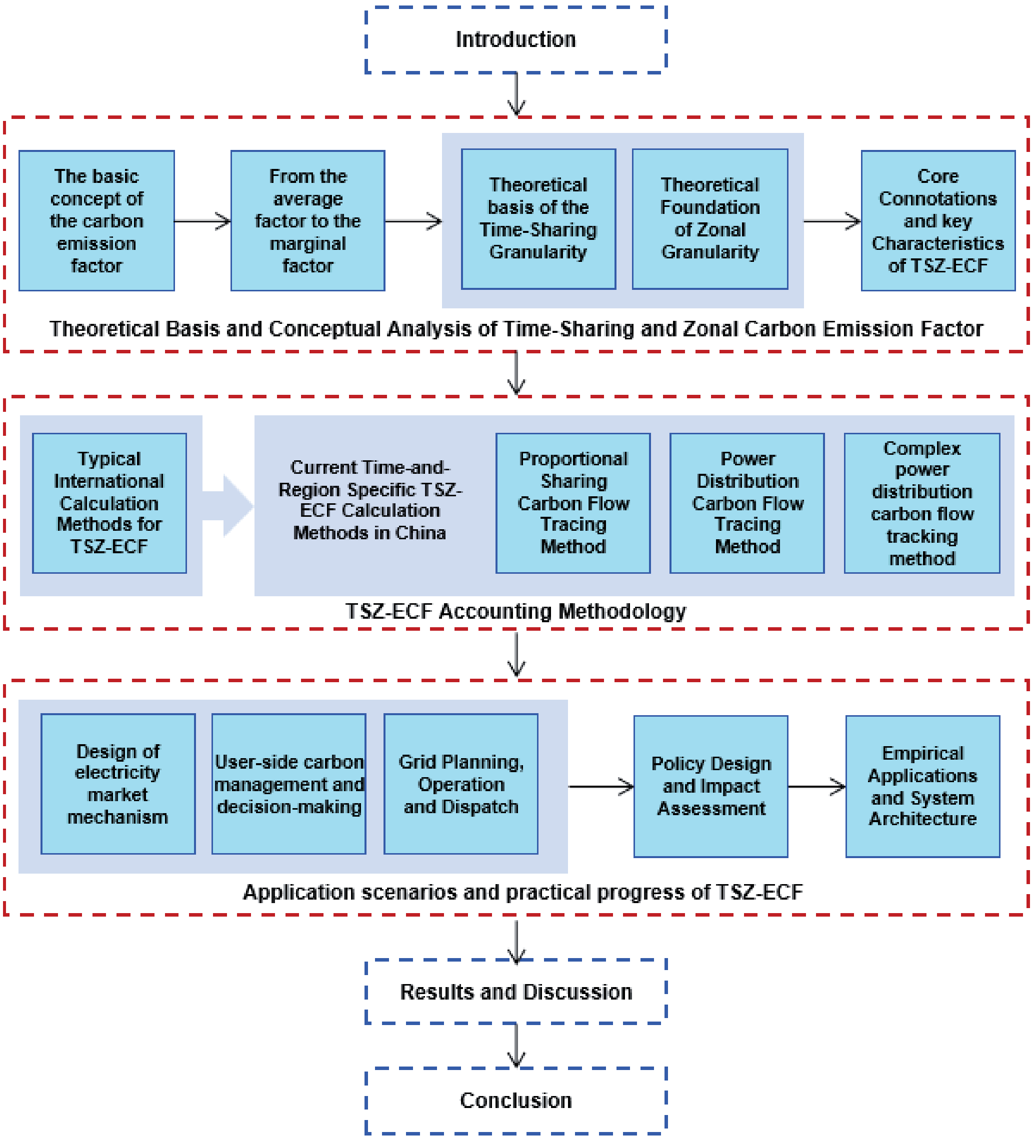

Fig. 1. The research framework of this article.

is to summarize the relevant research both internationally and domestically, hoping to provide readers with a comprehensive and detailed development status of the electro-carbon factor, offer theoretical references for relevant departments and personnel, and contribute to the realization of carbon reduction targets. The research framework of this paper is shown in Fig. 1.

Theoretical Basis and Conceptual Analysis of Time-Sharing and Zonal Carbon Emission Factor

The Basic Concept of the Carbon Emission Factor

The carbon emission factor refers to the amount of carbon dioxide emissions generated in the process of producing one unit of electricity, reflecting the carbon emission intensity in the electricity production process [22, 23]. The "carbon emission factor" is an important indicator for measuring carbon emissions. Enterprises and governments can use the carbon emission factor to assess the carbon emissions generated during power transactions, calculate the carbon footprint, and provide a basis for enterprises to adjust their emission reduction plans. At the same time, it can reflect the drawbacks of the energy structure and guide the direction for the implementation of energy conservation and emission reduction policies by the government [24, 25]. As a bridge connecting the electricity market and the carbon market, the "carbon emission factor" is of great significance in measuring and pricing carbon emissions in electricity transactions [26].

Average Emissions Rates

The average factor, also known as Average Emissions Rates (AER), is the ratio of total carbon emissions to total electricity generation over a period of time or a region, i.e., the total direct carbon dioxide

(CO_2) emissions from the electricity production sector divided by the total electricity generation over a certain period of time (usually 1 year) [27], usually expressed in units of grams of carbon dioxide per kilowatt-hour (gCO_2/(kWh)) [4].

The average factor is used to describe the average level of emissions from all sources of generation in the grid over a specific region and time period. This type of indicator has attributional properties and requires an equal apportionment of responsibility for emissions from the electricity sector, ensuring that each electricity user bears the same proportion of responsibility for emissions. The average factor can be calculated both historically, based on empirical data, and to predict future grid conditions, and it is suitable for assessment and analysis at any time period (e.g., annual, hourly level) [28].

In China, the average factor is mainly used for carbon accounting of enterprises participating in the national carbon market trading, which can effectively ensure fair trading among enterprises in different regions. With the in-depth promotion of China's carbon market and unified power market construction, as well as the gradual implementation of the European Union carbon border adjustment mechanism, regional power grids will strengthen the scheduling between the regional power grids and will be converged, the selection of the whole of China's power grids carbon emission factors for carbon accounting and carbon verification is more advantageous [29]. Specifically, for industries included in China's carbon market, including the power sector and the cement, steel, and electrolytic aluminium industries to be included, enterprise carbon accounting should be calculated using a uniform electric carbon factor across China [30].

From an international perspective, in the United States, the U.S. Environmental Protection Agency (EPA) adopts the eGRID methodology in measuring the electric carbon factor, which calculates the average electric carbon factor by collecting data on power generation and carbon emissions from power plants across the country. The method's visualisation page presents statistical distributions including total carbon emissions and carbon emission rates for each US state, as well as fuel ratios for electricity generation, allowing users to analyse and compare the environmental performance of different power systems [4].

The average factor reflects the pattern of change in greenhouse gas emissions over time and is widely used because of its ease of calculation. However, average factors are less accurate in estimating emissions due to changes in demand [31], and the average factor also does not reflect well the changes in emissions due to power sector interventions [32]. In order to make up for the shortcomings of the average factor and better monitor the changes in carbon emissions, some scholars have started to calculate the marginal emission factor.

Marginal Emission Factors

Marginal factors, also known as Marginal Electricity Carbon Factors (MEF), are the additional carbon emissions produced by the power system when electricity generation is increased by one unit [33]. This indicator describes the changes in carbon emissions due to changes in electricity loads and is divided into short-term marginal factors (SRMER) and long-term marginal factors (LRMER). The general definition Equation is:

$$MEF = \frac{\Delta Emissions}{\Delta Electricity}$$

Where: $\Delta Emissions$ indicates a change in CO_2 due to a change in demand, $\Delta Electricity$ indicates the change in power [34].

SRMER are used to characterise the impact of changes in electricity loads on emissions, provided that the grid structure (i.e., capital assets such as generating units, transmission lines, etc.) is fixed. This indicator reflects the impact of interventions on short-term emissions from the grid by assessing the emission characteristics of each type of generating unit for a given group of generating units during a given period of time when "marginal dispatch" (i.e., adjusting generation in response to changes in load) occurs. Commonly used sources of hourly short-term marginal emission rate data include the U.S. Environmental Protection Agency's Avoided Emissions and Generation Tool (AVERT), WattTime, Resurity, PowerMap, and the National Renewable Energy Laboratory's (NREL) Cambium. The Marginal Emission Factor database developed by the Center for Climate and Energy Decision Making at Carnegie Mellon University provides data at a monthly-hourly resolution.

LRMER is a measure of the impact of changes in electricity load on emissions, which takes into account the potential impact of load fluctuations on the structure of the grid, and can be calculated through the capacity expansion model for the power sector. The model predicts whether the grid structure will be adjusted in response to load changes. Long-term marginal factors are mostly used to assess the carbon impact of new buildings, heat pumps, and electric vehicles [35].

In general, both the average factor and the marginal factor are the main tools for reflecting the intensity of carbon emissions, and both reflect the current power structure and operation of the power system, but there are also differences between the two: Firstly, the average factor is easy to calculate, with historical values available, and is well suited to systematic analyses, mainly for stock analyses. For example, based on an average factor, it is possible to compare the magnitude of carbon emissions from the electricity systems of two countries. On the other hand, the marginal factor is relatively complicated to calculate, mainly focusing on the local, for the analysis of carbon emissions generated by incremental electricity, which can more accurately reflect the carbon emission changes of the power system in different time and space [36-38]. Secondly, the average factor is suitable for comparing carbon emission intensity over time, while the marginal factor is generally used to compare the emission reduction effect of new electricity use [39]. Thirdly, the marginal factor is more responsive and accurate to changes in grid demand than the average factor, and the use of the average factor for analyses of changes in demand may ignore the impact of specific generators, such as fossil-fuel-fired power plants, which adjust to fluctuations in demand, while hydroelectric or nuclear power plants, which are base loads, remain unchanged, and whose emission characteristics are different from those of the average value [40, 41].

From the Average Factor to the Marginal Factor

Accurately calculating the electric carbon emission factor for the power sector is critical to driving energy savings and emission reductions in the sector. Marina [42] et al. used regional data from the Italian market to compare the widely used emission factor approach and found that region-specific factors are superior to average factors. Yi Jun et al. [43] analysed the international and Chinese domestic grid average factor and found that the average factor method is simple but not real-time enough, and the method should be optimised in terms of accounting period, accounting granularity, and green power. Eelke et al. [44] combined emission data from the Netherlands, Sweden, and France and found that applying the annual average factor directly to the hourly series would result in measurement errors, and that seasonal, intra-day fluctuations would be ignored.

In general, the average factor method is easy to calculate at the macro-accounting level, but it introduces bias when assessing short-term emission reduction measures, demand-side management, and other immediate decisions. Because it cannot reflect spatial and temporal differences, researchers have temporally resolved the average factor and begun studying the time-sharing and zonal carbon emission factor.

Time-Sharing and Zonal Carbon Emission Factor

Theoretical Basis of the Time-Sharing Granularity

The Time-Sharing characteristic of the carbon emission factor refers to the fact that the carbon emission factor changes with time and presents different numerical values. Based on this characteristic, the concept of time-varying carbon emission factor was introduced. The time-varying carbon emission factor refers to the carbon dioxide emission volume corresponding to each unit of power generation, reflecting the carbon emission differences of the power system in the time dimension [45]. The source of the Time-Sharing characteristics of the carbon emission factor is as follows: Firstly, the topological structure and power supply structure of the power grid exhibit significant time-varying characteristics. The proportion of power generation from various sources at different times directly affects the carbon emission factor. For instance, due to the influence of seasons and sunlight, the proportion of hydropower increases during the rainy season, which significantly reduces the carbon emission factor. Photovoltaic power has a greater effect during the day when the sunlight is strong, thereby influencing the overall carbon emission factor [46]. Secondly, the time-varying nature of electricity load will alter the system dispatching methods, thereby indirectly affecting the carbon emission factor. For instance, during periods of high electricity demand, the system requires a large amount of electricity and may resort to power generation methods with higher carbon emissions, resulting in an increase in the carbon emission factor. Additionally, the Time-Sharing nature of the carbon emission factor makes the scheduling policy of the electricity-carbon system dependent on time, giving rise to numerous studies on low-carbon economic scheduling strategies [47-49].

Theoretical Foundation of Zonal Granularity

The zonal characteristics of the carbon emission factor refer to the fact that the carbon emission factor varies in different values as the space changes. Based on the zonal characteristics of the carbon emission factor and the different application scenarios, the carbon factor can be divided into the national power grid carbon emission factor, the regional power grid carbon emission factor, and the provincial power grid carbon emission factor [50, 51]. The reasons mainly include the following aspects:

First, there are differences in energy structures across various regions. The carbon emissions produced by different fuels are also different. Moreover, factors such as the size of the power plant and the intensity of power generation load can also affect the carbon emission factor. Therefore, the carbon emission factor is influenced by regional variations [52]. For instance, regarding the carbon emission factors of thermal power units in different regions of China, those in the northwest region are relatively higher. If we break it down to specific provinces, the carbon emission factor in Yunnan Province is higher than that in Beijing. As the scale of the units increases, the carbon emission intensity will show a decreasing trend. The higher the power generation load of a unit, the greater its efficiency will be, and the lower the carbon emission factor will be [53].

Second, the calculation elements of carbon intensity are missing. Due to the characteristics of timeliness and efficiency of power transmission, the flow path of electricity in the power grid is difficult to accurately track, and the regional differences in the carbon emission factor are greatly affected and vary significantly [54].

Third, as the research on the electricity-carbon market deepens, the carbon market and the electricity market have developed into a coupled state where they influence each other. In order to accurately purchase sufficient carbon emission rights, enterprises need to calculate their carbon emissions more accurately. This results in the zonal characteristics of the carbon emission factor having a more significant influence [4].

Core Connotations and Key Characteristics of TSZ-ECF

The traditional electro-carbon factor mainly takes years as the time unit and uses the average electro-carbon factor as the emission situation of each region, which has poor accuracy and pertinence. The time-of-use and zonal electricity-carbon factor refers to the amount of carbon dioxide emissions per unit of electricity within a specific time period and geographical area [30], which can reflect the dynamic changes in the electricity-carbon factor over the course of a year. This measurement indicator is different from the traditional method of calculating the electro-carbon factor and is more targeted. It can mainly be summarized into the following four aspects (as shown in Fig. 2):

1) Regionality: This method makes up for the defect that average data is affected by extreme data. By calculating local indicators by region, it can better reflect the carbon emission characteristics of power plants in different regions and enhance the pertinence of the results [30].

2) Dynamics: This method produces different results at different times, reflecting the changes in the system's carbon emissions in real time. It can promptly correct and update the system model, achieving timely handling of errors [30].

3) Marginal nature: It can inform users how the carbon emissions of the system change when they use one more or one less kilowatt-hour of electricity. Since this method can accurately produce the carbon emissions of electricity at a specific moment, it can calculate the additional carbon emission intensity (i.e., marginal electricity-carbon factor) generated per new unit of electricity consumption [55].

4) Complexity: This method requires considering the changes in different regions and times, taking into account regional differences and the fluctuations in electricity consumption at different times, to construct a model that suits local conditions, and to conduct risk prediction to deal with extreme situations, which demands a certain degree of flexibility [55].

Materials and Methods

TSZ-ECF Accounting Methodology

Typical International Calculation Methods for TSZ-ECF

International methods for calculating TSZ-ECF vary in temporal resolution, ranging from annual averages to hourly intervals. Spatially, the granularity of division extends from national, sub-regional, to municipal levels. In terms of calculation content, most methods focus on direct emissions from the generation side, while some incorporate inter-regional power transmission, imported electricity, green

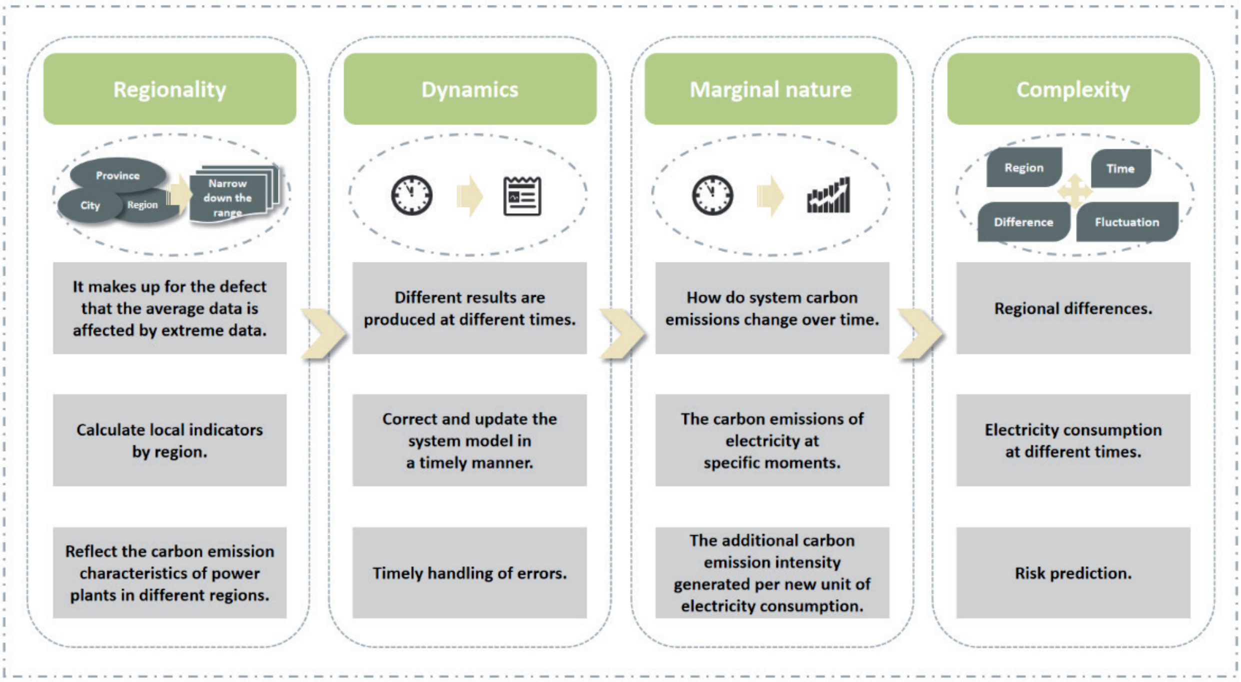

Fig. 2. The key characteristics of the TSZ-ECF.

power/certificate deductions, or lifecycle indirect emissions. The core objective is to improve accounting accuracy by reflecting spatiotemporal variations, though these methods commonly face challenges such as high data requirements, computational complexity, or insufficient timeliness.

(1) United States

The US relies on the eGRID all-source dataset to construct time-sharing and zonal carbon balance equations. It couples inter-regional electricity transfers with time-varying generator emissions into a five-level factor system (from power plant to sub-region), enabling standardization of Scope 2 accounting. While its precision is an advantage, this method simultaneously exposes stringent demands for the availability, timeliness, and computational capacity required to handle high-frequency data.

The US employs a time-sharing and zonal carbon balance equation that accounts for inter-regional power transmission and temporal variations in carbon emissions, enabling a more accurate reflection of actual emission conditions [20].

$$f_i = x_i(d_i + \sum_k v_{ki}) - \sum_j x_j u_{ij}$$

Where: f_i represents the carbon emissions generated from electricity production in region i; x_i is the grid carbon emission factor for region i; d_i is the electricity consumption in region i; v_{ki} is the electricity exported from region i to region k; u_{ij} is the electricity imported into region i from region j, x_{ij} is the grid carbon emission factor for region j.

The US EPA has established a comprehensive dataset covering nearly all US power generation sources, containing operational data (electricity output and heat input) and emissions data (CO_2, Hg, CH_4, N_2O, NO_x, PM, and sulfur oxides) for Electricity Generating Units (EGUs). Through aggregation and calculation, this data yields total system emissions and emission rates at the power plant, state, Balancing Authority, eGRID sub-region, NERC region, and national levels:

$$E_{Fgen,grid} = \frac{E_{mgrid}}{E_{grid}}$$

$$E_{mcon} = \frac{E_{Fgen,grid} \times E_{con}}{1\text{-}E_{loss\%}}$$

$$E_{mcon,loss} = \frac{E_{Fgen,grid} \times E_{con} \times E_{loss\%}}{1\text{-}E_{loss\%}}$$

Where: $E_{Fgen,grid}$ is the generation-side grid-average CO_2 emission factor; E_{mgrid} and E_{grid} denote the direct emissions from the generation side and the net electricity fed into the grid, respectively; E_{mcon} and E_{con} represent the carbon emissions and electricity consumption on the user side, respectively; $E_{mcon,loos}$ and $E_{loss\%}$ are the emissions associated with grid losses and the average grid loss rate, respectively.

EGUs report hourly emissions and operational data to the EPA within 30 days after each calendar quarter using the Emissions Collection and Monitoring Plan System. Enterprises typically use eGRID data for Scope 2 accounting. The EPA recommends using the eGRID sub-region model for Scope 2 calculations. Estimating Scope 2 emissions using eGRID sub-regional emission rates more accurately reflects the regional emissions associated with electricity consumption in specific areas.

By comprehensively analyzing various factors and refining spatiotemporal dimensions, the US methodology more accurately reflects actual grid carbon emissions, providing reliable data support for scientifically formulating emission reduction policies and energy planning. By fully considering inter-regional power transmission and emissions across all stages, it effectively addresses complexity and meets the carbon accounting needs of different regions and market entities. Simultaneously, the EPA's rules standardize the accounting of carbon emissions from corporate-purchased electricity, helping regulate carbon management in the power market, encouraging emission reduction measures, and promoting green development in the power sector.

However, the US method demands high-quality data that is often difficult to obtain, relying on extensive, detailed data such as inter-regional power transmission volumes, regional generation and consumption time-series data, and direct emissions from the generation side. Data collection channels are complex, and some data may be missing, inaccurate, or outdated, increasing the difficulty and cost of data compilation. Additionally, the time-sharing and zonal carbon balance calculations involve multiple variables and inter-regional data interactions, while EPA's rules incorporate multiple formulas and stages, requiring high computational capacity and expertise, making it challenging for ordinary enterprises and institutions to independently achieve precise accounting.

(2) United Kingdom

The UK constructs its grid carbon emission factor using a "Direct + Import + Lifecycle" tripartite framework. It quantifies international electricity exchanges and Combined Heat and Power (CHP) allocation via weighted averages, incorporates multi-gas accounting (including CH_4 and N_2O), and integrates with the Climate Change Agreement (CCA). However, its annualized averaging obscures intraday fluctuations caused by renewable energy variability, fails to deduct locally generated green electricity, lacks sufficient spatiotemporal resolution, and requires further adaptation to accommodate high-penetration renewable power systems.

The calculation of TSZ-ECF in the UK includes various methods such as direct emissions, indirect emissions, and combined heat and power (CHP), each with different emphases and scopes [6]. For direct emissions, the basic grid carbon emission factor (excluding imported electricity) represents the average CO_2 emissions per kilowatt-hour of electricity generated by the UK National Grid. The calculation formula is as follows:

$$E_1 = \frac{E_2}{E_3}$$

Where: E_1 is the grid carbon emission factor excluding imported electricity, expressed in kg CO_2/kWh; E_2 is the CO_2 emissions from electricity generation in the United Kingdom, expressed in kg; E_3 is the electricity generated, expressed in kWh.

For the emission factor including imported electricity, the UK accounts for net electricity imports via interconnectors with Ireland, the Netherlands, France, Belgium, and Norway. This calculation covers direct CO_2, CH_4, and N_2O emissions from UK power plants and generator sets, as well as emissions from imported electricity, but excludes emissions from fuel production and transportation. The weighted average emission factor is calculated as:

$$E_4 = \frac{E_2 + \sum k\,(E_{5k} \times E_{6k})}{E_3 + \sum k\,E_{6k}}$$

Where: E_4 is the grid carbon emission factor, including imported electricity, expressed in kg CO_2/kWh; E_{5k} is the average CO_2 emission factor for electricity generation in country k that is net-exported to the United Kingdom, expressed in kg CO_2/kWh; E_{6k} is the net electricity exported from country k to the United Kingdom, expressed in kWh.

Indirect emissions include upstream carbon emissions from fuel extraction, transportation, and distribution. The UK applies a life-cycle assessment (LCA) approach, but due to delays in updating well-to-tank (WTT) coefficients, the timeliness of indirect emission calculations is limited. For combined heat and power (CHP), the UK uses the 1/3:2/3 DUKES method to allocate emissions:

$$HE = \left(\frac{TFI}{(2 \times E0) + HO}\right) \times HO$$

$$E = \left(\frac{2 \times TFI}{(2 \times E0) + HO}\right) \times EO$$

Where: TFI is the total fuel input to the prime mover; HO is the useful heat generated by the prime mover; EO is the electricity (or the electrical equivalent of mechanical energy) produced by the prime mover; HE is the portion of the prime mover's fuel allocated to heat generation; E is the portion of the prime mover's fuel allocated to electricity generation.

When calculating emission factors, the UK not only considers carbon emissions from imported electricity by obtaining emission coefficients from neighboring countries (e.g., France, Norway) through international cooperation and applying weighted calculations to assess cross-border electricity impacts, but also separately accounts for CH_4 and N_2O emission factors. These are integrated with the Climate Change Agreement (CCA) to establish clear emission allocation rules for combined heat and power (CHP). However, the UK's use of annual average emission factors fails to reflect intraday variations in carbon intensity caused by renewable energy fluctuations. Additionally, the calculation does not deduct local green power generation (e.g., wind, solar), thereby failing to capture the emission reduction value of renewable energy.

Drawing on the UK's weighted calculation method for imported electricity and considering the characteristics of China's "West-to-East Power Transmission" initiative, we can optimize cross-regional carbon emission allocation mechanisms. By referencing the UK's CCA framework, we can promote the alignment of emission allocation standards for distributed energy sources like CHP with China's domestic carbon market.

(3) European Union

The EU establishes a unified framework based on the JRC multi-dimensional factor library (IPCC, LCA, NEEFE), termed "Local Emissions–Green Power Deduction–Grid Loss Internalization". It embeds emission factors within the Carbon Border Adjustment Mechanism (CBAM) to assess the embodied electricity carbon in imported goods, aiming to prevent carbon leakage. However, it currently overlooks electricity exchanges between Member States, and Guarantee of Origin (GO) updates lag, resulting in insufficient timeliness. Consequently, its response to dynamic carbon markets under high renewable penetration remains relatively static.

The greenhouse gas emission factors in the EU are periodically published by the Joint Research Centre (JRC) of the European Commission. This emission factor system comprises two categories: emission factors for individual EU member states and aggregated emission factors for the EU as a whole. Currently, the EU does not account for electricity exchanges between member states and includes carbon emissions from transmission and distribution losses within the scope of indirect user emissions. In practical applications of emission factors, the EU encourages member states to make appropriate adjustments based on local conditions, such as renewable energy generation and certified green electricity consumption [19].

$$E_{Fgen,grid}=\frac{E_{mgrid}}{E_{grid}}$$

$$E_{mcon}=\frac{E_{Fgen,grid}\times E_{con}}{1\text{-}E_{loss\%}}$$

$$E_{mcon,loss}=\frac{E_{Fgen,grid}\times E_{con}\times E_{loss\%}}{1\text{-}E_{loss\%}}$$

Where: E_{Fgrid} is the grid-average emission factor, expressed in kg CO_2/kWh; E_{con} is the electricity consumption on the user side, calculated as E_{gen} minus grid-loss electricity E_{loss}, expressed in kWh; E_{Flocal} and E_{local} are the local grid-average CO_2 emission factor and the local user-side electricity consumption, respectively; $\sum E_{RES}$ and $\sum C_E$ are the electricity generated from local green power sources and the certified green electricity obtained, respectively, expressed in kWh; $C_{Epurchased}$ and C_{Esold} are the certified green electricity purchased locally and sold, respectively, expressed in kWh.

Survey research reveals that the EU employs a multidimensional approach (IPCC, LCA, NEEFE) covering both direct and indirect CO_2 emissions. It strengthens the fairness of cross-border carbon accounting through the CBAM mechanism, calculating emission factors to evaluate the indirect carbon emissions from electricity embodied in imported goods, thereby ensuring the effectiveness of EU climate policies and preventing "carbon leakage". Simultaneously, it supports carbon accounting for transnational electricity transactions and refines the green electricity deduction mechanism to ensure the reasonable allocation of environmental attributes, thereby enhancing accounting accuracy. Nevertheless, it inadequately considers the impact of electricity exchanges between Member States, and delays in updating green certificate data affect timeliness. China could reference the EU's cross-regional carbon pricing mechanism to improve green electricity accounting standards and promote carbon-electricity market coordination.

(4) Australia

Australia divides its grid into seven major regions based on state administrative boundaries. Within its annual factor framework, it incorporates inter-regional electricity transfers, forming a "Generation–Import–Export" tripartite carbon balance model to achieve dynamic reallocation of interstate emission responsibilities. Its National Greenhouse and Energy Reporting Act explicitly defines the traceability rules for Scope 2 purchased electricity, supporting national climate targets and energy efficiency reviews for infrastructure projects. However, this method imposes high demands on the accuracy of real-time exchange data, entails significant integration costs, and its dynamic update capability remains constrained by the annual reporting cycle.

Australia calculates and publishes electricity average emission factors corresponding to different geographical boundaries. Essentially, it releases provincial or state-level electricity average emission factors based on administrative boundaries. Simultaneously, Australia considers electricity exchanges between grids, where the calculation of electricity average emission factors for major grids incorporates inter-regional electricity transfers [5].

Australia's National Greenhouse and Energy Reporting Act categorizes purchased electricity emissions into Scope 1 and Scope 2. The former refers to direct emissions from facilities, while the latter covers greenhouse gas emissions resulting from a facility's consumption of purchased electricity, heat, and steam that are not generated by the facility itself. The emissions from purchased electricity equal the product of electricity consumption and the corresponding emission factor, with distinctions made based on the source of purchased electricity: if the purchased electricity comes from an Australian state or territory grid, the emission factor is that of the corresponding major grid; if the purchased electricity originates from other regions, the emission factor is provided by the generator or based on the Northern Territory emission factor.

Australia divides the nation into seven regions: New South Wales and the Australian Capital Territory, Victoria, Queensland, South Australia, the South West Interconnected System of Western Australia, Tasmania, and the Northern Territory. This division results in seven major grid emission factors, which are updated annually.

$$E_{Fgrid}=\frac{E_{mgrid}}{E_{grid}}$$

$$E_{mgrid}=E_{mlocal}+\sum_k\left(\frac{E_{k,grid}}{E_{gen,k}}\times E_{mk}\right)\text{-}\sum_i\left(\frac{E_{i,grid}}{E_{gen,i}}\times E_{mi}\right)$$

$$E_{grid}=E_{local}+E_{k,grid}\text{-}E_{i,grid}$$

Where: E_{mlocal}, E_{mk} and E_{mi} are the direct power-generation-side CO_2 emissions from the local region, region k, and region i, respectively; E_{local}, $E_{k,grid}$ and $E_{i,grid}$ are the electricity generated within the local region, the electricity imported into the local region from region k, and the electricity exported from the local region to region i, respectively; $E_{gen,k}$ and $E_{gen,i}$ are the electricity generated in region k and region i, respectively.

The study of Australia's approach to calculating grid carbon emission factors reveals that it effectively combines regional delineation with dynamic factors to accurately reflect spatiotemporal variations. Additionally, Australia's collaboration among government, industry, and academia enhances data transparency. However, challenges remain in integrating electricity exchange data across regions, and the dynamic model relies on high-precision real-time data, resulting in elevated costs. Australia's electricity carbon emission factors are primarily used to estimate emissions from the power sector, supporting the formulation and assessment of national climate targets. Additionally, they are applied in the carbon emission evaluations conducted during energy efficiency reviews of infrastructure projects, encouraging new projects to commit to using renewable energy.

For China, the dynamic factor model could serve as a reference to optimize regional accounting in line with the characteristics of the "West-to-East Power Transmission" initiative. Furthermore, strengthening provincial-level data platforms would improve the transparency of green electricity trading.

(5) Japan

Japan constructs a concise carbon intensity model using a three-dimensional matrix ("Generation Type–Region–Time Period"). Its differentiated emission factor system is linked with a Green Certificate (Non-Fossil Fuel Certificate, NFC) deduction mechanism, ensuring fulfillment of renewable energy consumption responsibilities while preventing double-counting of environmental value. However, its focus is primarily on the generation phase, neglecting transmission and distribution losses and inter-regional exchanges, resulting in a relatively narrow accounting boundary. This approach holds significance for China in designing a lightweight factor system that prevents double-counting.

Japan employs a time- and region-specific carbon emission factor calculation method. Based on the electricity generation of different power sources and their respective emission factors, combined with regional electricity demand, it calculates carbon emission factors for specific regions and time periods [21].

$$CF_{i,t}=\frac{\sum_j EF_j \times Gen_{j,i,t}}{Demand_{i,t}}$$

Where: $CF_{i,t}$ is the carbon emission factor for region i at time t; EF_j is the emission factor for generation type j, $Gen_{j,i,t}$ is the electricity generated by generation type j in region i at time t; $Demand_{i,t}$ is the electricity demand in region i at time t.

Japan's time-and region-specific carbon emission factors primarily enable enterprises holding NFCs to use them for offsetting the indirect carbon emissions from purchased electricity, thereby promoting renewable energy consumption. Secondly, electricity retailers bear renewable energy consumption obligations and use adjusted emission factors to calculate carbon emissions, ensuring environmental attributes are not double-counted. Its calculation methodology is relatively simpler compared to other countries, requiring fewer data types and involving a more straightforward computational process. Subdivision by region and time period allows it to reflect differences in electricity-related carbon emissions across different regions and times, offering a degree of specificity. Furthermore, the algorithm adequately considers Japan's diversified energy structure, distinguishing and calculating emissions from different generation types.

However, this method has limitations. It primarily focuses on emissions from power generation, with insufficient consideration of emissions from other stages of the power system (e.g., transmission and distribution), potentially leading to incomplete accounting results. It also lacks inter-regional coordination, failing to fully account for the impact of cross-regional electricity exchanges on emission factors. In cases where regional power grids are closely interconnected, this may affect the accuracy of the accounting results.

While ensuring accounting accuracy, China could draw lessons from the simplicity of Japan's algorithm to optimize the design of its own grid carbon emission factor calculation, thereby reducing computational costs and implementation complexity. Additionally, China could reference Japan's practice of categorizing emission factors into base emission factors and adjustment emission factors, ensuring that only adjustment emission factors are used to calculate emissions from purchased electricity to avoid double-counting environmental benefits.

Comparative Analysis of International Calculation Methods

Significant differences exist among countries in terms of temporal-spatial granularity, model structure, data foundation, and validation depth, resulting in carbon intensity for the same kilowatt-hour of electricity potentially differing by more than 30% due to methodological variations. This severely undermines the basis for international comparisons and policy benchmarking. By constructing a systematic comparison framework (Table 1) that encompasses dimensions such as time-space resolution, computational complexity, data requirements, grid loss, cross-border adjustments, and green power deduction mechanisms, the trade-off relationships of different methods within the "accuracy-cost-feasibility" triangle are quantitatively revealed.

Using this indicator framework, the performance differences of TSZ-ECF methods across countries are compared. The results are shown in Table 2 and Table 3.

Table 3 quantifies the TSZ-ECF methods of various countries across seven dimensions: time resolution, spatial granularity, data demand, computational complexity, model type, grid loss/cross-border adjustment, and green power deduction mechanism. The results clearly reveal two trade-off chains. The first is the "high-frequency + high-spatial" route represented by the USA, where $\Delta t = 5$ and $\Delta x = 4$ enable capturing intraday fluctuations of renewable energy, but come with the high thresholds of D = 4 and C = 3. The second is the "low-frequency + lightweight" route typified by Japan, achieving $\Delta t = 5$ while keeping C = 1, relying on simplified matrices and single-region boundaries, but sacrificing the completeness of T and G. The EU and UK enhance fairness within a static factor

Table 1. TSZ-ECF Method Comparative Analysis Framework.

Dimension	Quantification Symbol	Definition and Grading
Time Resolution	Δt	Annual = 1, Quarterly = 2, Monthly = 3, Daily = 4, Hourly = 5, Minutely = 6
Spatial Resolution	Δx	National = 1, State/Province = 2, BA/ISO = 3, Sub-region = 4, Plant-level = 5, Unit-level = 6
Data Requirement Intensity	D	Low = 1, Medium = 2, High = 3, Very High = 4
Computational Complexity	C	$O(1) = 1$, $O(n) = 2$, $O(n^2) = 3$, $O(n^3) = 4$, $>O(n^3) = 5$
Model Type	M	Average = 1, Marginal = 2, Traceability = 3, Hybrid = 4
Cross-border/Grid Loss Adjustment	T	None = 0, Grid Loss = 1, Cross-border = 2, Both Combined = 3
Green Power Deduction Mechanism	G	None = 0, Annual Deduction = 1, Hourly Deduction = 2, Real-time Deduction = 3

Table 2. Comparative Results of International Representative TSZ-ECF Methods.

Country / Region	Temporal Resolution	Spatial Resolution	Green Power/ Certificate Deduction Approach	Calculation Method	Advantages	Disadvantages
United States [20]	Hourly (EIA)	26 sub-regions (EPA)	Adjusts emission factors with RECs & green-power trades, but data updates lag	eGRID database; time-sharing and zonal carbon-balance equation	High real-time resolution; fine regional breakdown	Inter-sub-regional transfers not fully captured; REC updates delayed
United Kingdom [6]	Annual average	National (including imports)	Adjusts import-emission coefficients; does not deduct domestic green power	Combines direct and indirect emissions	Comprehensive data (imports included)	Coarse temporal granularity; domestic green power not deducted; WTT factors updated slowly
European Union [19]	Quarterly (CBAM)	EU-wide and Member States	Encourages Member States to correct factors via RES generation & GO/ REC trading	(LCA)IPCC guidelines; Life-Cycle Assessment (LCA)	Holistic, covers full life-cycle emissions	Cross-border electricity exchanges not fully captured; GO/REC deductions voluntary
Australia [5]	Annual (dynamic pilots)	7 main grid regions	Distinguishes power sources for imports; incorporates green-power trade data	Dynamic inter-regional exchange calculation	Clear regional division; accounts for dynamic exchanges	Limited real-time data; dynamic methods still immature
Japan [21]	Hourly (Tokyo)	Prefecture-level (e.g., Tokyo)	Separate baseline & adjustment factors to avoid double-counting of environmental value	Multi-energy system coupling; dynamic simulation and forecasting	Granular down to prefecture; avoids double-counting	High implementation complexity; data acquisition difficult

Table 3. Quantitative Comparison of Performance Dimensions for International Representative TSZ-ECF Methods.

Country/Region	Δt	Δx	D	C	M	T	G
US	5	4	4	3	2	1	1
UK	1	2	3	2	1	2	0
EU	2	2	3	2	2	2	2
Australia	1	3	2	2	1	2	1
Japan	5	3	2	1	1	0	2

framework through cross-border adjustments (T = 2), yet struggle to respond to spot market rhythms due to Δt≤2; Australia introduces dynamic terms for interstate exchanges, but the annual update cycle lowers the overall response speed.

In summary, if the goal is implementation within China's power grid characterized by high renewable penetration, inter-provincial exchanges, and a real-time market, a compromise must be sought between "US-level spatiotemporal precision" and "Japan-level computational burden". That is, maintaining Δt≥5, Δx≥3, while simultaneously compressing C to 2, elevating T to 2 (hourly deduction), is necessary to achieve an operable balance among accuracy, cost, and policy adaptability.

Current Time-and-Region Specific TSZ-ECF Calculation Methods in China

China's approach to calculating time-and-region specific TSZ-ECF primarily focuses on integrating the unique characteristics of its power system operation and energy structure to achieve precise computation and analysis of carbon emission factors. Currently, the main methods for calculating these factors include: the proportional sharing carbon flow tracing method, the power distribution carbon flow tracing method, and the complex power distribution carbon flow tracing method.

The Proportional Sharing Carbon Flow Tracing Method uses active power flow as the sole variable. It assumes that nodal inflow power is uniformly distributed to outflow lines proportionally to incoming lines. This approach features low computational burden and intuitive results, making it best suited for scenarios requiring rapid carbon emission responsibility determination with low sensitivity to reactive power. Typical applications include provincial grid inter-provincial transmission carbon allocation, the State Grid's "Carbon Meter" system, and minute-level updated low-carbon scheduling for EV charging or industrial loads using nodal carbon potential as signals.

The Power Distribution Carbon Flow Tracing Method employs power distribution factors to characterize the active power transfer relationship between sources and loads. It explicitly identifies generation-side carbon emissions corresponding to electricity consumption by enterprises or regions within a specific period. Consequently, it is widely applied in corporate product carbon footprint accounting, green manufacturing certification, spatial precision correction of provincial grid emission factors, and carbon label generation for green electricity consumption. Its core advantage lies in delivering physically transparent carbon emission traceability without significantly increasing computational load.

The Complex Power Distribution Carbon Flow Tracing Method concurrently accounts for both active and reactive power flows, employing complex power distribution matrices for carbon flow computation. While theoretically more rigorous, due to its capability to capture reactive power support effects on carbon distribution, this method necessitates inversion of the full-network complex power matrix, resulting in substantially increased computational overhead. Its principal applications encompass: fine-grained carbon emission analysis in scenarios characterized by significant reactive power flows such as long-distance heavily loaded transmission lines and highly inductive load areas; research on carbon property rights demarcation between generation and consumption entities; and utilization as a reference benchmark in academic investigations validating simplified methodologies.

Proportional Sharing Carbon Flow Tracing Method

Yang Yi et al. proposed a direct carbon flow tracing method based on carbon emission flow, which allocates generation-side carbon emissions to the demand side using the proportional sharing principle, thereby avoiding negative carbon emission issues caused by complex power calculations. This method first computes the system's carbon flow distribution and then directly traces the carbon emission path according to power flow direction, achieving shared carbon emission responsibility between generation and demand sides [56].

Carbon Flow Calculation Basis. Carbon emission flow depends on active power flow, with nodal carbon intensity defined as the weighted average carbon flow density of incoming power:

$$e_n = \frac{\sum_{iN^+} R_i}{\sum_{iN^+} P_i}$$

Where: R_i is the carbon flow rate of the branch (t CO_2/h); P_i is the active power of the branch (MW).

Tracing logic. Based on the proportional-sharing principle, the carbon responsibility of a load R_{L_k} is determined by the nodal carbon intensity e_k and the load power P_{L_k}:

$$R_{L_k} = e_k \times P_{L_k}$$

Grid Loss Allocation. Grid loss-related carbon emissions are allocated proportionally between generation and demand sides to ensure fairness.

This method directly traces carbon flow paths, avoiding negative carbon emission issues from complex power calculations, with clear physical meaning. It innovatively proposes a shared responsibility mechanism between generation and demand sides, particularly through proportional bidirectional allocation of grid loss carbon emissions, enhancing fairness in responsibility assignment. The method is suitable for lossy network scenarios and demonstrates relatively high computational efficiency.

However, this method does not explicitly consider the impact of reactive power on grid loss distribution, resulting in insufficient dynamic adaptability in high renewable energy penetration scenarios. The real-time computation relies on high-precision power flow data, leading to substantial data acquisition costs in practical applications. Furthermore, cross-regional carbon flow tracing still depends on the proportional sharing assumption without incorporating electricity market mechanisms for optimization.

Power Distribution Carbon Flow Tracing Method

Wang Chaoqun proposed a carbon emission flow calculation method for power systems based on the power flow distribution matrix, as shown in Fig. 3. By constructing a power flow distribution matrix, this method allocates generation power to nodal loads, branch power flows, and network losses, addressing the limitations of existing methods in power and carbon flow allocation. The matrix establishes generation-load power mapping relationships and incorporates thermal power carbon emission models to achieve carbon flow allocation in lossy networks, enabling traceability of carbon emission flows from generation to load [15].

The power flow distribution matrix can be expressed as:

$$(A_u)_{ji}=\begin{cases} 1, & i=j \\ -P_{ji}/P_i, & i\in U_j \\ 0, & other \end{cases}$$

Where: P_{ji} is the active power flowing from node i to node j (kW); P_i is the net active-power injection at node i (kW); U_j is the set of neighboring nodes that supply node j.

The load carbon emission responsibility is calculated as:

$$R_{L_k}=\sum_g\left(\frac{P_{L_k}}{P_k}\times e_k^T A_u^{-1} e_g\times E_{G_g}\right)$$

Where: P_{L_k} is the active power of load k (kW); P_k is the total active-power injection at the node where load k is located (kW); E_{G_g} is the carbon emission of power source g (kg CO_2/h).

This method overcomes lossless network limitations by explicitly addressing loss allocation in lossy grids through the power flow distribution matrix, significantly improving calculation accuracy in complex networks. It establishes precise generation-load power mapping for accurate load-side carbon emission traceability and incorporates thermal unit operating states in dynamic carbon emission modeling to enhance source-load carbon correlation rationality. However, the matrix inversion operation has high computational complexity, resulting in low real-time calculation efficiency for large-scale systems. The model neglects the reactive power's impact on loss distribution, reducing accuracy with high renewable penetration. Renewable unit carbon intensity uses simplified equivalent models that inadequately reflect spatiotemporal variations.

Zuo Weilin abstracted the power system as a weighted directed graph using graph theory concepts. The proposed carbon flow network distribution algorithm and the path tracing algorithm employ breadth-first

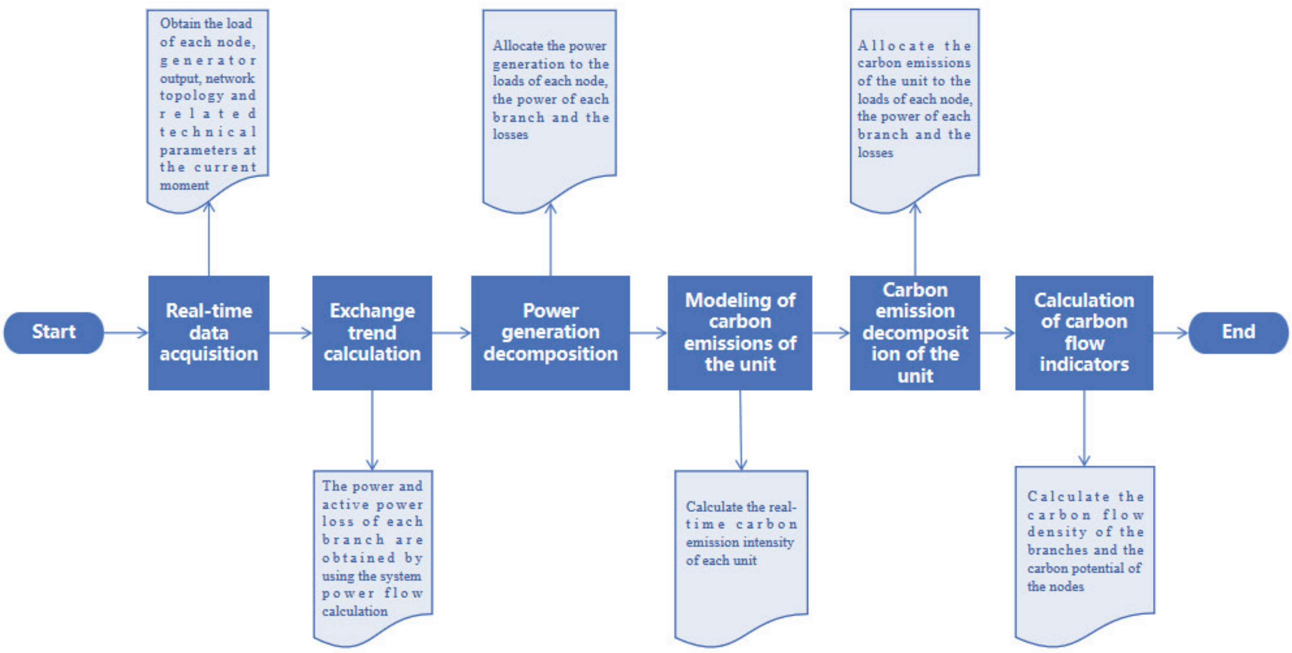

Fig. 3. Carbon emission flow calculation method for power systems based on power flow distribution matrix.

search (BFS) for hierarchical carbon flow distribution and depth-first search (DFS) for tracing source-load path contributions, solving system-wide carbon flow distribution and path analysis problems. This provides data support for higher spatiotemporal resolution TSZ-ECF calculation and load-side low-carbon response [16].

Network distribution algorithm. BFS calculates nodal carbon potential layer by layer, with branch carbon flow rate expressed as:

$$R_{ij}=e_i \times P_{ij}$$

Where: e_i is the carbon intensity at the sending-end node i of the branch (kg CO_2/kWh); P_{ij} is the active power flowing from branch i to branch j (kW).

Path tracing algorithm: DFS identifies all feasible generation-load paths, with path carbon flow decomposition:

$$R_{path}=E_g \times P_{path} \times \prod_{(m,\ n)path} \alpha_{mn}$$

Where: E_g is the carbon-emission intensity of the generation node g (kg CO_2/kWh); P_{path} is the active power transmitted along the path (kW); a_{mn} is the carbon-flow allocation coefficient for the branch from m to n.

This innovative graph-based approach (BFS/DFS) enables visual carbon flow path tracing, clearly showing source-to-load transmission links and improving interpretability. It avoids high-dimensional matrix operations, offering better computational efficiency than matrix methods, and handles lossy networks through equivalent loss processing for complex grid topologies. However, DFS may cause path combination explosions in very large systems, limiting practical application. Network loss emissions are oversimplified as virtual loads allocated entirely to starting nodes without distinguishing generator-consumer responsibilities. The lack of dynamic power flow models hinders response to minute-level carbon intensity fluctuations with high renewable penetration.

Zhou Tianrui et al. developed a comprehensive carbon accounting method (Fig. 4) and implementation system (Fig. 5) based on power system carbon emission flow theory. It calculates direct emissions from source-side fuel consumption data and allocates indirect emissions to the grid and load sides using power flow data with "carbon flow labeling" technology. The real-time, granular measurement approach enables "minute-level" and "user-level" carbon emission tracking.

Nodal carbon potential (load-side emission intensity per unit electricity):

$$e_n=\frac{\sum_{iN^+} R_i}{\sum_{iN^+} P_i}$$

Where: R_i is the carbon emission of power source i (kg CO_2/h), P_i is the active-power output of power source i (kW).

Branch carbon-flow density, characterizing the carbon emission per unit of electricity transmitted along a branch, is expressed as:

$$\rho=\frac{R}{P}$$

Where: R is the carbon flow rate of the branch (kg CO_2/h); P is the active power of the branch (kW).

Lossless network assumption: Carbon flows are linearly allocated along power flow directions, neglecting network losses.

This foundational work established the carbon emission flow theory framework, defining key concepts like nodal carbon potential and branch carbon flow density with clear physical interpretations, creating a unified paradigm for subsequent research. The nodal carbon potential directly reflects real-time carbon intensity of user-side consumption, supporting low-carbon electricity usage analysis. However, the lossless

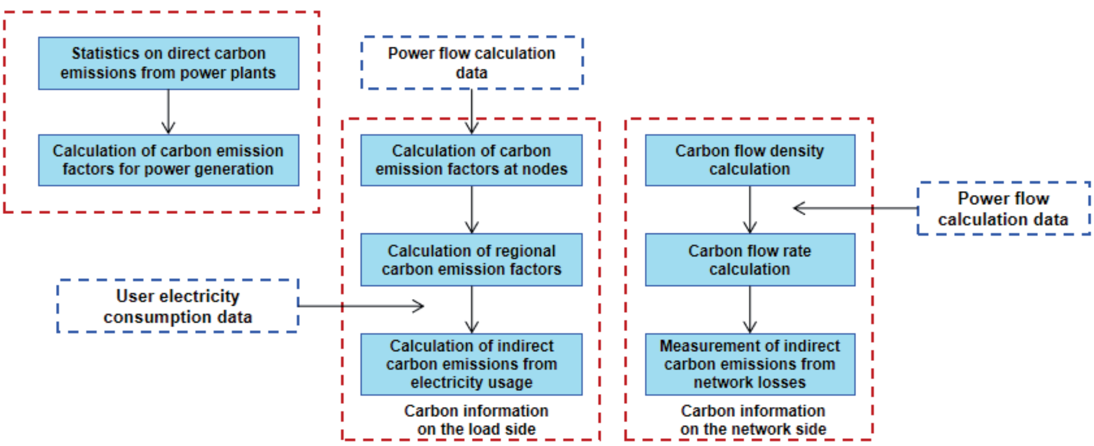

Fig. 4. Schematic diagram of the power system comprehensive carbon accounting system.

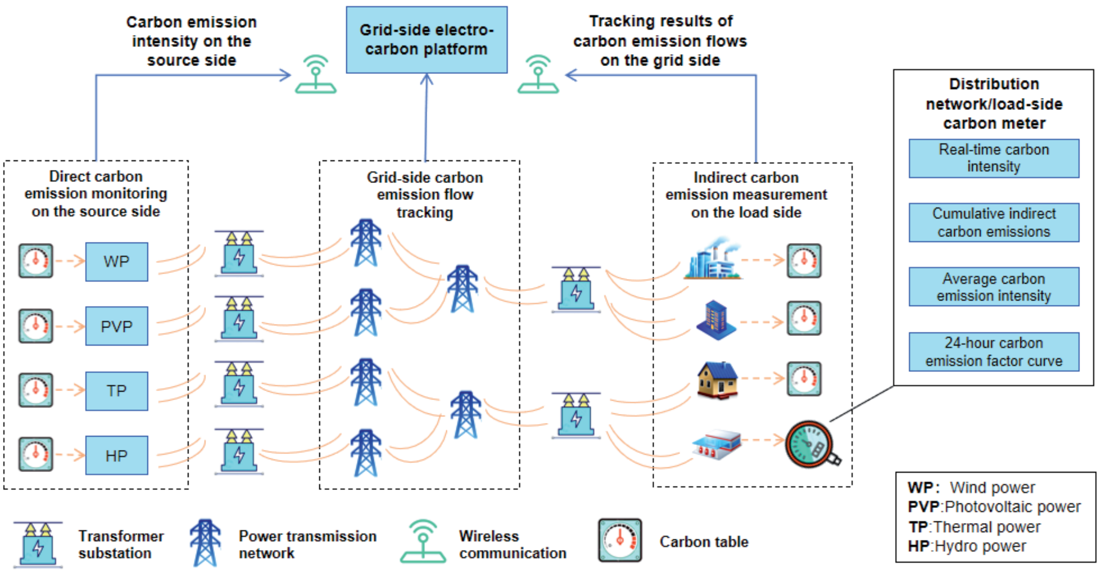

Fig. 5. Comprehensive carbon accounting method and implementation system based on the power system carbon emission flow theory.

network assumption introduces allocation errors from transmission losses, limiting practical applicability. Static power flow models cannot capture minute-level dynamic impacts from renewable fluctuations. The framework lacks mechanisms for tracing cross-regional power exchanges, hindering multi-grid collaborative accounting.

Complex Power Distribution Carbon Flow Tracking Method

Yan Limei et al. proposed a carbon flow tracing method based on a complex power distribution matrix, as shown in Fig. 6, which combines active and reactive power in power systems to more accurately analyze the distribution of carbon emission flows in lossy networks. This method achieves precise tracing of carbon flows in power grids and clearly identifies the carbon emission sources of different loads, branches, and network losses [18].

The complex power distribution matrix is defined as:

$$AS=S_G$$

Where: A is the complex-power distribution matrix; S is the nodal complex-power column vector (kVA); S_G is the generator-injected complex-power column vector (kVA).

Matrix elements are defined as:

$$A_{ij}\begin{cases}1 & i=j\\ \dfrac{\dot{S}_{ij}}{\dot{S}_j} & j\epsilon\phi_i\\ 0 & other\end{cases}$$

Where: $\dot{S}_{ij}$ is the complex power flowing from branch i to branch j; ϕ_i is the set of upstream nodes with active power supplying node i.

The load carbon flow rate is expressed as:

$$C_{LK}=R_e\left(\frac{\dot{S}_{LK}}{\dot{S}_k}\times e_k^T\times A^{-1}\times diag(\dot{S_G})\right)\times c_G$$

Where: $\dot{S}_{LK}$ is the complex power of load k (kVA); $\dot{S}_k$ is the total complex power at node k; c_G is the carbon emission intensity of the generators.

The branch carbon flow rate is expressed as:

$$C_{ij}=R_e\left(\frac{\dot{S}_{ij}}{\dot{S}}\times e_j^T\times A^{-1}\times diag(\dot{S_G})\right)\times c_G$$

Where: $\dot{S}_{ij}$ is the complex power flowing from branch i to branch j (kVA); $\dot{S}_j$ is the total complex power at the receiving-end node j (kVA).

The network loss carbon flow rate is decomposed as:

$$\begin{cases}C^P_{ij,loss}=\dfrac{P_{ij}^2}{P_{ij}^2+Q_{ij}^2}\times C_{ij,loss}\\ C^Q_{ij,loss}=\dfrac{Q_{ij}^2}{P_{ij}^2+Q_{ij}^2}\times C_{ij,loss}\end{cases}$$

Where: $C_{ij,loss}$ is the total carbon-flow rate attributable to losses on branch i-j (t/h); P_{ij} is the active power of the branch (MW); Q_{ij} is the reactive power of the branch (Mvar); $C^P{}_{ij,loss}$ is the active-power component of the loss carbon-flow rate (t/h); $C^Q{}_{ij,loss}$ is the reactive-power component of the loss carbon-flow rate (t/h).

The node carbon intensity calculation:

$$e_j = \frac{\sum_{i\phi_j} C_{ij} + C_{G_j}}{Re(S_j)}$$

Where: $\sum_{i\phi_j} C_{ij}$ is the sum of the branch carbon-flow rates entering node j (t/h), C_{G_j} is the carbon-flow rate from the generator located at node j (t/h); $Re(S_j)$ is the total active power at node j (MW).

This method explicitly handles loss allocation through the complex power distribution matrix, overcoming lossy network limitations and significantly improving carbon flow calculation accuracy. It is the first to quantify reactive power carbon responsibility based on active-reactive coupling relationships, clearly revealing reactive power's impact on carbon emissions and providing a basis for carbon reduction through reactive power compensation. By incorporating historical data of thermal units to construct dynamic coal consumption models, it better reflects actual operations compared to Wang Chaoqun's static model. However, the complex power matrix inversion has high computational complexity, resulting in low real-time calculation efficiency for large-scale systems. The assumption that complex power flows in the same direction as active power doesn't consider bidirectional power flow scenarios with renewable energy, and the decomposition of loss carbon emissions lacks validation for cross-voltage-level applicability. The method has limited engineering applicability, lacking cross-regional carbon flow tracing mechanisms, and the complete allocation of reactive power carbon responsibility to starting nodes may be controversial.

Table 4 systematically catalogs the core characteristics of five predominant carbon flow tracing approaches developed by Chinese research teams. This comparative analysis examines four critical dimensions: originators, theoretical foundations, technical merits, and practical constraints. The framework reveals inherent trade-offs among computational efficiency, physical accuracy, and engineering applicability, thereby establishing a structured reference framework for context-optimized method selection.

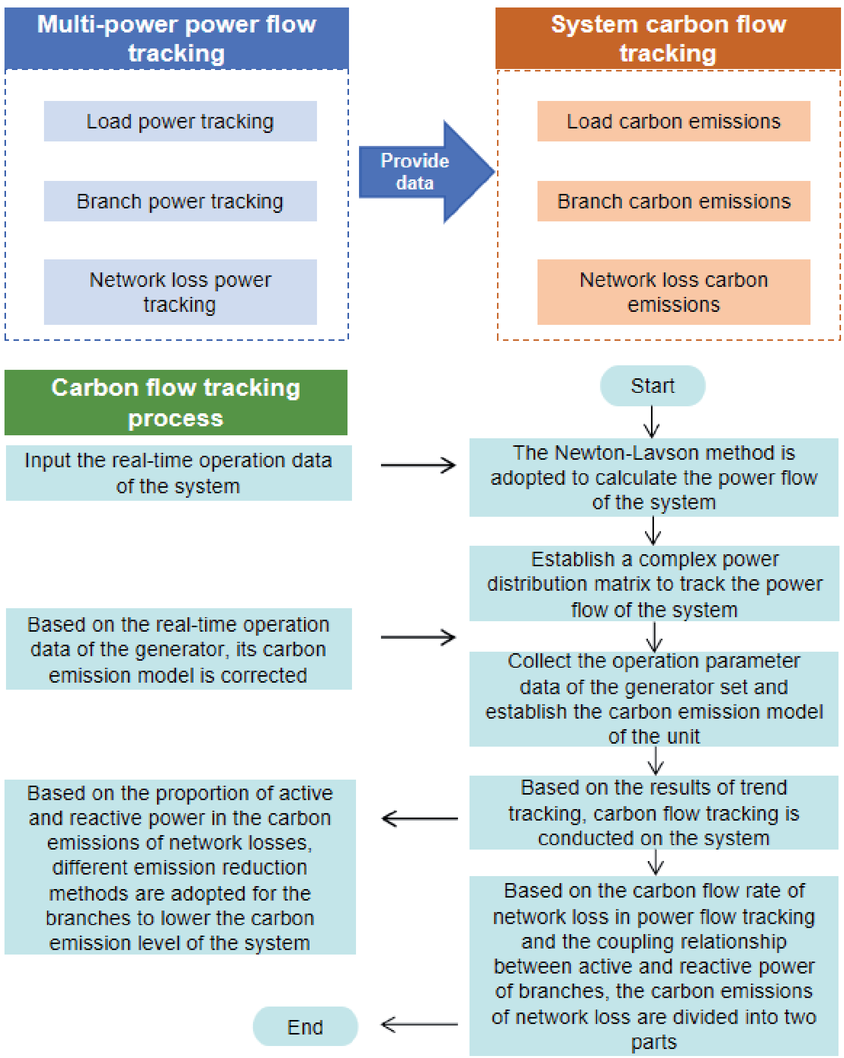

Fig. 6. Carbon flow tracking method based on a complex power distribution matrix.

Table 4. Comparison table of each method.

Method	Proposer(s)	Core Principle	Advantages	Disadvantages
Proportional Sharing Carbon Flow Tracing Method [46]	Yang Yi et al.	Direct carbon-flow tracing based on carbon-emission-flow theory; allocates generation-side emissions to demand side via the proportional-sharing principle	Avoids negative-carbon-emission artifacts that can arise from complex-power calculations	Does not explicitly account for the influence of reactive power on loss allocation
Power Distribution Carbon Flow Tracing Method [15]	Wang Chaoqun et al.	Uses a power-flow distribution matrix to apportion generation output to nodal loads, branch flows, and network losses, thereby calculating carbon flows.	Overcomes the lossless-network assumption; explicitly allocates loss-related carbon emissions in lossy grids	Matrix-inversion complexity is high, limiting real-time performance in large-scale systems
Carbon-Flow Network Distribution Algorithm [16]	Zuo Weilin et al.	Represents the power system as a weighted directed graph; employs Breadth-First Search (BFS) and Depth-First Search (DFS) for layered carbon-flow distribution and path contribution analysis	Novel use of graph-theoretic algorithms (BFS/DFS) enables visual path tracing and enhances interpretability	DFS can suffer from path-combinatorial explosion in ultra-large systems, constraining engineering practicality
Whole-Chain Carbon Accounting [53]	Zhou Tianrui et al.	Integrates carbon-flow labeling with carbon-emission-flow theory to allocate emissions to both network and demand sides, achieving indirect-emission traceability and quantification	Pioneered the carbon-emission-flow framework for power systems; introduced key concepts such as nodal carbon potential and branch carbon-flow density	Relies on lossless-network assumption; ignores carbon misallocation caused by transmission losses, limiting practical applicability
Complex power distribution carbon flow tracking method [18]	Yan Limei et al.	Utilizes a complex-power distribution matrix that incorporates both active and reactive power to achieve precise carbon-flow tracking	Explicitly allocates loss-related emissions via the complex-power matrix, overcoming the lossless-network limitation and improving accuracy	Still based on lossless-network assumption; ignores carbon misallocation from transmission losses, reducing practical applicability

Application Scenarios and Practical Progress of TSZ-ECF

TSZ-ECF has been implemented in five domains both domestically and internationally: electricity market mechanism design, user-side carbon management, grid planning and operation, policy formulation and assessment, and platform development; its core value lies in characterizing electricity-carbon co-fluctuation with high spatiotemporal resolution, thereby enabling carbon-electricity price linkage, precise matching of green electricity entitlements, collaborative optimization of carbon-cost load management, low-carbon dispatch, and refined allocation of carbon tax/allowances, thus driving continuous improvement of supporting technologies including data platforms, forecasting systems, and blockchain-based traceability.

Design of Electricity Market Mechanism

TSZ-ECF reconstructs the power market mechanism through innovative carbon-electricity price linkage mechanisms and precise matching of green electricity environmental rights and interests.

In the innovative domain of carbon-electricity price coupling, the minute-level volatility of renewable generation causes the marginal unit's carbon intensity to vary at sub-hourly scales. This spatiotemporal heterogeneity of carbon cost can only be borne by TSZ-ECF. Empirical evidence from Zhu et al. [57] indicates that carbon price signals instantaneously reshape both the clearing price and the awarded energy of generators in the electricity market. Using a CGE model, Zhang et al. [58] demonstrate that annual-average factors cannot capture renewable fluctuations, severely constraining the effectiveness of the coupling mechanism. Li et al. [59] further reveal, via a dynamic pass-through model, that the pass-through efficiency declines by 40 % when wind penetration exceeds 30 %, thereby achieving an intraday-scale breakthrough in carbon-electricity linkage.

Regarding the matching of green-electricity environmental attributes, TSZ-ECF precisely quantifies the carbon-abatement contribution of green power at specific times and locations, resolving the environmental-attribute decoupling inherent in fixed green-certificate schemes. Although Zhang et al.'s virtual-power-plant model enables green-power trading, it triggers double counting of environmental attributes. Li et al. [60] employ a bi-level game-theoretic model to show that the market-power imbalance between renewable and thermal generators hinders load balancing for large consumers. Wang et al. [61] implement atomic bundling of green certificates via consortium-blockchain smart contracts, providing a technological cornerstone for precise attribute matching. In response to the wave of defaults in European PPAs driven by TSZ-ECF volatility, Guo et al. [62] propose a “green-certificate carbon-quota swap” mechanism that successfully recalibrates dynamic environmental entitlements, ultimately establishing a volatility-resilient system for green-power attribute matching.

At the international level, energy regulatory bodies in regions such as the European Union and the United States are actively advancing the calculation and publication mechanisms for high-spatiotemporal-resolution electricity-carbon emission factors. Presently, official energy agencies across numerous developed countries and regions have successively released hourly-level and even minute-level temporospatial electricity-carbon emission factors. China has also undertaken proactive measures in this domain, having officially published the 2021 and 2022 electricity CO_2 emission factors as well as the 2023 electricity carbon footprint factor. Jiangsu Dual-Creation Center provides comprehensive support to the provincial grid company in developing electricity-carbon factor calculation methodologies, benchmarking against international frontiers. Leveraging time-of-use/region/voltage-level power calculation models and real-time metering data covering generation-grid-demand full-chain processes, the center has established a granular and traceable electricity-carbon factor database across temporal, regional, and voltage-level dimensions. This achievement enables high-precision accounting, traceability, and verifiability of power carbon emissions.

User-Side Carbon Management and Decision-Making

The user-side application focuses on three core scenarios, namely high-precision carbon footprint dynamic accounting, load-carbon cost synergistic optimisation, and intelligent decision-making for green power procurement.

Carbon footprint dynamic accounting needs to reflect the spatial and temporal distribution differences of grid currents, and TSZ-ECF can penetrate the fuzzy boundary of the regional average factor. Zhou et al. pioneered the theory of “carbon flow” to achieve hourly mapping of carbon intensity [63], and Li et al. established a matching model for power purchase paths [64]. The traditional framework of WRI leads to homogenisation of carbon footprints due to the regional average factor, and Zhu et al. [56] developed the coupled framework of LCA-Carbon flow to invert carbon emissions through coal consumption, which can be used to estimate carbon emissions with accuracy and precision in the context of data limitations up to 90%, providing a universal solution for dynamic accounting [57].

Load-carbon cost co-optimization hinges on the sub-hourly responsiveness of the power system’s carbon intensity – an attribute that constitutes the core advantage of TSZ-ECF. Khan et al. [65] demonstrate that shifting 10% of industrial demand into high-wind hours reduces aggregate emissions by 5%. Valenzuela et al. [66] employ minute-level carbon-price signals to enable dynamic load modulation at Google data centers yet omit the carbon cost of reactive power. Wang et al. [67] integrate life-cycle assessment (LCA) with carbon trading in an integrated energy system, achieving an additional 3.4% abatement through “electricity-hydrogen-heat” co-supply. Li et al. [68] propose a “carbon potential voltage” co-optimization model that attributes a further 2% emission reduction to reactive-power compensation, thereby extending load-carbon cost optimization to generation, transmission, and consumption.

Intelligent green-power procurement mandates real-time tracking of the actual carbon intensity of renewable electricity, a requirement that TSZ-ECF fulfills by disentangling the coupled effects of resource endowments and transmission paths. Levasseur et al. [69] reveal a 300% disparity in hydropower carbon intensity between dry and wet seasons, overturning the uniform-value premise of green certificates. Bie et al. [70] design a “contract path carbon factor” model that reduces corporate procurement emissions by 12%, embedding power-flow tracing within green-power trading to allow buyers to select the lowest-carbon supplier based on actual flows. Li et al. [71] compress green-power verification latency to under five seconds via zero-knowledge proofs, delivering a key breakthrough for second-scale intelligent decision-making.

Internationally, WattTime in the United States provides temporal-regional marginal electricity-carbon emission factors, enabling users to monitor power grid carbon emissions in real-time and thereby select cleaner, low-carbon electricity resources. Concurrently, in certain UK regions, temporal-regional electricity-carbon emission factors guide EV users to charge during periods of lower carbon emissions. Smart charging systems automatically adjust EV charging schedules based on dynamic grid carbon emission factors, prioritizing time slots with higher renewable energy generation shares to reduce EV carbon footprints [4].

Domestically, temporal-regional electricity-carbon emission factors assist EV users and charging infrastructure operators in optimizing charging time/location planning. Users may select low-carbon-emission periods and regions for charging based on emission factor fluctuations, reducing their EVs’ carbon footprints. Simultaneously, operators leverage emission factor dynamics to optimize charging facility deployment and operational strategies, enhancing energy utilization efficiency [72]. In photovoltaic module manufacturing, these factors enable high-precision accounting of production-process carbon emissions, supporting enterprises in optimizing production schedules to lower carbon emissions.

Grid Planning, Operation, and Dispatch

Grid-side applications revolve around the three dimensions of low-carbon dispatch strategy optimisation, new energy consumption benefit assessment, and carbon-reducing oriented investment decision-making.

Low-carbon dispatching requires capturing the switching effect of nodal marginal units, a task for which TSZ-ECF quantifies the transmission of carbon emissions through grid topology. Wang et al. [67] base their dispatch on nodal average carbon potential and therefore do not represent this switching effect. Wei et al. [73] innovatively define a nodal marginal carbon emission factor and reveal that the photovoltaic benefit in the Yangtze River Delta is 9% higher than in Gansu, thereby initiating refined scheduling strategies. Shi et al. [74] couple a line-loss model and demonstrate that 5% of storage capacity is required to offset network-loss deviations, further improving dispatch accuracy.

Evaluating the carbon-mitigation benefits of renewable integration necessitates ex-ante assessment of the carbon lock-in risk associated with interprovincial transmission; TSZ-ECF disentangles the dynamic coupling between power flows and carbon flows. The Energy Foundation does not quantify such risk, whereas the State Grid Research Institute applies a "carbon-flow–power-flow" model and projects that the carbon benefit of the Shaanxi-Wuhan HVDC corridor will decline by 34% by 2030, uncovering the long-term evolution of renewable-integration risk.

Carbon-oriented investment decisions demand precise comparison of technological pathways; TSZ-ECF decomposes the per-kWh carbon-abatement cost differences across grid segments. The CSG Research Institute constructs a "carbon-benefit investment" price-ratio model and shows that expanding the distribution network achieves a per-kWh abatement cost only one-fifth that of ultra-high-voltage options, providing quantitative grounds for resolving the imbalance in backbone-grid investment. Shi et al.'s [74] campus microgrid study further indicates that storage investment can cumulatively reduce Scope 2 emissions by 12% percent over a decade.

Internationally, in 2022, the US Congress legislatively mandated the U.S. Energy Information Administration (EIA) to publish hourly-level average and marginal carbon emission factors, providing foundational data for product carbon footprint accounting. Concurrently, the UK National Grid collaborates with research institutions to forecast carbon intensity trends across 14 regional zones at 30-minute temporal resolution with 96-hour lead times. Furthermore, the European Union, jointly with Japan, Canada, and the US, promotes establishing an hourly electricity traceability mechanism and researches reducing temporal granularity to 15-minute levels to align with energy spot market clearing times.

The UK National Grid's forecasting initiative delivers high-precision carbon emission predictions for grid dispatch, facilitating priority scheduling of renewable energy during low-carbon periods. Finland's grid operator now publishes carbon emission intensity every 3 minutes, enabling real-time dispatch optimization [72].

Domestically, China's research and application of temporal-regional grid carbon emission factor calculation methodologies remain nascent. Tsinghua University has pioneered a carbon emission flow analysis framework integrating carbon emission analysis with power flow calculations. This framework defines correlation matrices and vectors to compute power system carbon emission flows, accounting for emissions across generation, transmission, and distribution processes, thereby revealing carbon emission patterns across spatiotemporal scales.

Additionally, State Grid Big Data Center partners with Shanghai Envision Innovation to develop a next-generation electricity carbon intensity accounting system. This system defines regional and marginal carbon intensity calculation methods, constructs coupled carbon accounting models for generation and consumption sides and integrates these into green electricity trading mechanisms. State Grid Anhui Provincial Branch has developed a pilot application for blockchain-based carbon verification integrated with power data, delivering multifunctional capabilities; while State Grid Qinghai Provincial Branch leverages the Qinghai Grid Data Platform to construct a provincial carbon emission monitoring model, achieving province-wide daily-frequency carbon emission analysis [4].

Policy Design and Impact Assessment

TSZ-ECF has important application value in the design of carbon tax mechanisms, carbon allowance allocation, and policy effectiveness evaluation. First, TSZ-ECF can accurately reflect the marginal carbon emissions of electricity generation in different regions and at different times. Based on real-time carbon emission levels, carbon taxes can be levied more precisely, encouraging enterprises to optimize their electricity load and promote low-carbon transformation. Cui et al. proposed a comprehensive demand response scheduling method for the user side based on the characteristics of dynamic electricity carbon emission factors and carbon taxation. The study shows that carbon taxes can guide users to pay attention to the differences in electricity carbon emission factors at different times, thus promoting low-carbon electricity usage behavior [75]. The U.S. Internal Revenue Service (IRS) and Department of the Treasury mandate under the Inflation Reduction Act that the clean hydrogen production tax credit requires compliance with hourly matching and geographic deliverability. This framework permits hour-by-hour lifecycle emission accounting during the hourly matching phase, thereby substantively embedding temporal-regional grid emission factors into tax incentive thresholds [76].

Secondly, in the carbon emissions trading market, the application of TSZ-ECF can provide more refined allocation criteria for electricity-consuming enterprises, more accurately reflecting their actual carbon emission responsibilities and guiding them to improve electricity usage behavior. Lu et al. introduced the concept of Locational Marginal Carbon Emission (LMCE), grounded in market-clearing mechanisms. Building on this, they derived the Locational Average Carbon Emission (LACE) metric to quantify the total carbon liability associated with electricity consumption. This approach helps correct the over-attribution of emissions on the demand side [75]. In China's practice, the Guangzhou Municipal People's Government has directed research on city-level dynamic grid emission factors to enable precise calculation of temporal-regional grid emission factors, laying the technical groundwork for subsequent carbon accounting systems [77].

Finally, TSZ-ECF serves as a tool to evaluate the real-world impact of policy interventions on carbon reduction. By accurately quantifying the emission reductions, it is possible to verify policy effectiveness and further improve policy guidance and incentive mechanisms. Amir Shahin Kamjou et al. compared the use of historical data and real-time data in estimating marginal emission factors in electricity generation. They suggested that real-time marginal emission factors allow policymakers to better understand the temporal and regional variation in emissions. This supports more effective emission reduction policies and energy structure optimization [76].

Empirical Applications and System Architecture

At present, the world is actively addressing climate change and promoting the clean and low-carbon transition of energy. Countries are paying increasing attention to the completeness, accuracy, and transparency of electricity carbon emission data. They are also promoting the calculation and application of TSZ-ECF. In response, many countries and regions have introduced relevant policies and launched platform development initiatives.

In 2022, the US Congress enacted legislation requiring the US Energy Information Administration (EIA) to publish hourly average and marginal carbon emission factors. These data serve as a basis for calculating product carbon footprints. The California Independent System Operator (CAISO) platform (Fig. 6) provides hourly-updated regional carbon intensity data, which are further disaggregated by subregional grids. In partnership with academic institutions, the UK National Grid has developed a system to forecast carbon intensity trends across 14 national regions, with 30-minute resolution and a 96-hour forecast horizon. Meanwhile, the Carbon Intensity API platform (Fig. 7) provides regional electricity carbon intensity updates every 5 minutes, supporting both real-time and forecasted data. It has been widely adopted in mobile applications and corporate carbon reduction systems. In terms of EU and international cooperation, the European Union has worked with Japan, Canada, the United States, and others to promote the establishment of an hourly electricity traceability mechanism. It is also exploring reducing the temporal granularity to 15-minute intervals to align with electricity spot market clearing times. In Finland, the power grid already releases carbon intensity data every 3 minutes. In addition, Electricity Maps (Fig. 8) provides data on power generation mix, electricity prices, and carbon intensity for over 190 countries and regions. It provides real-time, historical, and 72-hour forecast data. Using the flow-tracing technology, it calculates TSZ-ECFs that let users monitor the carbon intensity and energy source mix of each region at any time.

China has also launched national initiatives to improve carbon tracking. State Grid Corporation of China, in collaboration with multiple institutions, has

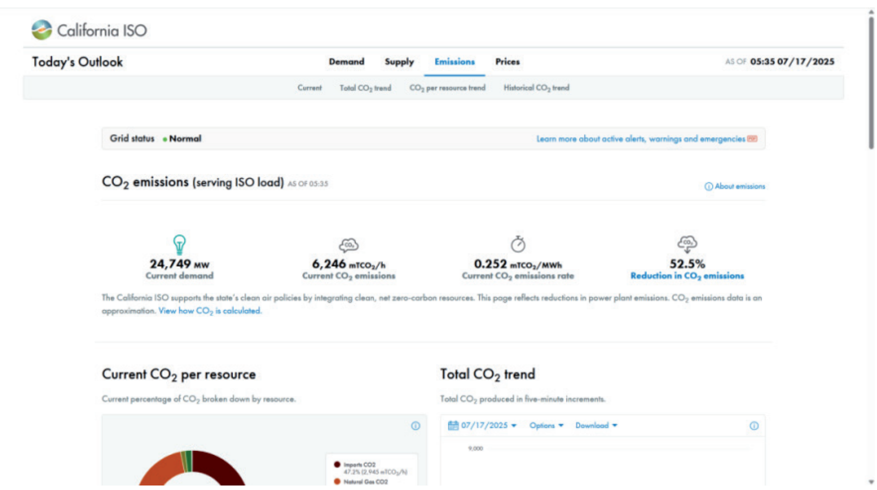

Fig. 6. California Independent System Operator (CAISO) platform.

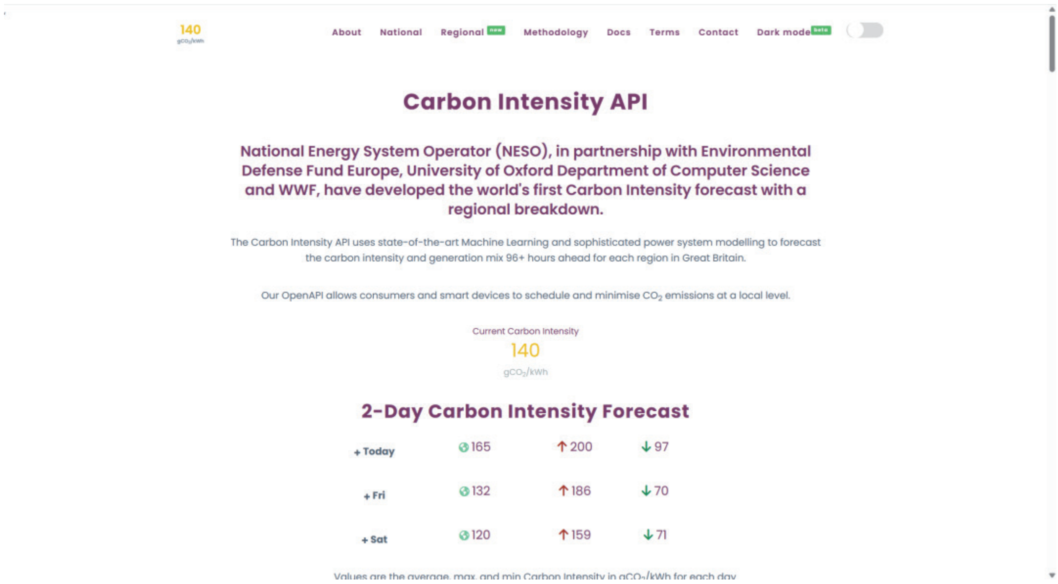

Fig. 7. UK Carbon Intensity API platform.

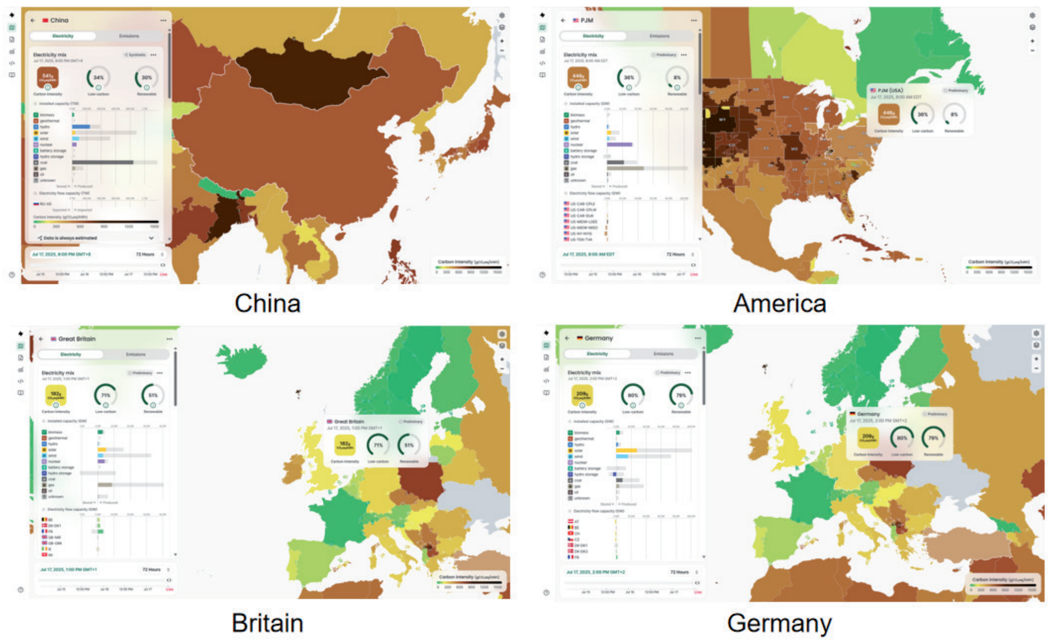

Fig. 8. Electricity Maps.

established a national carbon emission monitoring and analysis platform. Pilot programs have been conducted for calculating regional electricity carbon emission factors, enabling monthly estimation of carbon emissions at national, regional, and sectoral levels. China Southern Power Grid has established a carbon emission monitoring platform focused on energy consumption. The system enables the calculation and dynamic monitoring of total carbon emissions and carbon intensity per unit of GDP across different regions, sectors, and even individual enterprises within its service area.

Results and Discussion

Despite significant advances in Temporal-Regional Grid Emission Factors (TSZ-ECF) research, six critical challenges persist in scaling toward large-scale engineering applications.

Firstly, insufficient data accessibility and transparency constitute the primary barrier. Core data, including real-time electricity flows and power generation unit coal/gas consumption, are fragmented among grid operators, power plants, trading centers, and third parties, lacking unified open interfaces; renewable electricity, green certificates, and carbon emission monitoring data suffer from low update frequencies and inconsistent metrics, impeding minute- or even second-level factor calculations. This stems from intertwined data silos and commercial confidentiality clauses, compounded by the absence of real-time carbon monitoring in China's Regulations on Security Protection of Power Monitoring Systems, resulting in ambiguous data quality accountability. As Zhou et al. [78] demonstrated in emerging economies, data availability dominates uncertainty in carbon emission quantification, necessitating institutional designs to dismantle administrative and sectoral barriers.

Future initiatives should leverage the UK Carbon Intensity API and US eGRID models to establish a national electricity-carbon data hub, formulating Minimum Dataset (MDS) standards; integrate blockchain and privacy-preserving computing to achieve "visible utility without raw data exposure". We propose that the National Development and Reform Commission (NDRC) establish and chair an Electricity-Carbon Data Alliance to draft standards, followed by deploying federated learning nodes in the Yangtze River Delta and Jing-Jin-Ji regions toward province-level node coverage. Concurrently, amend the Regulations on Security Protection of Power Monitoring Systems to: (1) classify real-time carbon measurements under Security Level II, (2) grant data-sharing exemption clauses for carbon accountability purposes.

Secondly, the trade-off between model complexity and computational efficiency intensifies in provincial-level grids. Algorithms such as complex power distribution matrices, graph-theoretic DFS/BFS, and carbon flow networks exhibit exponential computational growth for matrix inversions or traversals in large-scale systems. High renewable penetration induces frequent node-branch state changes, invalidating traditional linearized assumptions and requiring nonlinear optimal power flow or rolling horizon optimization – compromising real-time performance. Fundamentally, carbon flow tracing is a nonlinear-nonconvex-high-dimensional problem, while existing EMS/DMS CPU-GPU heterogeneous computing lacks deep customization for carbon flow kernels, creating dual algorithm-hardware bottlenecks. Zhang et al. [79] revealed analogous effects in China's high-carbon industries: capital misallocation driven by carbon risks hinges on computational latency; delays beyond 5 minutes lock in 28-million-yuan inefficient capital, directly applicable to TSZ-ECF scenarios.

Future initiatives should establish a national electricity-carbon data hub informed by the UK Carbon Intensity API and US eGRID frameworks, instituting Minimum Dataset (MDS) standards while integrating blockchain and privacy-preserving computing to enable visible utility without raw data exposure. We propose that the National Development and Reform Commission (NDRC) convenes an Electricity-Carbon Data Alliance to formulate standards, subsequently deploying federated learning nodes across the Yangtze River Delta and Jing-Jin-Ji regions to achieve provincial node coverage. Concurrent amendments to the Regulations on Security Protection of Power Monitoring Systems must classify real-time carbon measurements under Security Level II with data-sharing exemption clauses. Subsequent phases require implementing physical-data dual-driven methodologies, where graph neural networks and Transformer architectures train spatiotemporal carbon potential surfaces offline via power-flow–carbon-flow coupling models. Online inference executes lightweight forward propagation for minute-second responsiveness within an edge-cloud orchestration framework. Critical milestones comprise: developing an open-source–carbon-flow graph neural network library using PyTorch Geometric with a 100-node benchmark system; adapting GPU-accelerated optimal power flow kernels for sub-500 ms cloud inference latency; and deploying INT8-quantized models on edge devices by 2028, featuring sub-300 MB memory footprints compliant with county-level embedded gateway constraints.

Thirdly, it is difficult to choose the appropriate spatiotemporal scale. Excessively fine spatiotemporal granularity (such as 5 minutes per node) can improve accuracy but leads to the "curse of dimensionality"; overly coarse divisions cannot capture local fluctuations in new energy output, resulting in distorted demand response and green electricity trading incentives. Current Guidelines for Power System Security and Stability specify only 15-minute security constraints without carbon granularity guidance. Future work should establish a hierarchical-domain-adaptive mechanism dynamically adjusting granularity based on renewable penetration, load density, and grid congestion; employ multi-objective optimization (accuracy real time economy) for automatic optimal-scale selection, enabling scalable spatiotemporal resolution. Implementation requires: (1) clustering typical provinces via penetration-congestion matrices, (2) developing Python toolkits with NSGA-III for minute-level switching, (3) advancing the TSZ-ECF Multi-scale Application Guideline from group to industry standard.

Fourth, inadequate uncertainty quantification and robustness persist. Compound uncertainties – from stochastic source-load behaviors, market price volatility, and intrinsic carbon factor variability – risk misleading deterministic factors. Current studies predominantly provide point estimates, lacking confidence intervals, robust intervals, or scenario analyses. This originates from heteroscedastic multi-source distributions in carbon factor chains, exacerbated by China's carbon market MRV system using fixed ±5% error bands that ignore real-time tail quantiles. Zhou et al. [78] emphasized that neglecting confidence intervals in emerging economies systematically underestimates carbon emission elasticity, distorting policy simulations.

Future research shall establish a probabilistic interval scenario tri-dimensional uncertainty representation framework to generate posterior distributions of carbon emission factors through Bayesian deep learning, subsequently embedding carbon factor confidence intervals into spot market clearing and renewable energy trading mechanisms for robust low-carbon decision-making. Implementation requires initially developing an open-source Bayesian neural network framework to deliver 95% confidence intervals; subsequently, piloting robust carbon curves clearing in Guangdong's spot electricity market to quantify cost efficiency against deterministic carbon factor benchmarks; and ultimately, incorporating confidence intervals into renewable energy trading contractual templates to form underlying derivatives.

Fifth, misalignment with existing carbon/power markets creates friction. National/provincial GHG inventories still use annual/regional average factors, while corporate carbon disclosures and CBAM calculations adopt inconsistent metrics; power spot markets, renewable electricity trading, and carbon quota settlements operate with divergent temporal-spatial boundaries. Rooted in segregated governance between electricity and carbon authorities, this institutional friction manifests through unaligned statistical frameworks, reporting protocols, and data dictionaries.

Future policy should establish national Technical Specifications for Time Spatial Zonal-Electricity Carbon Factors (TSZ-ECF), standardizing boundaries, methodologies, data protocols, and interfaces while aligning with international regimes, including the EU Carbon Border Adjustment Mechanism (CBAM), ISO 14067, and the GHG Protocol to develop cross-border carbon labeling mutual recognition protocols for export verification. Implementation requires: initially launching the standardization initiative with parallel bilingual CBAM-alignment studies; then establishing a Guangdong-Hong Kong-Macao-EU renewable energy pilot to achieve TSZ-ECF and EU Emission Factors (EF) mutual recognition; concurrently embedding carbon labels in Harmonized System (HS) codes at customs for single-pass export verification.

Finally, the lack of standardization and interoperability has resulted in siloed regional platforms, hindering carbon accountability for cross-border renewable electricity or imported power. This deficiency originates from two critical gaps: TSZ-ECF remains excluded from the IEC 61970/61968 Common Information Model (CIM) extension package, while China's Guidelines for Power Carbon Metrology currently holds only voluntary group-standard status without legally binding force.

To resolve these barriers, TSZ-ECF must serve as the nexus integrating the full "generation scheduling-market clearing-carbon quotas-demand response" chain. Concretely, day-ahead and real-time electricity markets should adopt carbon curve bidding, carbon markets need to permit TSZ-ECF-driven dynamic quota adjustments, and demand-side strategies (including interruptible loads, virtual power plants, and storage dispatch) should embed real-time carbon factors. A regulatory sandbox mechanism is proposed for pilot deployment in Beijing-Tianjin-Hebei, Yangtze River Delta, and Guangdong-Hong Kong-Macao regions to establish replicable electricity-carbon synergy paradigms. Implementation will follow a phased approach: First, conduct carbon curve bidding simulations in the Beijing-Tianjin-Hebei grid and publish technical reports. Subsequently, enable ±5% quota adjustments based on TSZ-ECF in the Yangtze River Delta carbon market. Finally, integrate TSZ-ECF into virtual power plant storage strategies across Guangdong-Hong Kong-Macao to achieve sub-5-minute closed-loop response cycles.

Conclusions

The Time Space-Zone Electricity Carbon Factor (TSZ-ECF), characterized by its dynamic, marginal, and spatially refined nature, is emerging as the "yardstick" that connects the electricity market, carbon market, and energy internet. This paper systematically reviews the theoretical basis of TSZ-ECF, the evolution of its calculation methods both internationally and domestically, and its diverse values in electricity market design, user-side carbon management, grid operation, and policy evaluation. The research results show that the shift from "annual-regional average values" to "minute-node marginal values" enables TSZ-ECF to capture the spatio-temporal heterogeneity brought by high proportions of renewable energy, significantly improving decision-making accuracy in scenarios such as carbon footprint, green power trading, and demand response.

International experience indicates that economies like the United States, the United Kingdom, Europe, Australia, and Japan have formed a "government-university-enterprise" collaborative data and algorithm ecosystem, but have yet to solve key challenges such as cross-border power interaction and green power deduction. China, on the other hand, has achieved original breakthroughs in carbon flow tracking theory, graph theory algorithms, and full-process carbon measurement, but still faces shortcomings in data openness and standard mutual recognition. The four major bottlenecks of data, algorithms, standards, and markets are intercoupled, and a systematic solution is urgently needed through national-level data infrastructure, lightweight AI algorithms, unified technical norms, and cross-market mechanism innovation. Looking ahead, as the "dual carbon" goals enter the critical stage, TSZ-ECF will move from academic research to large-scale engineering applications, becoming the "baton" for real-time low-carbon dispatch in power systems, the "price tag" for enterprise carbon asset management, and the "passport" for mutual recognition of carbon footprints in international trade.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. A Y., YANG W.J., CHENG Y.Y., DU Z.X., LV Y., MA L.Y. Global climate governance and organizational carbon inventory check. Yi Ra. **51** (6), 81, **2025** [In Chinese].
2. ZHANG Q., WANG Y., ZHAO L.W., FANG Z.H. Analysis of policy system, structural transformation and systematic challenges under the ‘Carbon peak’ and ‘carbon neutrality’ goals. Chinese Battery Industry. 1, **2025** [In Chinese].
3. JIANG L.L., LI Y.P., HE X., ZHOU Q. Research progress on low-carbon transition pathways in the power sector toward “Dual Carbon” targets. High Technology and Industrialization. **31** (6), 65, **2025** [In Chinese].
4. LIU G.Y., WANG J.Y., TANG Y.C., WANG D. Evolution process of research directions and application requirements of electricity carbon emission factors. Power System Technology. **48** (1), 12, **2024** [In Chinese].
5. HARDISTY P.E., CLARK T.S., HYNES R.G. Life cycle greenhouse gas emissions from electricity generation: a comparative analysis of Australian energy sources. Energies. **5** (4), 872. **2012**.
6. DE CHALENDAR J.A., TAGGART J., BENSON S.M. Tracking emissions in the US electricity system. Proceedings of The National Academy of Sciences of The Unifed States of America. **116** (51) 25497, **2019**.
7. HE G.S., ZENG J.C., ZHU H.J., CHEN A.Z. Summary of statistical accounting methods for average carbon emission factors of power grid. Environmental Impact Assessment. **46** (4), 64, **2024** [In Chinese].
8. GU Y.F. Research on power carbon emission accounting method for the grid side. Ph.D. Dissertation, Huazhong University of Science and Technology, Wuhan, China, **2024** [In Chinese].
9. MA M.C., LI Y.W., DU E.S. Analysis of multi-period marginal carbon emission factors and their uncertainties. Automation of Electric Power Systems. 1, **2025** [In Chinese].
10. WAN Y.X., SUN X.C., BAO M.L., DING Y. WANG X.R. Carbon-green certificate mutual conversion mechanism and market benefit analysis based on marginal carbon intensity. Power System Technology. 1, **2025** [In Chinese].
11. PENG T.H., CAI X., ZHAI Z.H., TANG A.H., SHEN R., WANG Q.M., YU W.H. Research on calculation model of power supply carbon emission factor in regional power grid considering hierarchical and regional decoupling of large-scale power grid. Proceedings of the CSEE. **44** (3), 894, **2024** [In Chinese].
12. LIN W.J., CAO H.Y., TIAN W., LIU H.Y., WENG R.X., ZHANG Y. Research on real-time carbon measurement system for the entire process of power system considering distributed generation. Electrical Measurement & Instrumentation. **61** (10), 113, **2024** [In Chinese].
13. ZHAN G.H., ZHANG X.Y., WEI S.Y., ZHANG X.S., LI L. A prediction method for power grid carbon emission factor based on T-Graphormer. Integrated Intelligent Energy. **47** (6), 30, **2025** [In Chinese].
14. SONG J.W., YANG W., ZHOU C. L., ZHANG N., CHEN X., KANG C.Q. Distributed calculation method for regional power carbon emission factors across power grids. Automation of Electric Power Systems. 1, **2025** [In Chinese].
15. WANG C.Q., CHEN Y., CHI C.Y., TAO Y., LI X.B., JIANG X.D. Calculation method of power system carbon emission flow based on power flow distribution matrix. Science Technology and Engineering. **22** (12), 4835, **2022** [In Chinese].
16. ZUO W.L., QIN X.H., XU Y.P., FAN C.H., PAN R. Carbon flow network distribution and path tracing algorithm based on graph theory. Power System Technology. **49** (4), 1305, **2025** [In Chinese].
17. ZHANG N., LI Y.W., HUANG J.H., LI Y.H., DU E.S., LI M.X., LIU Y.L., KANG C.Q. Carbon measurement method and carbon meter system for whole chain of power system. Automation of Electric Power Systems. **47** (9), 2, **2023** [In Chinese].
18. YAN L.M., HU W.S. Carbon flow tracking method of power systems based on the complex power distribution matrix. Integrated Intelligent Energy. **45** (8), 1, **2023** [In Chinese].
19. LEAL-ARCAS R., FAKTAUFON M., KYPRIANOU A. A legal exploration of the European Union’s carbon border adjustment mechanism. European Energy and Environmental Law Review. **31** (4), **2022**.
20. MILLER G.J., NOVAN K., JENN A. Hourly accounting of carbon emissions from electricity consumption. Environmental Research Letters. **17** (4), 044073, **2022**.
21. HE H.J., ZHOU S.L., ZHANG L.P., ZHAO W., XIAO X. Dynamic accounting model and method for carbon emissions on the power grid side. Energies. **16** (13) 5016, **2023** [In Chinese].
22. BERTOLINI M., DUTTILO P., LISI F. Accounting carbon emissions from electricity generation: a review and comparison of emission factor-based methods. Applied Energy. **392**, 125992, **2024**.
23. LI Y.W., YANG X.X., DU E.S., LIU Y.L., ZHANG S.X., YANG C., ZHANG N., LIU C. A review on carbon emission accounting approaches for the electricity power industry. Applied Energy. **359,** 122681, **2024**.
24. LI Z., PAN Q., SHI J., JI H. Construction and Application of Enterprise Electric Carbon Model: A Study Based on Key Enterprises in Qinghai Province. Sustainability. **17** (5), 2243, **2025**.
25. YANG Y.Y., PAN F., LI J.L., JI Y.L., ZHONG L.H., ZHANG J. Electricity consumption optimization of power users driven by a dynamic electric carbon factor. Frontiers in Energy Research. **12**, 1373206, **2024**.
26. TANG Y.Z., LI Y., YUAN X.L., PIMM A., COCKERILL T.T., WANG Q.S., MA Q. Estimation of emission factors from purchased electricity for European countries: Impacts on emission reduction of electricity storage. Environmental Science & Technology. **56** (8), 5111, **2022**.
27. ZUO J., ZHONG Y.S., YANG Y., FU C., HE X.Z., BAO B., QIAN F. Analysis of carbon emission, carbon displacement and heterogeneity of Guangdong power industry. Energy Reports. **8**, 438, **2022**.

28. HU Z., WANG M., CHENG Z. YANG Z. Impact of marginal and intergenerational effects on carbon emissions from household energy consumption in China. Journal of Cleaner Production. **273**, 123022, **2020**.
29. ZHONG Z.W., YU Y., ZHAO X.L., XIAO L. Revisiting electric vehicle life cycle greenhouse gas emissions in China: a marginal emission perspective. iScience. **26** (5), 106565, **2023**.
30. YU H., YANG Y., LI B., LIU B.W., GUO Y.H, WANG Y.Q., GUO Z.F., MENG R.H. Research on the community electric carbon emission prediction considering the dynamic emission coefficient of power system. Scientific Reports. **13** (1), 5568, **2023**.
31. FANG B., ZHANG J.Y., CHEN S.Y., LI L., WANG S.L., WEN M.Z. A data-driven method for deriving the dynamic characteristics of marginal carbon emissions for power systems. Energies. **18** (13), 3297, **2025**.
32. YANG T.Y., DANG Z.S., WANG X.J., WANG B., GAO Y., WANG Q.C. Comprehensive carbon accounting for power systems considering hybrid power trading mode. Energy. **333**, 136897, **2025**.
33. WANG H., ZHANG Y.Y., LIN W.F., WEI W.D. Transregional electricity transmission and carbon emissions: evidence from ultra-high voltage transmission projects in China. Energy Economics. **123**, 106751, **2023**.
34. SU W.Q., CHEN F.X., SHAO Z.G., HUANG T.H., WU H.B. A low-carbon economic scheduling of power systems considering marginal carbon emission factor. Journal of Physics: Conference Series. **2935**, 012027, **2025**.
35. YANG L.J., GAO Y.J., ZHANG P., TAN X.L., AN J.K. Two-stage low-carbon economic dispatch of an integrated energy system considering flexible decoupling of electricity and heat on sides of source and load. Sustainable Energy Grids □ Networks. **40**, 101552, **2024**.
36. WENG G.P., REN J.R., YAO Y., WANG L., HUANG F. Low-carbon economic dispatch of integrated energy systems in industrial parks considering time-varying electricity-carbon factors. Zhejiang Electric Power. **41** (10), 106, **2022** [In Chinese].
37. BAI M., LI C. Study on the spatial correlation effects and influencing factors of carbon emissions from the electricity industry: a fresh evidence from China. Environmental Science and Pollution Research. **30** (53), 113364, **2023**.
38. WANG C., ZHAO Y.L., YAN H., JIANG X., KANG Q., ZHOU J.C. Prediction of electricity carbon emission peak in intelligent buildings with discrete second-order differential and time-sharing carbon measurement. Sustainable Energy Research. **12** (1), 20, **2025**.
39. QU J.B., QI S., LEI T.T., CHEN A.Z., ZENG J.C. Research on the analysis of thermal power plant's electricity-carbon factor based on units. Environmental Impact Assessment. **47** (2), 34, **2025** [In Chinese].
40. ZHANG X.C., ZHU Q.W., ZHANG X.Q. Carbon emission intensity of final electricity consumption: assessment and decomposition of regional power grids in China from 2005 to 2020. Sustainability. **15** (13), 9946, **2023**.
41. JIA Y.P. Research on measures for improving the calculation of electricity-carbon factors in the context of building a carbon emission statistical accounting system. China Business Guide. (17), 56, **2024** [In Chinese].
42. GUAN Z., YANG C., FENG H.R., CHEN L.P., CEN H.F., LI Y.W., DU E.S., ZHANG N. Low-carbon demand response technology considering uncertainty of marginal carbon emission factors. Southern Power System Technology. 1, **2025** [In Chinese].
43. YANG Y., YI W.F., WANG C.Q., WANG M.S., WU Z.J., MU Y.F., ZHENG M.Z. Low-carbon economic dispatch of power system sources, nets and loads based on carbon flow tracking. Electric Power Construction. **44** (5), 108, **2023** [In Chinese].
44. ZHU J.Z., XIE C.C., ZHANG D., LAN J., ZHOU J.L. Review of electric-carbon coupling market studies: status, challenges, and sustainability perspectives. Electric Power Construction. **46** (1), 158, **2025** [In Chinese].
45. ZHANG X.L., HUANG X.D., ZHANG D., GENG Y., TIAN L.X., FAN Y., CHEN W.Y. Research on the pathway and policies for China's energy and economy transformation toward carbon neutrality. Management World. **38** (1), 35, **2022** [In Chinese].
46. LI X., LIU Z.M., YANG D., WANG D.P. Power market efficiency evaluation and carbon market price design – estimation of pass-through rate based on the perspective of power-carbon market correlation. China Industrial Economics. **1**, 132, **2022** [In Chinese].
47. LI F., LI X.S, LU M.F., ZHANG L. Game optimization model of direct power purchase between power suppliers and large consumers with RPS assessment constrains. High Voltage Engineering. **49** (1), 1, **2022** [In Chinese].
48. WANG D., LI D., FENG L.J., JIA Q.G., PING J., YAN Z. Trustworthy and autonomous electricity trading method among multiple microgrids considering green property. Automation of Electric Power Systems. **46** (23), 1, **2022** [In Chinese].
49. GUO S.W., MEN X.J., SUN H.P., ZHANG S.J., SUN W.J. Comparison and analysis on current situation and future prospects of three policy tools of green power transaction, green energy certificate and CCER. Energy of China. **44** (3), 75, **2022** [In Chinese].
50. ZHOU T.R., KANG C.Q, XU Q.Y., CHEN Q.X. Preliminary theoretical investigation on power system carbon emission flow. Automation of Electric Power Systems. **36** (7), 38, **2012** [In Chinese].
51. LI B.W., HU Z.C., SONG Y.H., WANG G.H. Principle and model for regional allocation of carbon emission from electricity sector. Power System Technology. **36** (7), 12, **2012** [In Chinese].
52. KHAN I., JACK M.W., STEPHENSON J. Analysis of greenhouse gas emissions in electricity systems using time-varying carbon intensity. Journal of Cleaner Production. **184**, 1091, **2018**.
53. VALENZUELA L.F., DEGLERIS A., EL GAMAL A., PAVONE M., RAJAGOPAL R. Dynamic locational marginal emissions via implicit differentiation. IEEE Transactions on Power Systems. **39** (1), 1138, **2024**.
54. WANG Z.S., SHI Y., TANG Y.M., MEN X.Y., CAO J., WANG H.F. Low carbon economy operation and energy efficiency analysis of integrated energy systems considering LCA energy chain and carbon trading mechanism. Proceedings of the CSEE. **39** (6), 1614, **2019** [In Chinese].
55. LI Y.W., ZHANG N., DU E.S. LIU Y.L., CAI X., HE D.W. Mechanism study and benefit analysis on power system low carbon demand response based on carbon emission flow. Proceedings of the CSEE. **42** (8), 2830, **2022** [In Chinese].
56. LEVASSEUR A., MERCIER-BLAIS S., PRAIRIE Y.T., TREMBLAY A., TURPIN C. Improving the accuracy of electricity carbon footprint: estimation of hydroelectric reservoir greenhouse gas emissions. Renewable & Sustainable Energy Reviews. **136**, 110433, **2021**.

57. BIE P., LIN S.H., WANG N., WANG H.H. Calculation of carbon emission factors on the corporate electricity consumption side based on power flow tracing and green power trading. Southern Power System Technology. **17** (6), 34, **2023** [In Chinese].
58. LI X.Z., HAN B., LI G.J., WANG K.Y., XU J. Challenges of distributed green energy carbon trading mechanism and carbon data management. Journal of Shanghai Jiao Tong University. **56** (8), 1006, **2022** [In Chinese].
59. WEI Y.H., FAN S., XU S.L., ZENG F., XIAO J.C., HE G.Y. Evaluation method for renewable energy share of customers based on marginal contribution to renewable energy accommodation. Automation of Electric Power Systems. **47** (10), 14, **2023** [In Chinese].
60. SHI Y., LI W.J., YANG F.J., ZHOU X.L., LIU C.M. Two-layer low-carbon optimized dispatching for integrated energy systems considering carbon liability allocation and demand response. Modern Electric Power. **42** (4), 669, **2023** [In Chinese].
61. CUI Y., ZOU X.P., ZHAO Y.T., FU X.B., SHEN Y.P. Electricity-carbon integrated demand response scheduling method for new power system considering dynamic electricity-carbon emission factor. Electric Power Automation Equipment. **44** (10), 1, **2024** [In Chinese].
62. LU Z.L., YAN L., WANG J.X., KANG C.Q., SHAHIDEHPOUR M., LI Z.Y. A market-clearing-based sensitivity model for locational marginal and average carbon emission. IEEE Transactions on Energy Markets, Policy and Regulation. **2** (4), 579, **2024**.
63. KAMJOU A.S., MILLER C.J., ROUHOLAMINI M., WANG C.S. Comparison between historical and real-time techniques for estimating marginal emissions attributed to electricity generation. Energies. **14** (17), 5261, **2021**.
64. LI B.W., HU Z.C., SONG Y.H., WANG G.H. Principle and Model for Regional Allocation of Carbon Emission from Electricity Sector. Power System Technology. **36** (7), 12, **2012** [In Chinese].
65. KHAN I., JACK M.W., STEPHENSON J. Analysis of greenhouse gas emissions in electricity systems using time-varying carbon intensity. Journal of CleanerProduction. **184**, 1091, **2018**.
66. VALENZUELA L.F., DEGLERIS A., GAMAL A.E., PAVONE M. Dynamic locational marginal emissions via implicit differentiation[J]□IEEE Transactions on Power Systems. **39** (1), 1138, **2024**.
67. WANG Z.L., SHI Y., TANG Y.M., MEN X.Y., CAO J., WANG H.F. Low Carbon Economy Operation and Energy Efficiency Analysis of Integrated Energy Systems Considering LCA Energy Chain and Carbon Trading Mechanism. Proceedings of the CSEE. **39** (6), 1614, **2019** [In Chinese].
68. LI Y.W., ZHANG N., DU E.S., LIU Y.L., CAI X., HE D.W. Mechanism Study and Benefit Analysis on Power System Low Carbon Demand Response. Proceedings of the CSEE. **42** (8), 2830, **2022** [In Chinese].
69. LEVASSEUR A., MERCIER-BLAIS S., PRAIRIE Y.T., TREMBLAY A., TURPIN C. Improving the accuracy of electricity carbon footprint: estimation of hydroelectric reservoir greenhouse gas emissions. Renewable and Sustainable Energy Reviews. **136** (4), **2021**.
70. BIE P., LIN S.H., WANG N., WANG H.H. Calculation of Carbon Emission Factors on the Corporate Electricity Consumption Side Based on Power Flow Tracing and Green Power Trading. Southern Power System Technology. **17** (6), 34, **2023** [In Chinese].
71. LI X.Z., HAN B., LI G.J., WANG K.Y., XU J. Challenges of Distributed Green Energy Carbon Trading Mechanism and Carbon Data Management. Journal of Shanghai Jiao Tong University. **56**(8), 977, **2022** [In Chinese].
72. LU X.B., ZHAO L., YANG Y., SHU Y.B., HUANG H.W., SHU A.J., YE J.C., ZHU H. Calculation of Time- and Area-Specific Electric Carbon Factor and Its Application in Product Carbon Footprint Accounting. Strategic Study of CAE. **27** (5),1009, **2025** [In Chinese].
73. WEI Y.H., FAN S., XU S.L., ZENG F., XIAO J.C., HE G.Y. Evaluation Method for Renewable Energy Share of Customers Based on Marginal Contribution to Renewable Energy Accommodation. Automation of Electric Power Systems. **47** (10), 14, **2023** [In Chinese].
74. SHI Y., LI W.J., YANG F.J., ZHOU X.L., LIU C.M. Two-layer Low-carbon Optimized Dispatching for Integrated Energy Systems Considering Carbon Liability Allocation and Demand Response. Modern Electric Power. **42** (4), **2025** [In Chinese].
75. CUI Y., ZHOU X.P., ZHAO Y.T., FU X.B., SHEN Y.P. Electricity-carbon integrated demand response scheduling method for new power system considering dynamic electricity-carbon emission factor. Electric Power Automation Equipment. **44** (10), 1, **2024** [In Chinese].
76. BAKER BOTTS HYDROGEN PRACTICE GROUP. Final Section 45V Clean Hydrogen Production Tax Credit Regulations: A Closer Look. Available online: https://www.bakerbotts.com/thought-leadership/publications/2025/february/final-section-45v-clean-hydrogen-production-tax-credit-regulations-a-closer-look. **2025**.
77. GUANGZHOU MUNICIPAL PEOPLE'S GOVERNMENT. Notice of the Guangzhou Municipal People's Government on Printing and Distributing the Implementation Plan for the National Carbon Peak Pilot (Guangzhou). Available online: https://www.gz.gov.cn/gkmlpt/content/9/9757/post_9757506.html. (accessed on 2024-07-12).
78. ZHOU R., GUAN S., HE B. The Impact of Trade Openness on Carbon Emissions: Empirical Evidence from Emerging Countries. Energies. **18** (3), 697, **2025**.
79. ZHANG C.J., ZHANG S.H., ZHAO C.Y., HE B. Carbon Risk and Capital Mismatch: Evidence from Carbon-Intensive Firms in China. Sustainability. **17** (14), 6477, **2025**.