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The Carbon Allowance Allocation Model for Power Transmission and Transformation Projects from the Perspective of Sustainable Development

Zijia Guo [1], Lihong Li [2,*], Rui Zhu [3] and Sixing Zhao [2]

[1] School of Zhong Xin International Engineering, Shenyang Jianzhu University, Shenyang 110168, China; gzj200633@stu.sjzu.edu.cn
[2] School of Management, Shenyang Jianzhu University, Shenyang 110168, China; zsx5678@stu.sjzu.edu.cn
[3] School of Business Administration, Liaoning Technical University, Huludao 125105, China; ruizhu@stu.sjzu.edu.cn
* Correspondence: lilihong@sjzu.edu.cn

Abstract

Reasonable carbon allowance allocation for power transmission and transformation projects is critical for regional emission reduction, yet existing methods rarely address spatial heterogeneity or the fairness-efficiency trade-off at the city level. This study proposes a framework integrating entropy weighting with Zero-Sum Gains Data Envelopment Analysis (ZSG-DEA), applied to cities in Liaoning, China, to achieve objective initial distribution and efficiency-driven adjustments under a binding carbon cap. Empirical results reveal that regional quota levels are shaped not by economic scale or historical emissions alone, but by grid hub functions, load intensity, new energy transmission demand, and network density. The integrated approach avoids subjective bias and optimizes allocation efficiency, offering a replicable pathway for carbon quota allocation in similar contexts.

Keywords: power transmission and transformation project; carbon allowance allocation; methodology and application; ZSG-DEA

1. Introduction

The electric power industry is a major source of carbon emissions and places considerable pressure on the global climate system [1]. As a core component of grid infrastructure, power transmission and transformation projects enable efficient electricity transmission and stable dispatch, serving as a critical link between generation and consumption [2]. In recent years, integrating the entire power industry into the carbon market as a means of achieving low-carbon management through macroeconomic regulation has become a key concern. The EU Emissions Trading System (EU ETS), launched in 2005, has become deeply intertwined with the electricity market, with cumulative trading volumes exceeding €770 billion. California's linked carbon market manages electricity-related carbon costs through a consignment auction mechanism, achieving 85% coverage and contributing to a 42% reduction in power-sector emissions. In 2017, China officially launched its national carbon trading market, with major industries participating from the outset. Since then, notable progress has been made in reducing emissions on the generation side, reflected in declining coal consumption per unit of electricity supply and a steady drop in carbon intensity. The carbon market has played a constructive role in promoting the clean and efficient transformation of coal-fired power generation and has provided valuable practical

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experience for the low-carbon transition of the power sector. Nevertheless, carbon allowance allocation for transmission and transformation projects remains a practical barrier to fully integrating the entire electricity industry chain into the carbon market.

The stable functioning of the carbon market hinges on the rational allocation of emission allowances. Carbon emissions from transmission and transformation projects are characterized by full life-cycle coverage, a predominance of indirect emissions, marked regional and voltage-level disparities, and concentrated abatement potential [3]. These features directly affect the precision of allowance allocation and are therefore a key prerequisite for ensuring market stability. To facilitate the smooth integration of transmission and transformation into the carbon market, in-depth research on allowance allocation for this sector is urgently needed. Existing studies on carbon allowance allocation in the power sector have largely concentrated on power generation or the industry as a whole, with limited attention given to the specific characteristics of transmission and transformation projects. One model based on nodal carbon intensity provides a framework for assigning differentiated generation responsibilities [4]; another study uses power trading data to couple dispatch decisions with allowance allocation in order to optimize abatement costs [5]. In terms of allocation principles, the field has moved from single-criterion approaches to multi-criteria frameworks that incorporate fairness, efficiency, sustainability, and feasibility [6], thereby offering a conceptual foundation for this study. Methodologically, indicator-based approaches [7], optimization models [8], game-theoretic models [9], and hybrid methods [10] have all been widely applied. However, these methods are limited by weak sector-specific adaptability, considerable subjectivity, and a lack of dynamic adjustment mechanisms. Moreover, existing research has mostly focused on the national or provincial levels, or on industries such as manufacturing and transportation, while studies targeting power transmission and transformation projects remain scarce.

To address these limitations, this study, grounded in the four principles of fairness, efficiency, sustainability, and feasibility, integrates the entropy weight method with the Zero-Sum Gains Data Envelopment Analysis (ZSG-DEA) approach and incorporates the industry characteristics of transmission and transformation projects to construct a scientifically sound and feasible carbon allowance allocation model. The entropy weight method is employed to objectively assign weights to core indicators, thereby avoiding subjective bias. By embedding the industry attributes of transmission and transformation projects and utilizing the ZSG-DEA model to measure emission reduction potential, the model's adaptability is enhanced. A two-stage integration framework—initial allocation via entropy weighting followed by efficiency optimization via ZSG-DEA—is established. This framework balances multiple allocation principles and achieves optimal allocation under a total carbon cap constraint, thereby overcoming the limitations of previous approaches. The proposed method is then applied to cities in Liaoning Province, demonstrating its practical effectiveness. The remainder of this paper is organized as follows: Section 2 reviews the literature on transmission and transformation projects and carbon allowance allocation methods. Section 3 presents the allocation model. Section 4 reports and discusses the empirical results. Section 5 concludes and offers policy recommendations.

2. Literature Review

2.1. Carbon Emissions from Power Transmission and Transformation Projects

The research hotspots of power transmission and transformation projects have undergone a significant evolutionary process, with a deep focus on low-carbon transformation in recent years. Current research primarily concentrates on the life-cycle carbon emission accounting of power transmission and transformation projects and the qualitative analysis of low-carbon potential, forming a diversified accounting system based on life cycle assess-

ment (LCA) methods and carbon emission factor approaches. Based on the LCA method, some studies have focused on the raw material acquisition and manufacturing stages of key equipment in transmission and transformation projects, constructed carbon emission accounting models, and clarified the carbon emission proportion characteristics of core equipment such as conductors and towers [11]. Incorporating the GHG Protocol standard, other studies have established quantitative carbon emission models for the construction phase of transmission and transformation projects, identifying building and structural engineering as the main contributing stage of carbon emissions through case analyses [12]. Taking 500 kV transmission and transformation projects as the research object, some researchers have developed a specialized carbon emission accounting system, determining that raw material and equipment production are the core emission sources during the construction phase, and qualitatively analyzed the emission reduction potential of the engineering construction process [13]. In addition, several studies have qualitatively explored low-carbon transformation pathways for transmission and transformation projects, proposing emission reduction directions such as the application of recycled building materials and the replacement of energy-saving conductors [14]. Although existing studies have covered relevant research directions, few have deeply investigated the carbon allowance allocation mechanism.

Against the backdrop of the continuous advancement of the "dual carbon" goals, the importance of carbon emission allowance allocation has become increasingly prominent, emerging as a core component of emission reductions and efficient carbon resource allocation in the power sector. Existing research on carbon emissions from power transmission and transformation projects largely remains at the level of accounting or qualitative analysis, lacking consideration of allowance allocation and efficiency optimization methods specifically tailored to transmission and transformation projects. Nevertheless, research on carbon allowance allocation in the power industry provides academic references and research ideas for the field of power transmission and transformation projects. From the perspective of carbon allowance allocation and the principles of fairness and efficiency, current relevant studies mostly focus on the power industry as a whole, without fully considering the unique characteristics of transmission and transformation projects, such as long industrial chains, cross-regional layouts, and dispersed carbon emission points. Consequently, a dedicated allowance allocation model that balances regional fairness, project-specific differences, and emission reduction efficiency has yet to be established. Existing studies have explored the coupled optimization of carbon allowance allocation and trading in power systems [15], as well as the fairness and efficiency of allowance allocation in the power sector under the carbon market [16], proposing corresponding ideas and improvement suggestions from the perspectives of trading mechanism optimization and the design of key allowance allocation parameters. However, overall, current research has not yet developed an independent and dedicated allowance allocation scheme for power transmission and transformation projects, nor has it fully integrated the industry characteristics of such projects into targeted research, making it difficult to effectively address core issues of allowance allocation in this field. Existing research is unable to resolve the practical problems of uneven allowance distribution and low emission reduction efficiency among transmission and transformation projects across different regions and voltage levels, nor has it achieved the optimal allocation of carbon allowance resources in the field of power transmission and transformation projects. This constitutes a research gap that urgently needs to be addressed in this field.

2.2. Carbon Quota Allocation Methods

Carbon emission allowance allocation methods directly determine the incentive effect of the carbon market on industry emission reductions and are particularly critical for the low-carbon transformation of power transmission and transformation projects. Existing methods have laid a theoretical foundation for research on carbon emission allowance allocation but exhibit significant limitations when applied to the context of transmission and transformation projects. They struggle to simultaneously satisfy total cap constraints, cross-regional differences, and project-level allocation requirements, while also failing to fully consider the typical industry characteristics of transmission and transformation projects, such as network attributes, cross-regional nature, technology-intensive features, and complex operational losses. Traditional indicator-based approaches, which rely on subjective weighting, are highly arbitrary and cannot adequately capture the multi-stage emission characteristics across the full life cycle of projects [17]. Optimization models demand high data completeness and do not fully account for cross-regional heterogeneity among projects [18]. Game-theoretic models focus on balancing the interests of multiple parties but are incapable of adapting to the precise determination and implementation of project-level allowance allocation [19]. Consequently, no single method can simultaneously achieve both fairness and efficiency. It is worth noting that the entropy weight method adopted in this study differs fundamentally from these traditional subjective indicator approaches: it determines indicator weights objectively based on information entropy, thereby avoiding the subjectivity inherent in conventional weighting schemes. Based on this, and in light of the full life-cycle characteristics of transmission and transformation projects and the core objectives of allowance allocation, there is an urgent need to construct an allocation framework that can objectively reflect regional differences, achieve efficiency optimization under total carbon cap constraints, and simultaneously balance sustainable development with practical feasibility.

The principles of carbon emission allowance allocation have gradually expanded from the traditional two dimensions of fairness and efficiency to a four-dimensional collaborative framework encompassing fairness, efficiency, sustainability, and feasibility [20]. For power transmission and transformation projects, the fairness principle requires taking into account differences in grid development stages, project construction scales, and operation and maintenance costs across regions. Under the premise of safeguarding the equal development rights of all entities, it aims to achieve balanced allowance allocation and avoid inhibiting the construction or operation and maintenance upgrades of transmission and transformation projects in remote areas due to imbalanced allowances. The efficiency principle focuses on the emission reduction potential and energy utilization efficiency throughout the full life cycle of transmission and transformation projects, enhancing the allocation level of carbon resources through input–output logic. The sustainability principle emphasizes the proportion of renewable energy generation, green technology innovation, and low-carbon upgrade potential of projects, ensuring that allowance allocation aligns with long-term "dual carbon" goals. The feasibility principle, grounded in data availability, practical engineering conditions, and local implementation capacity, selects quantifiable and easily implementable indicators such as scale, investment, and urbanization level, ensuring that the allocation scheme is operable, monitorable, and replicable. A single evaluation indicator cannot fully align with the four-dimensional principles. Therefore, an integrated approach based on a multi-dimensional indicator system and an input–output efficiency model is better suited to the complex characteristics of transmission and transformation projects, facilitating the formation of a scientific, balanced, and implementable carbon allowance allocation scheme [21].

Existing research has laid a solid theoretical and practical foundation for explorations related to the low-carbon transformation of power transmission and transformation projects. In terms of research directions, it has clarified the central theme of low-carbon development for such projects, forming a relatively systematic body of knowledge around key issues including life-cycle carbon emission accounting and the coupling of carbon allowances with project operation. In terms of value orientation and methodological approaches, it has established the principle of balancing fairness and efficiency in carbon allowance allocation, gradually extending this framework to include sustainability and feasibility. Through a critical examination of the practical outcomes and inherent limitations of traditional allocation models, existing research has offered important insights for the innovation of integrated allocation methods and has preliminarily constructed a foundational framework that bridges industry-specific characteristics of transmission and transformation projects with the theory of carbon allowance allocation. Nevertheless, current research remains subject to several limitations. First, a four-dimensional collaborative solution for carbon allowance allocation that is tailored to the specific context of power transmission and transformation projects—encompassing fairness, efficiency, sustainability, and feasibility—has yet to be developed. General-purpose allocation frameworks fail to adequately account for the distinctive attributes of such projects, including cross-regional layouts and emission variations across multiple stages of the full life cycle. Second, there is a lack of an integrated model combining objective indicator weighting with efficiency optimization equilibrium, which makes it difficult to overcome the inherent limitations of any single allocation method with respect to either fairness or efficiency. In addition, the principles of sustainability and feasibility have not been systematically translated into quantifiable indicators or embedded into the allocation model, resulting in a disconnect between allocation schemes and long-term low-carbon development goals as well as the practical implementation needs of engineering projects. In light of these gaps, future research should closely adhere to the inherent characteristics of power transmission and transformation projects, strengthen the deep coupling between carbon allowance allocation and life-cycle carbon emissions, enhance adaptability to cross-regional heterogeneity, and construct an integrated allocation model that is both scientifically rigorous and practically operable, thereby achieving organic synergy among fairness, efficiency, sustainability, and feasibility, and providing theoretical support and methodological reference for the precise determination of carbon allowances for transmission and transformation projects. To this end, this study proposes an allocation approach that combines the entropy weight method with the ZSG-DEA model. Specifically, the entropy weight method is employed to objectively assign weights to indicators of fairness, sustainability, and feasibility at each stage, thereby avoiding subjective bias. Relying on the zero-sum game efficiency optimization mechanism inherent in ZSG-DEA, the emission reduction potential of different engineering units is precisely matched, and consequently, the multiple objectives of ensuring fairness, improving efficiency, achieving long-term sustainability, and ensuring practical feasibility are realized in the allocation of carbon allowances for power transmission and transformation projects.

3. Methodology

3.1. Research Framework

Figure 1 presents the logical framework of the two-stage carbon quota allocation for transmission and transformation engineering projects using the entropy weight method and ZSG-DEA, centering on the four core principles of fairness, efficiency, sustainability, and feasibility. The fairness principle requires coordinating the development stages of different municipal power grids, variations in project construction scale, and operation and maintenance costs, ensuring equal development rights for each decision-making

unit (DMU) and achieving a balanced allocation of responsibilities and benefits across regions [22]. The efficiency principle focuses on input–output efficiency, emphasizing the energy utilization efficiency and emission reduction potential throughout the full life cycle of transmission and transformation engineering projects, and promoting the concentration of carbon quotas toward high-efficiency units. The sustainability principle is grounded in the long-term "dual carbon" goals, with particular attention to new energy consumption levels, green technology innovation capability, and the potential for low-carbon upgrades of engineering projects, ensuring that quota allocation aligns with the low-carbon transition pathway of the power system [23]. The feasibility principle, based on the accessibility of engineering practice and statistical data, selects an indicator system that is quantifiable, easy to calculate, and convenient for supervision, ensuring that the allocation scheme is operable and replicable. The selection of these four synergistic principles is intended not only to accommodate the industry characteristics of transmission and transformation engineering—such as full life cycle coverage, a predominance of indirect emissions, prominent regional heterogeneity, and significant voltage-level differences—but also to address the limitations of existing allocation methods, including single dimensionality, strong subjectivity, insufficient industry adaptability, and lack of dynamic optimization mechanisms, while aligning with the core institutional requirements of carbon markets regarding aggregate control and efficient allocation. This systematically resolves key contradictions in quota allocation among fairness assurance, efficiency improvement, long-term sustainability, and practical implementation. Based on this, the entropy weight method is used to complete the initial allocation of carbon quotas, avoiding subjective bias through objective weighting, determining initial quotas based on feasibility and sustainability indicators, and solidifying the fairness foundation from the outset. On this basis, the ZSG-DEA method is employed to construct an efficiency optimization model, achieving Pareto optimal allocation under aggregate constraints through zero-sum gaming, and making efficiency-oriented adjustments to the initial allocation results by transferring redundant quotas to high-efficiency units. Ultimately, through this two-stage integration path—determining initial quotas through objective weighting and adjusting the allocation structure via efficiency optimization—an optimal carbon quota allocation scheme for transmission and transformation engineering projects is formed that balances fairness, efficiency, sustainability, and feasibility.

Selection of Influencing Factors for Initial Carbon Quota Allocation in Urban Transmission and Transformation Projects Across Different Cities: Grounded in the industry characteristics of full-lifecycle carbon emission coverage of transmission and transformation projects and significant regional and voltage-level differences, this study addresses the research gaps of the lack of a specialized indicator system and the neglect of cross-regional heterogeneity in existing research. Strictly adhering to the four core principles of carbon quota allocation—fairness, efficiency, sustainability, and feasibility—and integrating the full-process characteristics of transmission and transformation project construction, operation, and maintenance with the differentiated dimensions of regional power development, this study screens 12 influencing factors from four core dimensions: responsibility sharing, emission reduction capability, efficiency assessment, and development support. These factors include population size, per capita GDP, proportion of technical transformation projects, and regional power generation, and the number of above-scale projects (defined as those with a total planned investment of at least 5 million CNY, covering power transmission and transformation projects of 110 kV or above), along with other indicators detailed in Table 1. Table 1 presents that each indicator corresponds to the core requirements of the four principles, achieving a deep coupling of allocation principles with the industry attributes of transmission and transformation projects while accounting for regional development heterogeneity and full-lifecycle emission characteristics. Ultimately, this study constructs

an initial carbon quota allocation indicator system tailored to the context of transmission and transformation projects, providing systematic and comprehensive indicator support for subsequent objective weighting using the entropy weight method and for scientifically implementing the initial quota allocation.

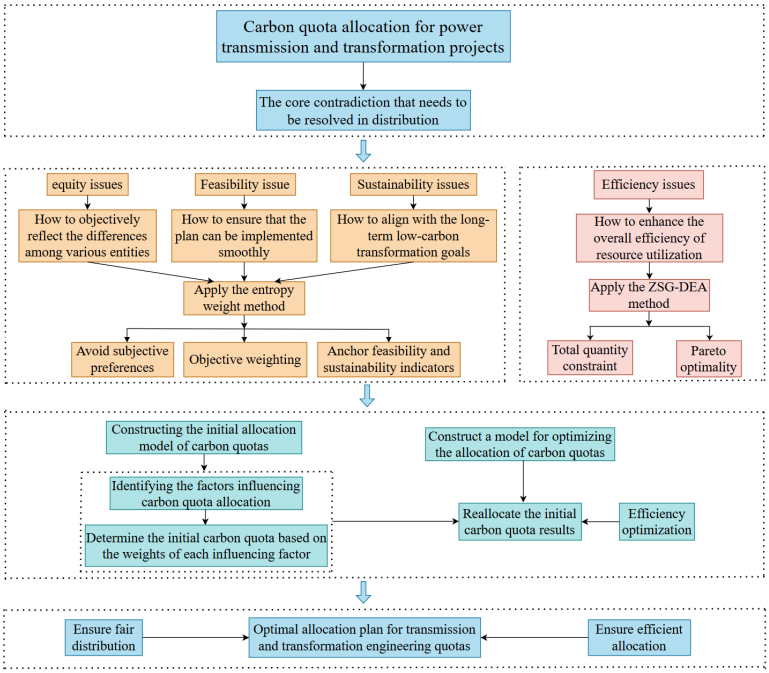


Figure 1. Carbon allowance allocation for transmission and transformation projects.

Table 1. Carbon allowance allocation factors for urban transmission and transformation projects.

No. (j)	Principle	Influencing Factors	Direction	Sources
1	Fairness	Data Population Size	(+)	
2	Fairness	Per Capita GDP	(+)	[6,24–26]
3	Fairness	Proportion of Technological Renovation Projects	(+)	
4	Efficiency	Regional Power Generation	(+)	
5	Efficiency	Value-Added of the Power Industry	(+)	[6,27–29]
6	Efficiency	Energy Intensity per Unit of Power Generation	(−)	
7	Sustainablility	Number of Projects Above Scale	(+)	
8	Sustainablility	Total Transmission & Transformation Investment	(+)	[20,30–32]
9	Sustainablility	New Energy Generation Share	(+)	
10	Feasibility	Power Industry Employment	(+)	
11	Feasibility	Number of Green Patents	(+)	[20,33–35]
12	Feasibility	Urbanization Rate	(+)	

"Projects above scale" are defined according to the Fixed Asset Investment Statistical Reporting System of the National Bureau of Statistics of China, with a threshold of total planned investment $\geq$ 5 million CNY. In the context of power transmission and transformation projects, this definition applies to new construction, expansion, and technical renovation projects with a voltage level of 110 kV or above, or those whose investment amount reaches the above-mentioned threshold. The project statistics from State Grid Liaoning Electric Power Co., Ltd. (Shenyang, China) are consistent with this national standard, thereby ensuring data comparability and traceability.

3.2. Initial Allocation of Carbon Allowances Based on the Entropy Weight Method

In the initial allocation of carbon quotas for transmission and transformation projects, the core purpose of selecting 12 influencing indicators is to construct a comprehensive and scientific allocation evaluation system, thereby avoiding the limitations of single-dimensional assessment and achieving fairness and rationality in quota allocation. Specifically, these 12 indicators systematically characterize the core features and allocation basis of each city's carbon emission reduction in transmission and transformation projects from four

dimensions: responsibility, capability, efficiency, and development foundation. Indicators in the responsibility dimension reflect the scale of transmission-and-substation-related carbon emission responsibility borne by each city, clarifying their emission reduction obligations. Indicators in the capability dimension measure the city's economic development level and carbon reduction support capacity, ensuring that quota allocation aligns with the city's carrying capacity. Indicators in the efficiency dimension assess the energy utilization efficiency and emission reduction potential of transmission and transformation operations, reinforcing the efficiency orientation of quota allocation. Indicators in the development foundation dimension reflect the development endowment of urban transmission and transformation projects, aiming to achieve synergy between emission reduction targets and power supply security.

The four dimensions outlined above correspond clearly to the four core principles of carbon quota allocation. The responsibility dimension aligns with fairness, using population size, per-capita GDP, and the share of technological renovation projects as proxies; it captures the objective differences among cities in electricity demand, economic capacity, and infrastructure upgrading, ensuring that quota allocation balances regional development levels and historical responsibilities, rather than perpetuating inequities based on past emissions alone. The efficiency dimension directly serves the efficiency principle: through regional power generation, value-added of the power industry, and energy intensity per unit of generation, it evaluates input–output performance and steers carbon quotas toward high-efficiency, low-loss decision-making units, thereby enabling an optimal allocation of emission-reduction resources. The development-foundation dimension underpins sustainability: by using the number of above-scale projects, total investment in transmission and transformation, and the share of new energy generation, it characterises the potential and structural progress of the power system's low-carbon transition, ensuring that quota arrangements remain adaptive to long-term decarbonisation goals. The capability dimension supports feasibility: employment in the power industry, green patent counts, and urbanisation rate are chosen to assess the practical conditions across cities in terms of human resources, technological innovation, and infrastructure maturity, guaranteeing that the allocation scheme is both operable and monitorable in practice. Through this mapping, the 12 indicators comprehensively cover the normative requirements of the four principles, establishing a coherent, traceable link between principle-driven allocation criteria and real-world engineering data. This, in turn, provides a unified and reliable foundation for the subsequent entropy-based weighting and ZSG-DEA efficiency optimisation.

Based on the above systematic analysis of the attributes of the 12 influencing indicators, and to scientifically quantify the importance of each indicator in carbon quota allocation, this study further introduces the entropy weight method [36] to calculate the weights for carbon quota allocation of transmission and transformation projects in different cities. The specific calculation steps of the entropy weight method are as follows:

Firstly, construct the original data matrix X (1) based on the established carbon quota allocation index system for power transmission and transformation projects. Suppose there are m cities, where X_{ij} represents the j-th influencing indicator of the i-th city (i = 1, 2, 3, . . ., m, j = 1, 2, 3, . . ., 12).

$$\begin{bmatrix} X_{11} & \cdots & X_{1j} \\ \vdots & \ddots & \vdots \\ X_{i1} & \cdots & X_{ij} \end{bmatrix} \quad (1)$$

The complete raw data matrix, normalized matrix, entropy weights, and all intermediate calculation steps are provided in Tables S1 and S2 in the Supplementary Materials.

To eliminate the dimensional differences among different impact indicators, the data are standardized. By scaling the value of each impact indicator to the range of [0, 1], the processing equation for positive indicators is as follows (2).

$$X_{ij}^{*\prime} = \frac{X_{ij} - m_j}{M_j - m_j} \tag{2}$$

The larger the positive indicators (such as population size, per capita GDP, etc.) are, the more carbon quotas are allocated. The equation for handling negative indicators is as follows (3):

$$X_{ij}^{*\prime\prime} = \frac{M_j - x_{ij}}{M_j - m_j} \tag{3}$$

Among them, the larger the value of the negative indicators is, that is, the greater the energy intensity per unit of electricity generation is, the fewer carbon quotas should be allocated.

In the formula, $X_{ij}^{*\prime}$ and $X_{ij}^{*\prime\prime}$ are the data obtained after standardization, representing the j-th indicator of the i-th city; M_j is the maximum value of X_{ij}, which is the maximum value of the j-th indicator of the i-th city; m_j is the minimum value of X_{ij}, which is the minimum value of the j-th indicator of the i-th city. The values after standardization of $X_{ij}^{*\prime}$ and $X_{ij}^{*\prime\prime}$ are collectively referred to as X_{ij}^{*}. As shown in Equation (4):

$$X_{ij}^{*} = \begin{cases} X_{ij}^{*\prime}, & j \in \{1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12\} \\ X_{ij}^{*\prime\prime}, & j = 6 \end{cases} \tag{4}$$

The ratio P_{ij} of the value of the j-th influencing indicator of the i-th city to the total sum of the values of the j-th influencing indicator of all cities is shown in Equation (5).

$$P_{ij} = \frac{X_{ij}^{*}}{\sum_{i=1}^{m} X_{ij}^{*}} \tag{5}$$

The entropy calculation process for each influencing indicator is as shown in Equation (6).

$$E_j = -ln(m)^{-1} \sum_{i=1}^{m} P_{ij} ln P_{ij} \tag{6}$$

E_j represents the entropy value of the j-th influencing indicator.

Determine the weights of each influencing indicator. Firstly, calculate the weights of each influencing indicator using information entropy. As shown in Equation (7).

$$W_j = \frac{1 - E_j}{12 - \sum E_j} \tag{7}$$

In the formula, W_j represents the weight of each indicator. E_j is the degree of difference for the j-th indicator. A larger entropy value indicates higher information uncertainty, a smaller degree of difference, and a lower weight.

After obtaining the objective weights W_j for each indicator through information entropy, the weights of each city are summed up to obtain the carrying capacity score, which serves as the core basis for carbon quota allocation. Finally, the comprehensive score of each city is calculated. As shown in Equation (8).

$$S_i = \sum_{j=1}^{12} W_j P_{ij} \tag{8}$$

The initial allocation weight V_i for the carbon quota of the i-th city as follows in Equation (9):

$$V_i = \frac{S_i}{\sum_{i=1}^{m} S_i} \tag{9}$$

The carbon quota q_i for each city in year t, using the following Equation (10):

$$q_i = C_t V_i \quad (10)$$

According to the entropy weight method, the results of the initial carbon quota allocation for transmission and transformation projects can be calculated. However, although the entropy weight method can provide a preliminary weight assessment and a reasonable allocation scheme for carbon quota allocation, it does not consider the actual efficiency differences among decision-making units (DMU_S) or the resource utilization effects after allocation. This implies that a data-driven initial allocation, though reasonable at first glance, may still result in over-allocation for inefficient units and under-allocation for efficient ones. Therefore, relying solely on the entropy weight method for initial allocation may not ensure the optimal allocation of resources in addressing the carbon quota allocation problem for transmission and transformation projects. To address this, this study introduces the ZSG-DEA method to adjust the efficiency of the allocation results, thereby optimizing the initial carbon quota allocation outcomes and improving the efficiency and rationality of the allocation [37]. The effectiveness of this integrated approach has been confirmed in recent city-level applications, where entropy weighting and ZSG-DEA were combined to allocate carbon emissions among cities under carbon-neutral scenarios [38].

3.3. Carbon Quota Efficiency Optimization Based on ZSG-DEA Method

The core objective of carbon quota allocation is to maximize resource allocation efficiency under a total constraint. Although the entropy weight method can complete the initial allocation based on objective data, it does not account for efficiency differences among DMU_S, which may lead to idle quotas or insufficient supply. The core value of the ZSG-DEA method lies in its correction of the relative efficiency of the initial allocation results—not in pursuing absolute emission reduction optimization in reality, but rather, through zero-sum game logic, adjusting the quota allocation of each DMU under the premise of a fixed total carbon quota so that all units achieve a DEA-efficient state under the model assumptions, ultimately realizing a Pareto optimal allocation of carbon resources [39]. This approach not only aligns with the foundation of fair allocation established earlier but also conforms to the policy orientation of the carbon market, which emphasizes stock optimization and efficiency priority [40].

The traditional Data Envelopment Analysis-Banker, Charnes and Cooper model can only evaluate the efficiency of each unit but cannot adapt to the quota allocation scenario with a fixed total amount. In contrast, the ZSG-DEA model, by introducing zero-sum game constraints, resolves the resource misallocation problem of "idle quotas for inefficient units and insufficient quotas for efficient units." Recent extensions of the ZSG-DEA approach have incorporated multi-objective optimization and sector-specific constraints. For example, a ZSG-DEA model with dual objectives of minimizing relative efficiency and emission reduction costs has been proposed for terminal industries in East China, explicitly accounting for sectoral tolerance capacity [41]. This study developed an input-oriented ZSG-DEA model, using initial carbon allowances as the input variable and the transmission volume of the power transmission and transformation network as the output variable. It should be noted that the function of transmission and transformation engineering assets is not power generation, but rather transmission, transformation, and distribution. The indirect emissions from these projects primarily stem from line losses during transmission and substation self-consumption, both of which are directly proportional to the volume of electricity transmitted. Therefore, the volume of electricity transmitted is a physically more reasonable output indicator for evaluating the efficiency of power grid infrastructure. In this empirical study, regional electricity generation is used as a practical proxy

for electricity transmission volume. In the power industry, electricity transmission and generation are highly correlated; a network DEA model was employed to evaluate the comprehensive performance of China's power generation and transmission system, confirming the feasibility of evaluating these two factors in tandem [42]. At the provincial level in Liaoning Province, all locally generated electricity must be transmitted through the provincial power grid, ensuring a strong empirical correlation between regional electricity generation and transmission volume. Furthermore, while municipal-level transmission volume data are not publicly available, regional electricity generation data are reported continuously in the Liaoning Statistical Yearbook 2024. Regarding the setting of inputs, the initial allocation results are used as the initial inputs, building upon the foundation of fairness established by the entropy weight method discussed earlier. By adjusting for efficiency, the model achieves the dual objectives of a fairness-oriented initial allocation and an efficiency-oriented optimization adjustment, thereby avoiding the waste of resources that would result from a purely fairness-oriented approach. It should be noted that using regional electricity generation as a proxy for transmission volume is a pragmatic choice given the current unavailability of municipal-level transmission data; future research may refine the output indicators by utilizing direct transmission volume measurement data when conditions permit. The model is solved iteratively, with the core aim of adjusting the input variable—the initial carbon quota—under the premise of a constant total quota, so that all decision-making units become DEA-efficient under the model assumptions. Since the logic of each iteration is consistent, the adjustment method is explained using a single iteration as an example:

In the ZSG-DEA model, to enable an inefficient DMU_k with an initial efficiency value of θ_0 and an initial carbon quota of x_{0k} to achieve a higher efficiency value, its input variable k needs to be reduced. The specific reduction is as shown in Equation (11).

$$\Delta x_0 = x_{0k}(1 - \theta_0) \tag{11}$$

In the formula, Δx_0 represents the reduction in carbon quota for DMU_k. The core meaning of this adjustment is to compress the redundant carbon quotas of inefficient DMU_k, eliminate their ineffective inputs, lay the foundation for the reasonable redistribution of carbon quotas, and at the same time ensure that the total carbon quota of the system remains unchanged.

To ensure that the total input remains unchanged, regardless of whether the efficiency of other decision-making units is high or low, the reduced carbon quotas of this decision-making unit will be proportionally allocated to all the other decision-making units. Then, the allocated carbon quotas for the remaining DMU_i ($i \neq 0$) are as shown in Equation (12).

$$v = \frac{x_{ik}}{\sum_{i \neq 0} x_{ik}} \times x_{0k}(1 - \theta_0) \tag{12}$$

In the formula, v represents the carbon quota allocation amount for the remaining DMU_i; x_{ik} represents the initial carbon quota of each DMU_i. This allocation rule embodies the "efficiency adaptation" principle, which allocates the surplus quota based on the proportion of each DMU_i initial carbon quota, ensuring a fair allocation process and alignment with the original quota scale of each unit.

After all decision-making units have completed the adjustments, the carbon quota adjustment amount for each DMU after iteration can be obtained. The adjustment is as shown in Equation (13).

$$x'_{ik} = \sum_{0 \neq i} \left[\frac{x_{ik}}{\sum_{i \neq 0} x_{ik}} \times x_{0k}(1 - \theta_0) \right] - x_{ik}(1 - \theta_i) \tag{13}$$

where x'_{ik} represents the adjustment amount of carbon quota for the i-th DMU after each iteration; x_{ik} represents the carbon quota of DMU_i at the beginning of each iteration; x_{0k} and θ_0 are the carbon quota and allocation efficiency of the ineffective DMU, respectively; θ_i is the allocation efficiency of the i-th DMU; $\sum_{i \neq 0} x_{ik}$ is the sum of the carbon quotas of other decision units except the ineffective decision unit. This formula clarifies the dynamic adjustment logic of the carbon quota for each DMU during the iteration process, achieving the gradual optimization allocation of ineffective quotas.

In summary, the input-oriented ZSG-DEA model can be represented by Equation (14):

$$\text{s.t.}\begin{cases} \sum_{i=1}^{m} \lambda_i x_{ik}\left[1+\frac{x_{0k}(1-\theta_0)}{\sum_{i \neq 0} x_{ik}}\right] \leq \theta_0 x_{0k} \\ \sum_{i=1}^{m} \lambda_i y_{ij} \geq y_{0j} \\ \sum_{i=1}^{m} \lambda_i = 1 \\ \lambda_i \geq 0 (\mathrm{i} = 1, \ldots, m) \end{cases} \tag{14}$$

where λ_i is the weight of the i-th decision-making unit in the entire system; y_{ij} is the output variable of the i-th DMU, which is the Electricity Transmission Volume; y_{0k} represents the output variable value of the DMU being evaluated. The core objective is to achieve the optimal allocation of carbon quotas among all DMUs through model solving, thereby improving the input–output efficiency of the entire system.

A further clarification concerns the convergence criterion and the input–output specification of the ZSG-DEA model. Figure 2 illustrates the iterative adjustment logic of the ZSG-DEA model. The iterative process terminates when all DMUs attain a DEA efficiency value of 1.0000, indicating that a Pareto-optimal state has been reached under the fixed total quota constraint; that is, no further quota reallocation can enhance any DMU_s efficiency without impairing that of another DMU. In the present study, convergence occurred after three iterations: the average efficiency progressed from 0.8851 initially to 0.9845 after the first iteration, 0.9998 after the second, and 1.0000 after the third, with efficiency gains tapering to zero thereafter. This trajectory confirms that three iterations are adequate for the system to converge to the efficiency frontier. With regard to the input–output specification, the selection of the initial carbon quota as the input and regional electricity generation as the output is defensible on three grounds. From a theoretical standpoint, carbon quotas constitute the "permitted emission cap" for transmission and transformation projects; their magnitude directly circumscribes the upper bound of carbon emissions and operational intensity, which is consistent with the canonical production-frontier logic of DEA whereby inputs constrain outputs. Methodologically, this specification has been employed in recent ZSG-DEA studies on carbon quota allocation at both provincial and municipal scales [21,39], thereby furnishing a valid precedent for our approach. From an institutional perspective, the specification aligns with the "cap-and-trade" rationale underpinning China's carbon market, wherein quotas act as a binding resource input that must be "consumed" to yield economic output, thus rendering the efficiency evaluation congruent with the actual operating mechanisms of the carbon market. Hence, the chosen inputs and outputs are theoretically grounded, methodologically corroborated by extant literature, and consonant with real-world policy design.

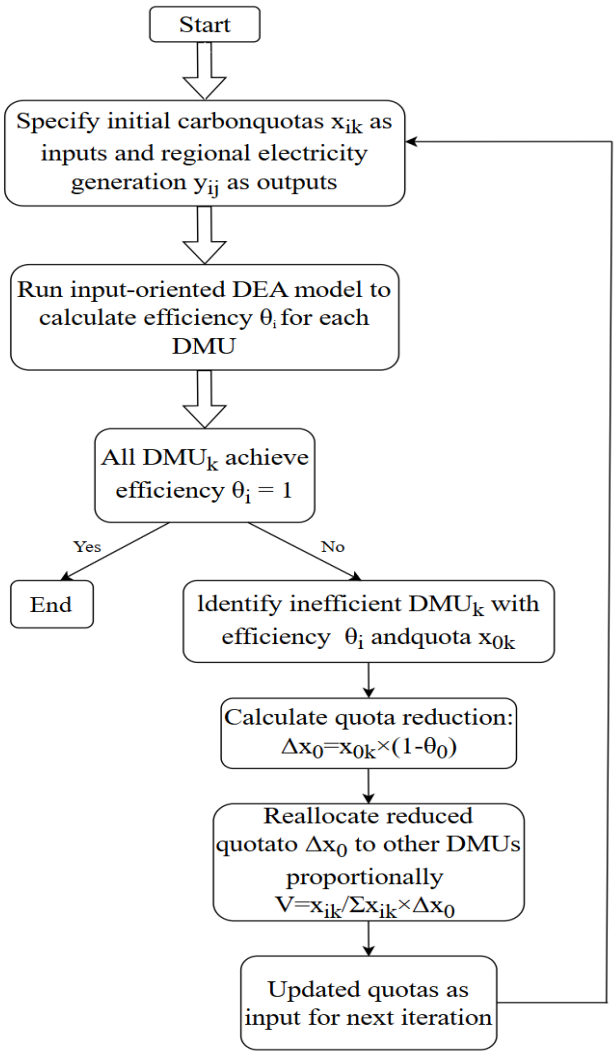


Figure 2. Flowchart of the iterative adjustment process.

3.4. Data Sources

As a core hub of the Northeast regional power grid, Liaoning Province possesses a dense and well-established transmission and transformation engineering network, frequent cross-regional power transmission, and a complete range of voltage levels. Moreover, the cities within the province exhibit significant differences in terms of transmission and transformation project scale, line losses, industrial electricity load, and new energy accommodation capacity. These characteristics highly align with the typical features of transmission and transformation project carbon emissions, including full-lifecycle coverage, strong regional heterogeneity, and a predominance of indirect emissions. Additionally, Liaoning provides access to authoritative and continuous power statistics and engineering data, making it the most industry-representative and practically applicable empirical region for conducting research on carbon quota allocation for transmission and transformation projects [43].

Based on Liaoning Province's typical energy structure, its status as a regional power grid hub, and the development needs of its cities and ecosystems, and leveraging the foundation of carbon trading pilot programs and data availability, the applicability of the aforementioned allocation method in terms of fairness, efficiency, and regional coordination can be effectively validated. This study examines the carbon quota allocation for each prefecture-level city in Liaoning Province for the year 2023. The relevant data are sourced from the Liaoning Statistical Yearbook, the statistical yearbooks and statistical

bulletins of cities in Liaoning Province, and the Economic Research Institute of State Grid Liaoning Electric Power Co., Ltd. To determine the carbon quota allocation scheme for the 14 prefecture-level cities in Liaoning Province, the total carbon quota for transmission and transformation projects in Liaoning Province for 2023 must first be established. This study uses the actual carbon macroeconomic indicators of transmission and transformation projects in 2015 as the benchmark value to estimate the total carbon quota for 2023. The specific calculation formula is as follows in Equations (15) and (16):

$$B_{2015} = C_{2015} / Q_{2015} \quad (15)$$

$$C_{2023} = B_{2015} \times Q_{2023} \quad (16)$$

where C_{2023} represents the total carbon quota for transmission and transformation projects in 2023, measured in tCO_2; B_{2015} represents the carbon dioxide emission benchmark for power consumption in power transmission and transformation projects in 2015; Q_{2023} represents the electricity consumption of power transmission and transformation projects in 2023; C_{2015} represents the total carbon emission of power transmission and transformation projects in 2015; Q_{2015} represents the electricity consumption of transmission and transformation projects in 2015.

The total carbon quota obtained from Equations (15) and (16) serves as a fixed constraint for the subsequent ZSG-DEA efficiency optimization. It is not intended to reflect a precise emission reduction target, but rather to provide an upper bound for the reallocation process. Since any proportional change to this total would affect all cities uniformly, the relative allocation shares, efficiency rankings, and all percentage-based conclusions remain unaffected. The output variable of the ZSG-DEA model is power transmission volume; in this empirical study, regional power generation is used as a proxy variable.

The selection of 2015 as the baseline year in this study is grounded in the following policy and data considerations:

A primary consideration is that 2015 marked a critical juncture in the formation of China's carbon intensity target system. In 2015, China formally announced its Nationally Determined Contribution (NDC) targets in the China–U.S. Joint Presidential Statement on Climate Change and at the Paris Climate Conference, committing to peak CO_2 emissions around 2030 and to reduce carbon intensity by 60–65% from the 2005 level. In the same year, the Chinese government further specified the timeline for achieving carbon emissions peaking before 2030. The year 2015 also marked a significant starting point for China's carbon market development, as China committed to "launch a national carbon emission trading system by 2017". Thus, 2015 represents a pivotal turning point in China's climate policy, transitioning from target-setting to institutional implementation.

Furthermore, 2015 serves as the baseline year for the 13th Five-Year Plan (2016–2020). The Work Plan for Controlling Greenhouse Gas Emissions during the 13th Five-Year Plan Period (State Council Document No. 61 [2016]) explicitly stipulated that by 2020, CO_2 emissions per unit of GDP should decrease by 18% compared to the 2015 level. This means that the 2015 carbon intensity level constitutes the statutory baseline for carbon reduction assessment during the 13th Five-Year Plan period and serves as the computational starting point for all subsequent carbon intensity reduction targets. Selecting 2015 as the baseline year allows the quota estimation in this study to maintain logical consistency with the national carbon reduction assessment framework of this period.

Moreover, 2015 was the preparatory year for the official launch of China's national carbon emission trading market. In December 2017, the National Development and Reform Commission issued the Plan for the Construction of the National Carbon Emission Trading Market (Power Generation Industry), formally initiating the construction of the national carbon market with the power generation sector as the breakthrough. This plan was

formulated on the basis of the commitments made in 2015. Selecting 2015 as the baseline year for carbon quota allocation in transmission and transformation projects aligns with the policy pathway that identifies the power sector as the entry point for the carbon market.

Concurrently, 2015 provides a comparable reference point for the national carbon intensity reduction targets of the 14th Five-Year Plan (2021–2025), facilitating the evaluation of this study's quota allocation results within a continuous policy framework. The outline of the 14th Five-Year Plan requires a cumulative 18% reduction in CO_2 emissions per unit of GDP over the five-year period. Using 2015 as the baseline enables full coverage of the carbon intensity trajectory across both the 13th and 14th Five-Year Plan periods, allowing the total quota estimation to reflect the full-cycle evolution from the 2015 benchmark to the 2023 actual values.

From a data availability standpoint, 2015 is the most recent complete baseline year for which authoritative emission factors are publicly available. According to data released by the National Development and Reform Commission, the national average emission factor for electricity in 2015 was 0.6101 $kgCO_2/kWh$, which is officially authoritative and publicly accessible. Although the 2015 provincial-level emission factor for Liaoning is not publicly available, the national factor serves as the most authoritative publicly accessible benchmark and provides a verifiable data foundation for this study.

Based on the above considerations, this study adopts 2015 as the baseline year. This choice is consistent with the institutional design of national carbon intensity assessment, aligns with the policy timeline of national carbon market development, and ensures that the quota estimation is solidly grounded in both policy logic and data reliability.

3.5. Sensitivity Analysis of Baseline Year Selection

To examine the influence of baseline year selection on the allocation outcomes, a sensitivity analysis was conducted by varying the baseline carbon intensity factor. Three scenarios were constructed using the electricity carbon dioxide emission factors for 2015 (0.6101 $kgCO_2/kWh$), 2020 (0.6101 $kgCO_2/kWh$, which remained unchanged from 2015 according to official sources), and 2023 (0.4878 $kgCO_2/kWh$). For each scenario, the total carbon quota was recalculated using Equations (15) and (16), and the ZSG-DEA model was re-run to obtain the final allocation vectors for the 14 municipalities.

Table 2 presents the final carbon quotas and city rankings under the three baseline scenarios. The city rankings remain identical across all three scenarios, with Dalian and Shenyang consistently at the top and Liaoyang and Jinzhou at the bottom. This stability is further supported by the Spearman rank correlation coefficients of 1.00 between the 2015-based and 2020-based allocations (reflecting the unchanged emission factor during this period) and 0.93 between the 2015-based and 2023-based allocations ($p < 0.01$). The proportional shares of quotas allocated to each city also exhibit limited variation, with the maximum deviation across scenarios being less than 2.5 percentage points for any given city. These findings confirm that the core allocation pattern, which identifies net contributors versus net recipients among cities, does not depend on the choice of baseline year. Although the absolute magnitude of the total quota is sensitive to the baseline intensity, the relative allocation structure and the efficiency rankings derived from the ZSG-DEA model are stable. This result supports the use of 2015 as the baseline year, while also suggesting that future applications should employ the most recent available emission factors to enhance temporal accuracy.

Table 2. Final carbon quotas and city rankings under different baseline scenarios (10^5 tCO_2e).

City	2015 Baseline	Rank	2020 Baseline	Rank	2023 Baseline	Rank
Shenyang	4.821	2	4.821	2	3.856	2
Dalian	5.493	1	5.493	1	4.393	1
Anshan	2.350	3	2.350	3	1.880	3
Fushun	1.658	6	1.658	6	1.326	6
Benxi	1.596	8	1.596	8	1.276	8
Dandong	1.163	13	1.163	13	0.930	13
Jinzhou	1.258	11	1.258	11	1.006	11
Yingkou	1.971	4	1.971	4	1.576	4
Fuxin	1.046	14	1.046	14	0.837	14
Liaoyang	1.257	12	1.257	12	1.005	12
Panjin	1.744	5	1.744	5	1.395	5
Tieling	1.285	10	1.285	10	1.028	10
Chaoyang	1.988	7	1.988	7	1.590	7
Huludao	1.239	9	1.239	9	0.991	9
Spearman ρ	—	—	1.00	—	0.93	—

Values are rounded to three decimal places. The 2023 scenario uses the Liaoning provincial emission factor of 0.4878 $kgCO_2/kWh$, while the 2020 scenario uses the same factor as 2015 (0.6101 $kgCO_2/kWh$). Spearman rank correlation coefficients are statistically significant at $p < 0.01$ for the 2015 vs. 2023 comparison; the coefficient of 1.00 for the 2015 vs. 2020 comparison reflects the unchanged emission factor, rather than a statistical estimate. "—" indicates not applicable.

4. Results and Discussion

4.1. Carbon Quota Allocation Results Under the Traditional Allocation Method

Table 3 presents the results of carbon quota allocation using the traditional historical emission method. Among them, Dalian City and Shenyang City received the highest allocated quotas, while Fuxin City received the lowest quota. Overall, the distribution exhibits a pattern where core cities with larger economic scales and higher historical emissions receive significantly higher quotas than small and medium-sized cities. This method is simple to operate, but it relies solely on historical data as the allocation basis, without accounting for regional development differences or emission reduction efficiency, making it difficult to balance the fairness and efficiency of allocation.

Table 3. The carbon quota allocation results are calculated based on the historical emission method.

City	Initial Carbon Quota (10^5 tCO_2e)	City	Initial Carbon Quota (10^5 tCO_2e)
Shenyang	4.801	Yingkou	2.065
Dalian	5.014	Fuxin	0.985
Anshan	2.208	Liaoyang	1.368
Fushun	1.885	Panjin	1.720
Benxi	1.692	Tieling	1.478
Dandong	1.145	Chaoyang	1.558
Jinzhou	1.590	Huludao	1.360

4.2. Initial Allocation Results of Carbon Quotas Based on Entropy Weight Method

Although the traditional historical emission method is straightforward to implement, it does not adequately capture regional development disparities, which can lead to a disconnect between carbon quotas and actual regional needs [44]. To overcome this shortcoming, the present study adopts the entropy weight method and introduces multi-dimensional influencing factors to achieve a more balanced treatment of regional equity and developmental heterogeneity. Taking Shenyang as an illustrative example, the relevant data for its power transmission and transformation projects are as follows: population of 9.204 million,

per capita GDP of 88,519 CNY, regional power generation of 42.99 billion kWh, value added of the power industry of 295.31 billion CNY, employment in the power industry of 61,610, green patents of 4606, energy intensity per unit of power generation of 18,070 tce per 100 million kWh, urbanization rate of 85.12%, 137 above-scale transmission and transformation projects, a technical renovation project share of 20%, total investment in transmission and transformation projects of 548.64 million CNY, and a new energy generation share of 42.5%. The same set of indicator data for all 14 cities was then substituted into Equations (1)–(10), completing the full calculation chain from data normalization to carbon quota allocation. The initial allocation results are presented in Table 4.

Table 4. Initial carbon quota allocation results based on the entropy weight method.

City	Initial Carbon Quota (10^5 tCO_2e)	City	Initial Carbon Quota (10^5 tCO_2e)
Shenyang	4.933	Yingkou	1.868
Dalian	5.173	Fuxin	1.006
Anshan	2.196	Liaoyang	1.503
Fushun	1.812	Panjin	1.846
Benxi	1.731	Tieling	1.392
Dandong	1.094	Chaoyang	1.703
Jinzhou	1.435	Huludao	1.177

Based on the initial carbon quota allocation results for transmission and transformation engineering projects in 14 cities of Liaoning Province in 2023, the municipal carbon quotas are divided into three tiers: 0–1.5 $\times$ 10^5 tCO_2e, 1.5–3 $\times$ 10^5 tCO_2e, and 3–6 $\times$ 10^5 tCO_2e. This division takes the population size and per capita GDP of each city as the core basis, while integrating multi-dimensional characteristics such as regional electricity demand, the scale of transmission and transformation engineering projects, and energy utilization efficiency, forming a gradient allocation pattern that matches urban development levels, power grid loads, and emission baselines. Specifically, the 0–1.5 $\times$ 10^5 tCO_2e quota distribution interval corresponds to cities with relatively small population sizes, low per capita GDP, limited transmission and transformation infrastructure, and weak industrial electricity demand. In these cities, both total carbon emissions and emission reduction pressure are at relatively low levels, and quota allocation primarily aims to ensure basic development needs. The 1.5–3 $\times$ 10^5 tCO_2e quota distribution interval corresponds to cities with medium population and economic development levels, moderate industrial loads and line losses, where emission scales and reduction capacities are close to the provincial average; quota allocation in these cities balances fairness and efficiency. The 3–6 $\times$ 10^5 tCO_2e quota distribution interval corresponds to core cities with dense populations, high per capita GDP, well-developed transmission and transformation networks, and intensive power dispatching and industrial production activities. In these cities, both consumption-side carbon footprints and production-side total carbon emissions are at high levels, requiring higher quotas to support their regional energy hub functions and corresponding emission reduction responsibilities. After objective weighting using the entropy weight method and efficiency optimization via ZSG-DEA, the above gradient division further achieves the synergistic integration of fairness-oriented initial allocation and efficiency-oriented optimal allocation, aligning with the inherent requirements of precise and efficient carbon quota allocation for transmission and transformation engineering projects under aggregate constraints.

Compared with traditional allocation methods, there are significant differences in the quotas of some cities. Among them, Chaoyang experienced a quota increase attributable to its relatively high share of new energy generation, while Shenyang and Dalian received

upward adjustments driven by their macroeconomic scale and the corresponding electricity demand associated with their large population sizes. The initial carbon quota allocation based on the entropy weight method can better reflect regional development differences and address the issue of allocation fairness. However, the allocation results depend entirely on the static indicator scores and weights of each city, making it prone to situations where there is no significant difference in quotas between high-efficiency and low-efficiency cities when transmission and transformation demands are similar. This makes it difficult to form an effective incentive and constraint mechanism through quota allocation, which is detrimental to improving overall emission reduction motivation in the long run. To this end, this study introduces the ZSG-DEA model to optimize the allocation scheme. Relying on zero-sum game constraints and efficiency evaluation, the originally static quota allocation is optimized into a balanced configuration with overall efficiency optimization. Through dynamic iteration, the efficiency of each decision-making unit is driven closer to the production frontier, guiding limited carbon quotas to tilt toward regions with higher utilization efficiency, ultimately achieving the optimal allocation of carbon quotas for transmission and transformation engineering projects across the entire province.

4.3. Optimization Results of Carbon Quota Efficiency Based on ZSG-DEA Method

Since the initial carbon quota allocation scheme failed to make all cities DEA-efficient, and some cities still have relatively insufficient allocation efficiency, the ZSG-DEA model is therefore applied to optimize the carbon quota allocation efficiency of the 14 cities. Figure 3 presents the efficiency changes during the optimization process. Table 5 presents the optimized results.

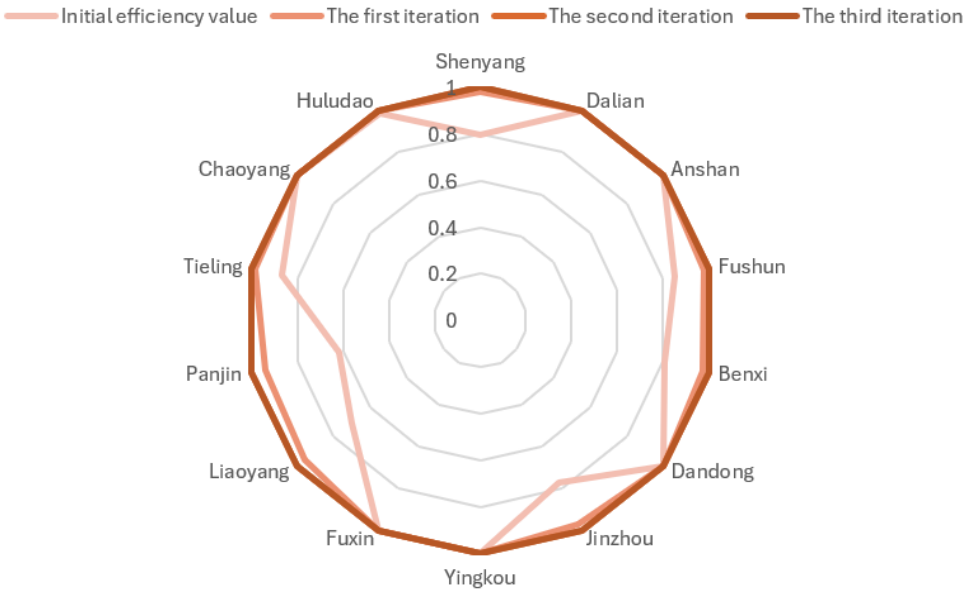


Figure 3. The process of optimizing the allocation of carbon quotas and the efficiency values of allocation for 14 cities.

Beyond efficiency scores, the input slack generated in each iteration clarifies the economic rationale behind quota changes. In this input-oriented model, the slack for decision-making unit i in a given iteration is defined as the quota reduction required for it to reach the efficiency frontier:

$$\delta_i = A_i \times (1 - e_i) \quad (17)$$

where A_i is the actual quota held by unit i at the start of that iteration, and e_i is its corresponding efficiency value. A positive δ_i indicates redundant quota, inputs that contribute

zero marginal output (regional electricity generation) and triggers a mandatory transfer in the zero-sum reallocation. Table 6 reports the input slack values for all 14 cities after the first and second iterations.

Table 5. The efficiency value of carbon quota allocation based on the ZSG-DEA method.

City	Initial Carbon Quota (10^5 tCO_2e)	ZSG-DEA Efficiency Value				Final Carbon Quota (10^5 tCO_2e)	Carbon Quota Adjustment Amount (10^5 tCO_2e)	Change (%)
		Initial Efficiency Value	The First Iteration	The Second Iteration	The Third Iteration			
Shenyang	4.933	0.7973	0.9803	0.9998	1.0000	4.821	−0.112	−2.27% ↓
Dalian	5.173	1.0000	1.0000	1.0000	1.0000	5.493	0.320	6.19% ↑
Anshan	2.196	1.0000	1.0000	1.0000	1.0000	2.350	0.154	7.01% ↑
Fushun	1.812	0.8508	0.9808	0.9997	1.0000	1.658	−0.154	−8.50% ↓
Benxi	1.731	0.8039	0.9736	0.9997	1.0000	1.596	−0.135	−7.80%
Dandong	1.094	1.0000	1.0000	1.0000	1.0000	1.163	0.069	6.31% ↑
Jinzhou	1.435	0.7687	0.9677	0.9996	1.0000	1.258	−0.177	−12.33% ↓
Yingkou	1.868	1.0000	1.0000	1.0000	1.0000	1.971	0.103	5.51% ↑
Fuxin	1.006	1.0000	1.0000	1.0000	1.0000	1.046	0.040	3.98% ↑
Liaoyang	1.503	0.7031	0.9573	0.9995	1.0000	1.257	−0.246	−16.37% ↓
Panjin	1.846	0.6150	0.9420	0.9993	1.0000	1.744	−0.102	−5.53% ↓
Tieling	1.392	0.8666	0.9825	0.9998	1.0000	1.285	−0.107	−7.69% ↓
Chaoyang	1.703	1.0000	1.0000	1.0000	1.0000	1.988	0.285	16.74% ↑
Huludao	1.177	0.9863	0.9983	1.0000	1.0000	1.239	0.062	5.27% ↑

The output variable in the ZSG-DEA model is power transmission volume; however, due to data availability constraints, regional power generation is used as a proxy variable in this empirical study.

Table 6. Input slack values after the first and second ZSG-DEA iterations (10^5 tCO_2e).

City	1st Slack	2nd Slack	City	1st Slack	2nd Slack
Shenyang	0.097	0.001	Yingkou	0.000	0.000
Dalian	0.000	0.000	Fuxin	0.000	0.000
Anshan	0.000	0.000	Liaoyang	0.064	0.001
Fushun	0.035	0.001	Panjin	0.107	0.001
Benxi	0.046	0.001	Tieling	0.024	0.000
Dandong	0.000	0.000	Chaoyang	0.000	0.000
Jinzhou	0.046	0.001	Huludao	0.002	0.000

Values are rounded to three decimal places. A reported value of 0.000 indicates that the slack is less than 0.0005×10^5 tCO_2e.

In the first iteration, cities with low initial efficiency exhibit substantial slacks; most notably, Panjin (0.107), Shenyang (0.097), Liaoyang (0.064), Benxi (0.046), and Jinzhou (0.046). These positive values pinpoint the sources of over-allocation: the initial quotas of these cities far exceed the minimum input required to sustain their current output. Under the ZSG-DEA mechanism, these units are designated as net contributors, and their slack volumes are redistributed proportionally to zero-slack cities already operating on the frontier (Dalian, Anshan, and Chaoyang).

By the second iteration, all slacks shrink to near-zero levels (maximum 0.001), indicating that efficiency disparities have been virtually eliminated. This rapid convergence—from double-digit slack in the first round to negligible values in the second—demonstrates that the ZSG-DEA reallocation does not rely on arbitrary percentage cuts. Instead, it operates strictly on quantified redundancy with zero marginal output, ensuring that only measurable waste is stripped and reallocated to high-efficiency units. The complete elimination of all positive slacks in the third iteration confirms that the final allocation achieves a Pareto-optimal state under the fixed aggregate carbon cap.

Figure 4 presents the optimized carbon quota allocation result, which indicates significant differences in the distribution of quotas among various cities within Liaoning Province. The final carbon quotas of Dalian and Shenyang are significantly higher than

those of other cities, accounting for 35.73% of the total provincial quotas; the carbon quotas of Tieling, Jinzhou, Liaoyang, Huludao, Dandong, and Fuxin are the lowest, all being less than 1.5×10^5 tCO_2e; the carbon quotas of the remaining cities are concentrated in the range of 1.5–2.5 $\times 10^5$ tCO_2e, with a relatively balanced distribution. Among them, the carbon quotas of Dalian and Shenyang are 5.493×10^5 tCO_2e and 4.821×10^5 tCO_2e, respectively. Dalian, as an economically developed city with a large population and a relatively high per capita GDP, has a strong demand for electricity for social production and daily operations, and frequent power transmission has increased equipment operation time and energy consumption, thereby raising the carbon emission level. Shenyang, as the provincial capital, relies on a large population size to generate huge electricity demand, and requires a higher carbon quota to support the operation of a large-scale power transmission network. In addition, Anshan and Yingkou have high carbon quotas due to large industrial loads and electricity demands; Fushun, Panjin, and Benxi have relatively high carbon quotas due to the influence of industrial electricity usage patterns and high-load electricity usage characteristics; Chaoyang benefits from the construction of a new energy-friendly power grid, with a significant increase in regional power generation, and the transmission of surplus power across regions generates line loss carbon emissions, thereby forming corresponding carbon quotas.

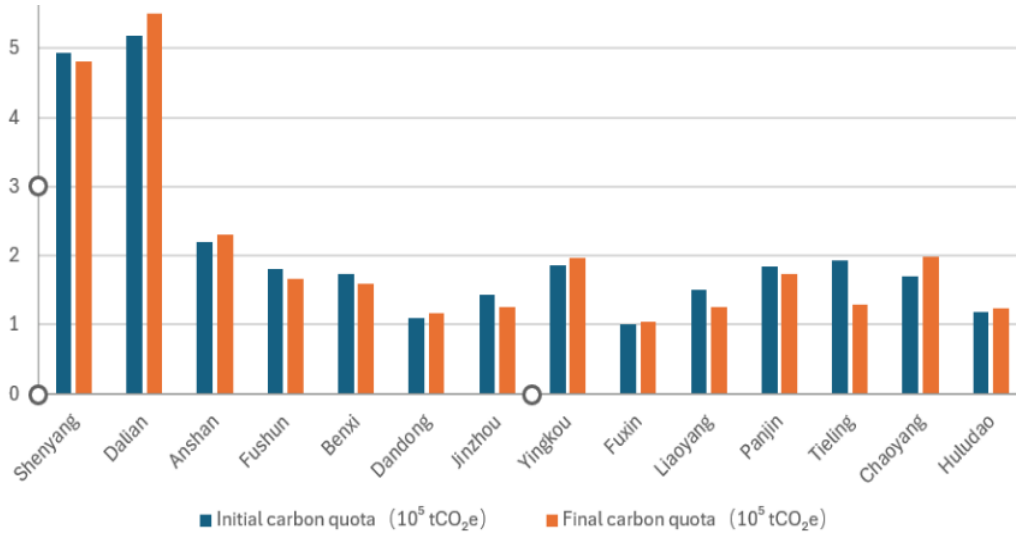


Figure 4. Carbon quota allocation comparison chart.

The carbon quotas for the other six cities do not exceed 1.5×10^5 tCO_2e. Jinzhou and Liaoyang mainly rely on traditional industries, and their electricity demand is relatively limited. Additionally, the scale of power transmission and transformation projects is small, resulting in relatively low total carbon emissions. Huludao is constrained by its economic volume and population size, and the scale of power transmission and transformation projects is not large, so its total carbon emissions are at a relatively low level. Dandong and Tieling have a low level of industrialization, with limited energy consumption and electricity demand. Their carbon emissions are also relatively low. Fuxin is a resource-depleted city, with its economy and population size continuously shrinking. It has a weak demand for power transmission and transformation systems, and insufficient investment in related projects, technological renovations, and infrastructure. Therefore, its carbon quota is also relatively low.

Compared with the traditional allocation methods, the "entropy weight method and ZSG DEA" allocation model constructed in this study has significantly improved both the allocation efficiency and fairness. It effectively verified the scientific and practical

applicability of this method in the allocation of carbon quotas for power transmission and transformation projects. The specific comparison results are shown in Table 7.

Table 7. Comparison of effects of different allocation methods.

Method	Average DEA Efficiency	Achieve DEA-Efficient City
Historical Emission Method	0.782	2
Entropy Weight Method	0.885	6
ZSG-DEA Method	1.000	14

The combination of the entropy weight method and the ZSG-DEA method features a core advantage in establishing an integrated allocation mechanism of fairness measurement, efficiency optimization and total quantity conservation, thereby achieving an organic unity of fairness and efficiency in carbon quota allocation. This approach not only fully respects the objective realities of regional development needs but also promotes the continuous optimization of resource allocation through an efficiency-oriented incentive mechanism. At the same time, it aligns with the institutional core of "cap and trade" in carbon trading. Consequently, this method can provide a theoretically robust and practically feasible decision-making framework and management scheme for the allocation of carbon quotas for transmission and transformation projects.

4.4. Discussion

This empirical study selects 14 prefecture-level cities in Liaoning Province as the research subjects, primarily because the region features a dense transmission and transformation engineering network, complete voltage level coverage, and frequent cross-regional power transmission. Moreover, these cities exhibit significant variations in economic development levels, industrial structures, grid scales, new energy installation and consumption levels, as well as line loss characteristics, which fully reflect the typical attributes of carbon emissions from transmission and transformation projects, such as strong regional heterogeneity, a high proportion of indirect emissions, and dispersed emission sources across the life cycle. At the same time, the 14 prefecture-level units completely cover the provincial administrative area, enabling the complete transmission of quota allocation from the provincial level to the grassroots level at the municipal scale. This meets the empirical requirements of carbon quota allocation in terms of fairness comparison, efficiency calculation, regional balance, and aggregate constraints, providing typical and comprehensive sample conditions for testing the applicability of the model.

At the methodological level, the entropy weight method relies solely on multidimensional indicators to perform objective weighting and initial quota allocation, which can effectively reflect regional development differences and uphold the principle of fairness in allocation. However, the entropy weight method does not quantitatively assess the input–output efficiency of carbon emissions for each decision-making unit, making it prone to mismatches between quota scales and the actual utilization efficiency of carbon resources in practical applications. The ZSG-DEA method, by contrast, leverages the mechanisms of fixed total amounts and zero-sum games to continuously adjust the initial allocation results, gradually driving each decision-making unit closer to the efficiency frontier through an iterative process. This integrated approach embodies the inherent unity of the four allocation principles established in our framework. The fairness principle is embedded in the initial allocation stage, where entropy weighting ensures that quotas reflect regional development disparities and historical responsibilities. The efficiency principle is operationalized through the ZSG-DEA iterative adjustment mechanism, which reallocates quotas from low-efficiency to high-efficiency units, thereby optimizing overall resource allocation.

The sustainability principle is reflected in the indicator system, which incorporates new energy generation share and green patent counts, ensuring that quota allocation aligns with long-term decarbonization goals. The feasibility principle is manifested in the selection of quantifiable and readily available indicators, such as urbanization rate and power industry employment, which guarantee the model's practical operability and replicability across different administrative contexts. In this study, the carbon quota allocation for transmission and transformation projects in Liaoning Province underwent a total of three iterative adjustments. The first iteration focused on reducing quotas for inefficient units and reallocating them across regions, significantly improving the efficiency levels of initially less efficient cities such as Shenyang, Liaoyang, and Panjin, while initially efficient cities such as Dalian, Anshan, and Chaoyang remained stable. As a result, the overall efficiency distribution converged rapidly, with some units approaching the efficiency frontier ahead of others. The second iteration built on the previous adjustments to carry out further optimization, continuously pushing cities that had not yet reached an efficient state closer to the efficiency frontier, such as Shenyang, Fushun, and Jinzhou. Overall efficiency values were further enhanced, and the internal efficiency disparities within the system continued to narrow. The third iteration followed a progressive correction logic, with the efficiency levels of all units steadily converging, and the overall allocation structure consistently evolving toward a balanced state. It can be seen from this that, in the allocation of carbon quotas for transmission and transformation projects, fair allocation and efficiency optimization are not substitutes for each other but can achieve synergy through a two-stage model. This also confirms that carrying out quota allocation at the municipal level can more accurately match local power grid operation realities and emission reduction capabilities, providing a feasible pathway for the refined decomposition and differentiated control of provincial carbon quotas.

From the perspective of allocation results, the final configuration of carbon quotas is highly consistent with the operational intensity, load characteristics, energy structure, and development positioning of transmission and transformation engineering in each city. By virtue of their role as regional energy hubs, Shenyang and Dalian shoulder core tasks such as provincial backbone grid transmission, cross-regional power dispatching, and power supply to load centers. transmission and transformation equipment in these cities operates under high load and high utilization hours for extended periods, featuring large-scale power transmission, extensive coverage, and high equipment density. The resulting line losses and operational energy consumption generate significant carbon emission demands, making their carbon quotas substantially higher than those of other cities in the province. Industrial cities such as Anshan, Yingkou, and Panjin rely on energy-intensive industries as their main economic support, characterized by concentrated power loads and high transmission intensity. Transmission and transformation engineering in these cities has long served industrial production power demands, with line losses and operational carbon emissions at moderately high to high levels, and their corresponding carbon quotas also fall within the medium-to-high range. Chaoyang City, leveraging the continuous expansion of new energy installed capacity and an increasing share of new energy power generation, has become an important regional node for new energy power production and outbound transmission. Large amounts of clean electricity are transmitted across regions via long-distance transmission and transformation lines, which, while improving power generation efficiency, also generate corresponding carbon emission demands. As a result, its quota was significantly adjusted upward during the efficiency optimization phase. Cities such as Dandong, Fuxin, Tieling, and Huludao, constrained by factors including economic aggregate, population size, industrial structure, and investment in transmission and transformation engineering construction, have relatively low power load levels and

weak equipment operational intensity. The overall scale and intensity of carbon emissions in these cities are at relatively low levels, and their final carbon quotas are correspondingly low across the province. These differences in quota distribution are closely related to the actual operational conditions of transmission and transformation engineering, energy utilization characteristics, power supply and demand structures, and urban development foundations in each city, intuitively reflecting the carbon emission demands and resource utilization status of different decision-making units in the transmission and transformation stage. The results of this study are comparable to those of recent city and provincial-level carbon quota allocation studies that similarly employed the combined entropy weight and ZSG-DEA framework. In terms of allocation patterns, the tiered distribution observed in Liaoning, with quotas concentrated in core economic and industrial hubs, is consistent with the spatial allocation pattern reported for Jiangsu [8]. Regarding efficiency improvements, both studies indicate that efficiency-oriented adjustments increase average DEA efficiency without compromising the equity established in the initial allocation [15]. These consistencies suggest that the ZSG-DEA approach, when combined with entropy weighting, exhibits strong adaptability across different regions and sectoral contexts.

From a policy perspective, this study provides an operational pathway for integrating the ZSG-DEA model into China's current transitional framework, which merges the "dual control of energy consumption" and "dual control of carbon intensity" policies. In the provincial quota allocation process, the ZSG-DEA efficiency values of each city can serve as the basis for dynamic annual quota adjustments: at the start of each compliance cycle, the provincial competent authority adjusts the initial quotas for the current year proportionally based on the previous year's efficiency values for each city. Cities with efficiency values above the provincial average receive quota increases, while those below the average face quota reductions; the magnitude of the adjustment correlates with the degree of deviation from the efficiency benchmark, while ensuring that the total provincial quota remains unchanged. This mechanism allows quota allocation to dynamically adjust in response to annual efficiency performance, creating a closed-loop adjustment system. The aforementioned efficiency values are calculated using regional electricity generation as a proxy for transmission volume and should be interpreted as broader power system performance indicators rather than a direct measure of power grid operational efficiency. This approach aligns with China's transition from "dual control of energy consumption" to "dual control of carbon intensity and total carbon emissions," as the ZSG-DEA efficiency values directly reflect the efficiency of carbon resource utilization while linking energy consumption targets to carbon emission outcomes. Furthermore, sustainability indicators embedded in the allocation framework, such as the share of renewable energy generation and the number of green patents, can be directly correlated with the evaluation criteria for China's low-carbon city pilot programs and the provincial carbon intensity reduction targets established in the 15th Five-Year Plan. The city-level decomposition method employed in this study provides a feasible pathway for converting provincial carbon budgets into binding municipal targets, helping governments at all levels to collaboratively advance carbon peaking efforts under a unified regulatory framework. By incorporating ZSG-DEA efficiency values into the annual quota adjustment mechanism, local regulatory authorities can establish an annual cycle of "efficiency evaluation—quota adjustment—performance feedback," thereby ensuring that the incentive and constraint functions of the dual-control framework are effectively implemented at the municipal level.

5. Conclusions and Limitations

5.1. Conclusions

Against the backdrop of China's "Dual Carbon" goals and the continuous development of the carbon emission trading system, this study establishes a universal method for allocating carbon quotas for transmission and transformation engineering projects, which has been validated at the municipal level. The main research conclusions are as follows:

(1) The spatial distribution of carbon quotas for transmission and transformation engineering projects is not determined unilaterally by economic scale or historical emissions but rather results from the combined effects of regional grid hub functions, power load intensity, cross-regional new energy transmission demand, and the density of transmission and transformation networks. Shenyang and Dalian, as core cities for regional energy dispatching, have significantly higher carbon quota levels. Anshan and Yingkou, where industrial sectors are concentrated, are affected by high power loads and line losses, placing their carbon quotas at medium-to-high levels. In cities such as Chaoyang, which have a solid foundation in new energy development, cross-regional power outflows generate additional transmission-related carbon emissions, thereby increasing their local carbon quotas. In contrast, cities undergoing economic transition or experiencing resource depletion tend to have slower engineering construction progress and consequently receive lower quotas.

(2) The four principles of fairness, efficiency, feasibility, and sustainability serve as important foundations for promoting the orderly allocation of carbon emission quotas for transmission and transformation engineering projects. The principle of fairness takes into account regional development disparities, the principle of efficiency optimizes the effectiveness of resource allocation, the principle of feasibility ensures smooth practical implementation, and the principle of sustainability aligns with long-term low-carbon development goals. Fair distribution is a prerequisite for efficiency optimization, while efficiency optimization is an extension of fair distribution. The principles of sustainability and feasibility are independent dimensions that impose substantive constraints on allocation outcomes. After transforming the four principles of fairness, efficiency, sustainability, and feasibility into a quantifiable indicator system, the fairness assurance in initial allocation and the subsequent efficiency optimization can complement each other. Fair distribution provides an acceptable starting point for efficiency optimization, while efficiency optimization improves the overall level of resource allocation without undermining the foundation of fairness. Together, they constitute an internal balancing mechanism for carbon quota allocation. The four principles are mutually reinforcing and supportive, jointly forming a complete logical framework for the quota allocation system.

(3) The combination of the entropy weight method and the ZSG-DEA model provides a practical and feasible solution for research on the allocation of carbon emission quotas for transmission and transformation engineering projects. Among them, the entropy weight method can effectively avoid subjective bias in weight assignment, while the ZSG-DEA model can coordinate overall resource totals, optimize the efficiency of quota allocation, and achieve synergistic improvement in regional benefits. The integrated application of the two methods not only ensures that the allocation results are objective and reasonable but also achieves overall efficiency optimization, further demonstrating the inherent unity of fairness and efficiency in the allocation of carbon emission quotas. This provides a scientific reference and practical basis for low-carbon management in the power industry and collaborative regional emission reduction efforts.

5.2. Limitations

Although this study has constructed a carbon quota allocation model tailored to transmission and transformation engineering projects and has validated it at the municipal level, certain limitations remain. First, the research conducts empirical analysis only using Liaoning Province as a case study, where the energy structure and grid layout of the sample region have specific local characteristics; thus, the generalizability of the model to transmission and transformation engineering carbon quota allocation scenarios with different energy endowments or across provincial administrative boundaries requires further verification. Also, this study does not incorporate external factors such as post-allocation market trading behavior or dynamic policy adjustments, and the discussion of the actual emission reduction effects and regulatory mechanisms following quota allocation needs to be deepened. Furthermore, this study assumes that all decision-making units can converge to the efficiency frontier through quota adjustments during the ZSG-DEA iteration process; however, the actual realization of emission reduction potential is constrained by multiple factors, including technological pathways, management capabilities, and policy implementation. The model does not sufficiently discuss the practical operability of iterative adjustments or the associated time costs. Future research should further integrate engineering measurement data and dynamic feedback mechanisms to enhance the practical guidance of the model. Finally, the use of the 2015 historical carbon intensity as the baseline for estimating the total quota does not explicitly account for technological progress or efficiency improvements in the power sector over the 2015–2023 period. While the ZSG-DEA model's efficiency-oriented reallocation mechanism partially mitigates this issue by rewarding high-efficiency units, and while the total quota's role as a fixed constraint ensures that relative allocation results are unaffected by proportional adjustments, the absence of an explicit decarbonization discount factor in the baseline estimation remains a methodological limitation. Future research should incorporate dynamic decarbonization factors to better reflect sectoral progress.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app16157463/s1, Table S1: Raw data; Table S2: Entropy weight calculation and results.

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