Research on Influencing Factors and Carbon Emission of Power Systems Based on Logarithmic Mean Divisia Index and Big Data Techniques

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Abstract

With global warming and the development of urbanization and industrialization, controlling carbon emissions has become an important issue facing all mankind. China's power sector exceeds 40% of overall societal carbon emissions, so transforming into a green and low-carbon system is what the power system needs. Two key research priorities are further exploring accounting methods for the sector and establishing a robust carbon emission measurement system in China. This paper aims to outline critical factors that influence the emissions of carbon dioxide in the power department in accounting methods based on electricity big data technologies. Then, the assessment of the carbon emissions system built on the Logarithmic Mean Divisia Index (LMDI) and big data technologies is proposed. These technologies enhance the power system's ability to efficiently monitor and manage its carbon emissions. These technologies help to take hold of its carbon emissions. thus achieving the power system's 'two-carbon' objective.

Keywords: Carbon emission, influencing factor, power system, driving factor, Logarithmic Mean Divisia Index (LMDI), big data techniques.

1. Introduction

With the rising energy demand in the power industry, resulting in increased carbon emissions. According to Statistical Yearbook of World Energy statistics, China's carbon dioxide emissions will be 12 billion tons in 2021, accounting for 30.9% of global carbon emissions, which notes the need to strengthen the research on greenhouse gas emission accounting methods for key industries and products in the future and establish and improve the carbon emission measurement system. Therefore, it is critical to break through the key technology of carbon measurement and carry out the research of carbon emission measurement and quantitative analysis model in power systems. It will support the country reach the power system's 'two-carbon' objective targets early by providing comprehensive control of the power system.

Electricity is the fundamental energy source that guarantees normal life and production for residents and enterprises. With energy demand continuing to increase and a strong link between economic growth and carbon emissions, China is still trying to industrialize. The national goal of achieving the 'two-carbon' objective clearly stated: by 2030, carbon intensity should be reduced by more than 65% from 2005 levels. By 2060, power efficiency will reach internationally advanced levels. Carbon emissions will be controlled in every aspect of economic activities and achieving the "dual control" target for carbon emissions will require significant foundational support. As a key sector, the energy industry needs to investigate influences on carbon issues, assess the current emission situation, and strive to meet regional and national carbon emission control targets.

At present, there has already been extensive research on carbon emissions. In past research, some literature has studied the motivations of carbon emissions, including the structure of thermal power plants, power consumption intensity, unit conversion efficiency, economic aggregate, and other factors [1]. Due to the huge difference in resource endowments between different cities and regions in China, some pieces of literature take into account influences like transmission line loss and power structure [2]. Through the calculation of contribution, it is found that it is also crucial to the power system. The factors influencing the restructuring of the energy industry and its efficiency are the focus of current research by the professors. LMDI is used to quantify the energy efficiency of electrical systems. This contributes to the development of an enhanced model for measuring the rebound effect of carbon emissions [3-4].

In recent years, big data techniques have become the mainstream of power system research, as evidenced by a large number of scientific papers in the field. Big data technology monitoring methodologies utilize cloud computing platforms and other techniques to analyze data, calculate emissions monitoring, and correlate power data with carbon emissions across industry sectors. This technique enables accurate accounting of carbon emissions in electrical energy production [5].

This article delves into the origins and key drivers of carbon emissions in electrical systems, considering both energy structure and electricity industry composition. It establishes a framework for identifying the primary factors, which contribute to carbon emissions, investigates the effect and significance of various driving forces, and constructs a quantitative analysis model to assess carbon emissions in electrical energy production. Firstly, the key drivers and causes of carbon emissions are thoroughly examined. Subsequently, contributed by these driving factors is explored using factor decomposition analysis. Leveraging power big data techniques, we delve into the driving factors that significantly influence carbon emissions in regional power systems. Finally, a carbon emission accounting method is established for the power system, providing technical support for its low-carbon transformation and green, coordinated development.

2. Background of Carbon Emissions from the Power System

At present, energy sector, the percentage of energy used to generate electricity is increasing every year. Due to the resource endowment of "more coal, less oil, and less gas", China's power production mode is mainly thermal power, accounting for more than 75%. China's thermal power installed capacity will be 12.97 billion kilowatts in 2021, an increase of 4.7% year-on-year. From January to July 2022, the installed thermal capacity was 12.21 billion kilowatts, 2.8% compared to the preceding year, which exceeded the installed thermal power last year. Coal combustion produces significant emissions of carbon dioxide, so the power system is accompanied by a large number of carbon emissions during power production [6].

Figure 1 presents carbon dioxide emissions from coal burning between 1900 and 2021. Despite the abundance of renewable resources in China, challenges related to access to capital and advanced technology hinder their large-scale exploration and utilization. As a result, renewable resources contribute only around 20% of China's total power generation. In the next 10-15 years, environmental problems such as carbon emissions and air pollution caused by coal-fired power generation will continue to deteriorate [7]. Therefore, the current priority research emissions focus factors in the power system. It is a magic weapon for protecting the ecological environment and a way to build a green power system.

2.1 Research progress factors of carbon emission in energy system

In 2019, Saige Wang et al. [8] introduced a revised power carbon emission decomposition model by adapting the structural decomposition approach. This model broke down key influencing factors of advancements in green power technologies. The power industry is a major energy supplier and a major consumer of fossil fuels. Power generation technology encompasses the carbon emission coefficients from coal, oil, and other fuels. The generation of power is represented by distinct mathematical matrix equations per unit of electricity produced. Lastly, energy demand refers to energy consumption categorization based on various industries. Power generation is represented by distinct mathematical matrix equations corresponding to each unit of electricity generated, while power demand pertains to the categorization of electricity consumption based on various industries. Yan et al. [9] used the generalized division method (GDIM) to analyze electricity carbon emissions into factors. Among them, electricity demand and power use are the absolute influencing variables. To ensure the sustainable development of Beijing-Tianjin-Hebei, and to determine the optimal path for thermal power generation, this paper designs various scenarios. Paulo et al. [10] selected the logarithmic mean division of exponential decomposition (IDA-LMDI) to decompose carbon dioxide emitted from power influenced by fuel composition, thermal efficiency, fossil energy proportion, and geographical factors. Lina Mai et al. [11] vigorously develop new energy generation by utilizing the rich renewable resources in the northwest region. Using the method of Kaya identity and exponential decomposition, the electricity carbon emissions are decomposed into carbon intensity, energy structure, power generation efficiency, electrification, economy, and population. These results show that the economy is the factor with the biggest effect on carbon dioxide. Gao et al. [12] decomposed China's electricity carbon emissions into 10 influencing factors: fossil fuel mix, the efficiency of power generation, transmission, and distribution energy losses, total population, per capita domestic electricity, coal consumption rate, power consumption intensity, and industrial structure. Due to the consideration of multi-link carbon emissions such as power generation, transmission, and distribution, the classification of influencing factors is more accurate and detailed. M. Karmellos et al. [13] used decomposition analysis (DA) and decoupling analysis models to decompose carbon dioxide emissions from EU power generation into seven influencing factors: economic activity impacts, population impacts, power intensity impacts, power trading effect, and power generation. Bolin Yu et al. [14] considered investment-production-consumption and decomposed renewable energy power generation in EU countries into seven influencing factors: technical structure effect, renewable energy power generation, and capacity ratio effect. Zheng et al. [15] decomposed China's electricity consumption carbon emissions into six influencing factors: carbon intensity, generation mix, electricity intensity, size of economy, and size of population in the LMDI approach and using decoupling models to analyze linking emissions to GDP growth, providing technical support for China's carbon emission reduction potential.

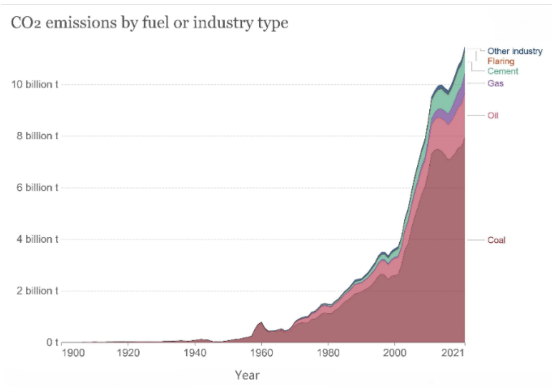

Figure 1 Carbon dioxide emissions from different fuels in 1900-2021

As shown in Table1, considering the impact of the power production process, transmission lines and distribution lines, and carbon emissions from electricity end-consumption activities, the latest progress is to decompose China's power carbon emission growth into 10 driving factors: carbon emission factor, power structure, transmission loss and distribution loss, power structure, power intensity, industrial structure, economic scale, and living consumption.

Table 1 The carbon emissions factors in the power system.

Angle	Influencing factors
Energy input	Lecture Notes Emission factors, the structure of energy, the structure of power
Economics	Economic, population scale, industrial fabric, residential use
Power generation	Power intensity, conversion efficiency
Electricity transmission	Power transmission and distribution loss

All of these factors stem from energy inputs. Despite China's active promotion of new energy generation, coal remains the main form of energy for power generation about input and utilization. Power intensity and conversion efficiency serve as indices for assessing the performance of thermal power plants. By enhancing these indices, we can improve the efficiency with which energy gets converted during power production. The economic scale, industrial structure, living consumption, and population scale are all from the economic perspective to scrutinize alterations from power generation. With the continuous and rapid economic development, the construction of large enterprises, and the increasing living standards of residents, the development of power enterprises has been promoted, increasing of emissions from power production. Furthermore, the state has now introduced a three-child policy. Projected over the next 10 years, the expansion of China's population will promote the development of power enterprises. Transmission and distribution loss refers to the loss of electric energy produced by the high-voltage grid and delivered to the user's home after production [16]-[17]. The higher the loss, the more serious the energy waste, which aggravates the carbon emission of electricity production.

2.2 The contribution of influencing factors was calculated based on the LMDI model

To deeply understand the internal mechanism of energy consumption and energy intensity changing with time and help the government to take targeted measures, quantitative analysis of multiple influencing factors of energy demand and overall energy intensity has gradually become a field of concern for researchers. To solve this problem, research related to decomposition analysis has begun to emerge, such as index decomposition analysis in economics, structural decomposition analysis by input-output method, etc. The LMDI decomposition technique redefines weight by introducing a new weight function, thus completely solving the problem of decomposition remainder [18]-[21]. Figure 2 demonstrates the LMDIA-based modeling of factors affecting carbon emissions from power systems. At the same time, due to the symmetry and simplicity of LMDI, it also has good universality for multi-factor decomposition. as is well known to analyze the influences of carbon emissions [22]. The LMDI principal steps are displayed:

Establish carbon emission decomposition formula

$$V = \sum_i V_i = \sum_i x_{1,i} x_{2,i} \dots x_{n,i} \tag{1}$$

where, this subscript, represents different influencing factors and different aggregation objects, such as fossil fuel types, energy structure, etc.

Characterize the change from 0 to T

$$V_0 = \sum_i V_{0,i} = \sum_i x_{1,0,i} x_{2,0,i} \dots x_{n,0,i} \tag{2}$$

$$V_T = \sum_i V_{T,i} = \sum_i x_{T,1,i} x_{T,2,i} \dots x_{T,n,i} \tag{3}$$

The multiplication form represents the ratio of the reporting period to the base period, which is equal to the product of the changing intensity of each influencing factor, reflecting the change in carbon emission intensity:

$$D_{total} = \frac{V_T}{V_0} = D_{x_1} D_{x_2} \dots D_{x_n} \tag{4}$$

The addition form signifies the disparity between the reporting and base periods, equivalent to the aggregated changes across various influencing factors, thereby mirroring carbon emissions:

$$\Delta V_{total} = V_T - V_0 = \Delta V_{x_1} \Delta V_{x_2} \dots \Delta V_{x_n} \tag{5}$$

Decomposition of the contribution of factors influencing Logarithmic average function:

$$L(a,b) = \begin{cases} \dfrac{(a-b)}{\ln a - \ln b} & a \neq b \\ a & a = b \end{cases} \tag{6}$$

Multiplication form decomposition:

$$D_{x_k} = \exp(\sum_i \frac{L(V_{T,i}, V_{0,i})}{L(V_T, V_0)} \ln(\frac{x_{T,k,i}}{x_{0,k,i}})) \tag{7}$$

Additive form decomposition:

$$\Delta V_{x_k} = \sum_i L(V_{T,i}, V_{0,i}) \ln(\frac{x_{T,k,i}}{x_{0,k,i}}) \tag{8}$$

where, $k = 1, 2, \ldots n$, k represents the number of influencing factors.

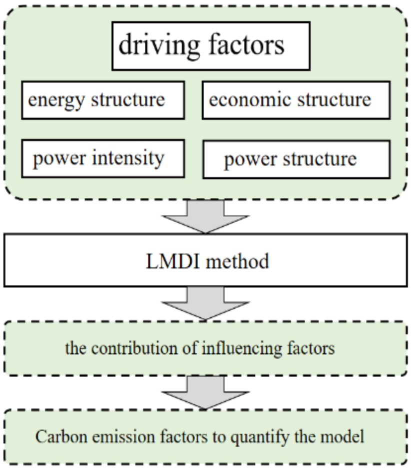

Figure 2 shows the model construction of influences of carbon emission in LMDI.

The following carbon emission decomposition factor model of the power system is established on the LMDI model among the influencing factors proposed in [23]and [24].

$$C = \sum_i \frac{E_{CO_2,i}}{E_i} \times \frac{E_i}{W_i} \times \frac{W_i}{W} \times \frac{W}{GDP} \times \frac{GDP}{POP} \times POP \tag{9}$$

Where $E_{CO_2,i}$ depicts carbon emission, E_i means to the i-th first power, W_i represents power generation of the i-th first power, W represents electricity production, and POP represents total population. Emission factor effect： $c_i = E_{CO_2,i} / E_i$, coal consumption effect： $g_i = E_i / W_i$, power structure effect： $e_i = W_i / W$, power intensity effect： $t_i = W / GDP$, economic scale effect： $r_i = GDP / POP$, and population scale effect： $p = POP$.

The volume of change in emissions and intensity from the initial to the reporting period is shown as follows:

$$\Delta C = C_T - C_0 = \Delta C_c + \Delta C_g + \Delta C_e + \Delta C_i + \Delta C_r + \Delta C_p \tag{10}$$

$$D = \frac{C_T}{C_0} = D_c \cdot D_g \cdot D_e \cdot D_t \cdot D_r \cdot D_p \tag{11}$$

LMDI decomposition is performed according to Formula (7):

$$D_g = \exp(\sum_i \frac{L(C_{T,i}, C_{0,i})}{L(C_T, C_0)} \ln(\frac{g_T}{g_0})) \tag{12}$$

$$D_e = \exp(\sum_i \frac{L(C_{T,i}, C_{0,i})}{L(C_T, C_0)} \ln(\frac{e_T}{e_0})) \tag{13}$$

$$D_t = \exp(\sum_i \frac{L(C_{T,i}, C_{0,i})}{L(C_T, C_0)} \ln(\frac{t_T}{t_0})) \tag{14}$$

$$D_r = \exp(\sum_i \frac{L(C_{T,i}, C_{0,i})}{L(C_T, C_0)} \ln(\frac{r_T}{r_0})) \tag{15}$$

$$D_p = \exp(\sum_i \frac{L(C_{T,i}, C_{0,i})}{L(C_T, C_0)} \ln(\frac{p_T}{p_0})) \quad (16)$$

2.3 Results analyse

In the model analysis, if the carbon emission factor is fixed. The change amount and contribution rate of carbon emission caused by each influencing factor can be obtained by LMDI decomposition. This technology decomposition method and the 2011-2020 data of our country, the contribution rates of coal utilization, power composition, electric intensity, economic, and population magnitude. to carbon emissions are displayed in Table 2.

As a result, it is possible to divide changes in carbon dioxide from coal-fired electricity production, power structure, GDP scale, and people size by the total alteration amount of carbon emissions [25]. Usually, the contribution is greater than 0, indicating that this factor contributes to carbon emissions. If the contribution rate is less than 0, it indicates that the drivers' impact on carbon emissions is slowing down.

Table 2 The factor applied below to carbon emissions.

Year	D_g	D_e	D_t	D_r	D_p
2011	1.198	0.875	0.882	2.079	1.091
2012	1.127	0.995	0.984	2.215	1.098
2013	1.115	0.999	0.919	2.394	1.101
2014	1.098	0.996	1.005	2.593	1.109
2015	1.112	0.994	0.988	2.787	1.113
2016	1.076	1.003	0.968	3.053	1.119
2017	1.058	0.994	0.799	3.369	1.131
2018	1.025	0.995	0.811	3.598	1.135
2019	1.012	0.993	0.801	3.819	1.137
2020	0.992	0.974	0.771	4.411	1.145

The results show that different influencing factors have different degrees of influence on electric power carbon emissions in different periods, which can be roughly divided into two stages. The change curve of contribution rate to time is displayed in Figure 3.

The first period is from 2011 to 2015. It is a five-year period of important strategic opportunities for China's development in this century. The structure of electricity production is relatively uniform. Therefore, the main factor influencing carbon dioxide is economic growth. Secondly, this phase spans from 2016 to 2020. Amidst the challenges of profound global economic adjustments and decelerating economic growth in China, economic scale effects on electricity-related carbon emissions are stabilizing. As the share of clean energy generation steadily increases, the power structure will undergo further optimization, leading to a continuous enhancement of the suppressive effect on carbon emissions.

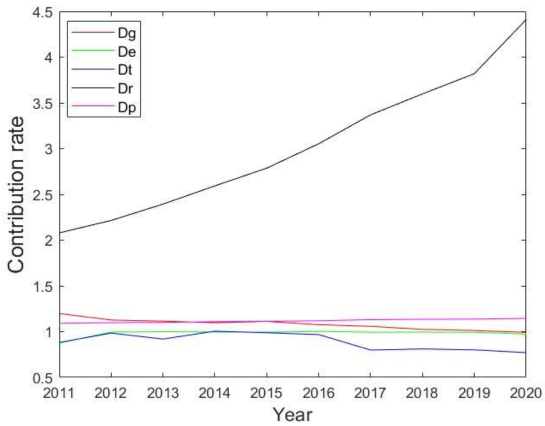

Figure 3 Evolution of contribution rates of various influencing factors

The data showed that the coal consumption on carbon emissions for electricity generation moderated in 2011, while economic size had a significant facilitating effect. The structure of the electricity supply, the intensity of the electricity supply, and the size of the population had a relatively small effect on carbon emissions. This indicates that the power structure and power intensity of Tianjin are improving year by year, which slows down the carbon emission of Tianjin. The economy and population of Tianjin increased year by year, which promoted the carbon emission of Tianjin. As the low-carbon economy continues to stimulate the reform of the power system, changes in renewable energy generation, grid optimization, and demand-side response will be made to optimize the energy use structure of all links of the power grid, reduction of dependence on energy sources with high emissions and a change in the social structure of energy use from the demand side, and promote the development of the society towards a low-carbon society. It can promote emission reduction of the power system, promote industrial transformation and upgrading, and better serve quality economic and social development. The company's responsibility and responsibility are reflected in the progress towards the power system's 'two-carbon' objective.

3. Conclusion

To sum up, applying electric power big data technology to establish a model for calculating carbon emission factors in the electric power system serves as the foundation for accurately computing and analyzing carbon emissions. Among the power systems, this approach can be effectively utilized to evaluate influencing factors of carbon emissions. It thereby facilitates implementing carbon emission reduction objectives, aligning with government-mandated scenarios for emission monitoring and emission reduction effect analysis. Additionally, it demonstrates forward-thinking potential and can offer technical support for emission monitoring, management, and policy formulation within relevant departments.

Based on electric power big data techniques analysis, it can be concluded that the power structure and power intensity moderated impact on carbon emissions in Tianjin from 2011 to 2020, while economic growth significantly contributed to carbon dioxide in Tianjin. The following two recommendations are therefore made:

(1) Tianjin should continuously improve its energy structure and reduce energy intensity; Strengthen the research and development of power devices for the grid and reduce the transformer equipment with SF6 as the insulating gas. To encourage the use of green electricity, renewable energy generation can be introduced by optimizing the structure of the electric power system. While ensuring that GDP development and carbon emissions are within manageable limits, it is important to control the size of the economy and population.

(2) If Tianjin wants to be carbon neutral by 2060, it must continuously enhance the reduction range of power intensity and carbon emissions. To ensure that carbon sequestration exceeds carbon emissions, the carbon sequestration project should be supported. Additionally, the establishment of carbon capture plants can further reduce carbon emissions.

China's power grid development aims to significantly increase local renewable energy, ensure the elimination of high-carbon units, and promote the integration of clean energy, and coal-fired electricity generation. In terms of economic benefits, can help the power system to carry out more targeted emission reduction work, promote the rational use of various types of electric energy on energy production, change energy structure for the better as expected by carbon emission reduction, avoid blind emission reduction resulting in the reduction of economic benefits, and realize the coordinated emission promotion abatement power system operations and economic development.

In the future, the power system should establish a comprehensive index system for stating, monitoring, and evaluating carbon emissions. Appropriate carbon emission trajectory analysis methods should be adopted to enable accurate calculation, monitoring, and evaluation of carbon emission factors, which will have an impact on companies' carbon emission reduction decomposition targets. As a result, power systems will be able to manage the distribution and trajectory of their carbon emissions more effectively. This will make a significant contribution to achieving the power system's 'two-carbon' objective.

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