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Monitoring the enterprise carbon emissions using electricity big data: A case study of Beijing

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ABSTRACT

Enterprises are major sources of anthropogenic carbon emissions, and high-quality data on enterprise carbon emissions are prerequisites for climate abatement policies and actions. However, most of the existing data are more than one-year lagging, easily manipulated, and concentrated at the industrial or regional level. To bridge these gaps, this study develops a monitoring approach for enterprise carbon emissions by combining electricity big data, bottom-up emission accounting model, and network model. The proposed approach has then been applied to monitor the real-time carbon emissions of 0.81 million enterprises in Beijing. Our major findings are that: (1) Owing to a large amount of embodied carbon emissions from electricity inflow, Beijing's electricity-related CO_2 emissions are 73.57 million tonnes in 2020, constituting 55% of its total. (2) The CO_2 emissions per kWh of electricity consumed in Beijing is 645.26 g, whose top three traceable contributors are Hebei (206.71 g), Shanxi (142.21 g), and Beijing itself (133.07 g). (3) The average monitoring error of enterprise carbon emissions is less than 7%, proving the effectiveness of the proposed approach using electricity big data.

1. Introduction

To address climate change and achieve high-quality development, the Chinese government has committed to peak carbon emissions before 2030 and achieve carbon neutrality before 2060 (Li et al., 2022). A successful accomplishment of these two climate targets needs coordinated efforts from all the stakeholders involved in the long-time span. Enterprises are important sources of carbon emissions, and 100 listed enterprises in China have emitted 5.1 Gigatonnes of carbon dioxide (CO_2), accounting for about half of the national total in 2021 (CAIJING, 2022). To ameliorate climate policies, it is urgent to monitor and track the carbon emissions of different enterprises, thus dynamically guiding, calibrating, and regulating the enterprise carbon emissions to be in line with the climate goals.

High-frequency, timely, and reliable carbon emission data are the prerequisites for tracking and regulating the carbon emissions of different enterprises. For a long time, subject to the statistical regimes and technical means, China's existing carbon emission data are mainly concentrated at the regional or industrial level, while the data at the micro level of enterprises are relatively scarce (Liu et al., 2022; Shamsuzzaman et al., 2021). For example, carbon emissions from the energy consumption of micro-enterprises are calculated to assess the potential benefits for pollution, which only covered the industry sectors (Qian et al., 2021). Moreover, most carbon emission accountings are based on annual energy consumption statistics, which lag for more than one year (Liu et al., 2022). CO_2 is a gas with colorless and odorless features, and cannot be directly observed during its emission process, making it difficult for the public and government supervision. Besides, the phenomenon of concealment and underreporting of carbon emissions occur frequently, and the authenticity of self-reported carbon emission data has often been questioned. With the establishment of a unified national electricity market and the continuous expansion in interregional electricity transactions, the traditional carbon emission accounting approach also needs to be revised and improved to consider the carbon emissions embodied in interregional electricity transmissions (Qu et al., 2018). However, due to the absence of high-quality data on enterprise carbon emissions, policymakers do not have a clear understanding of the behavior laws of enterprise carbon emissions, impeding the effective formulation of policies to guide the enterprises precisely. On Dec 31st, 2021, the State Council released Metrological Development Plan (2021–2035), emphasizing the necessity to propose and improve the carbon emission monitoring and measuring system of enterprises to

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support the realization of carbon peak and neutrality targets (State Council, 2021).

As evidenced by the continuous rising terminal electrification rate, electricity is becoming an indispensable part of modern life. Consequently, electricity big data come forth from the daily electricity consumption of enterprises and households. Characterized by high frequency, wide coverage, and rich information, electricity big data has played important roles in macroeconomic trend forecasting, industrial layout diagnosis, social security governance, housing vacancy rate detection, and poor population identification (Arif et al., 2022; Oprea et al., 2021; Poblete-Cazenave and Pachauri, 2021). This study plans to take advantage of the electricity big data to monitor real-time carbon emissions of enterprises, thus providing data support for climate policy designs. With this motivation, we aim to answer the flowing three questions:

(1) How to propose a comprehensive carbon emission accounting approach with consideration of emissions embodied in interprovincial electricity transmissions?
(2) How to establish a monitoring approach for real-time enterprise carbon emissions based on electricity big data?
(3) What is the performance of the proposed monitoring approach in real applications?

To answer these questions, this study first develops a comprehensive emission accounting method for different sectors including both electricity-related CO_2 emissions and non-electricity-related CO_2 emissions. The electricity-related CO_2 emissions are estimated using the network approach, while the non-electricity-related CO_2 emissions are calculated using the Intergovernmental Panel on Climate Change (IPCC) accounting approach. Then, the electricity-CO_2 transformation coefficients of different sectors are calculated based on the total electricity consumption and total CO_2 emissions. At last, by integrating the real-time enterprise electricity consumption data and the electricity-CO_2 transformation coefficients, a monitoring approach for high-frequency enterprise carbon emissions is established and applied to 0.81 million enterprises in Beijing.[1]

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the methodology. Section 4 shows the results and discussions. Conclusions and policy implications are drawn in Section 5.

2. Literature review

Due to the widespread impacts of global climate change, carbon emission monitoring has attracted extensive attention from the academic community in recent years. The volume of carbon emissions monitored depends on the carbon accounting principles, while the selection of carbon emission monitoring technology relies on the actual needs of monitoring objectives and application scenarios. To shed light on enterprise carbon emission monitoring in this study, we conduct a literature review of the existing carbon emission accounting principles and technologies.

There are three main principles of carbon emission accounting, including the producer responsibility principle, the consumer responsibility principle, and the comprehensive responsibility principle. The producer responsibility principle indicates that only the carbon emissions emitted within the territorial boundaries of a region would be counted. This principle mainly adopts the inventory method from the IPCC to calculate the total carbon emissions, which are measured by the sum product of activity data of different fossil fuels and their corresponding carbon emission factors (IPCC, 2006). The advantages of the IPCC inventory approach are its simplicity and operability, while the disadvantage is that the impact of interregional trade on carbon emissions is neglected, resulting in carbon leakage problems (Fan et al., 2019, 2022; Wang et al., 2018). Moreover, the fairness of emission responsibility-sharing may interfere with the realization of global carbon reduction targets (Zhu et al., 2018). The consumer responsibility principle means that the emission is calculated based on the consumption of final goods and services, and this popular accounting principle includes emissions embodied in bilateral trade (EEBT) and multi-regional input-output (MRIO) methods (Gao et al., 2018; Huang et al., 2020; Li et al., 2020; Peters, 2008; Wang et al., 2018; Yang et al., 2020). The advantage of this principle is that it extends the scope of emission accounting and clarifies the emission responsibility related to interregional trade and freight transportation, thus avoiding carbon leakage (Arif et al., 2022; Xie et al., 2017). Such an idea is widely adopted in the carbon emission calculation of electricity systems and deals with the embodied emission transfer caused by interregional electricity transmission. Previous works focused on point-to-point transmission (Kang et al., 2012), which traces emissions back to the last exporter rather than the actual producer. To obtain the network structure of electricity flows, the network analysis is modeled to trace emissions embodied in high-order transmissions, which calculated the emissions from the power consumption side based on a quasi-input-output theory (Ji et al., 2016; Qu et al., 2017; Wei et al., 2020). The application of network analysis on carbon emission flows inspires this study with the advantage of computing complex electricity flows. Reducing emissions from the consumption side is not as effective as that directly from the production side because of high data requirements and complex calculations (Shamsuzzaman et al., 2021; Zhu et al., 2022). Emission accounting under the comprehensive responsibility principle refers to the allocation of carbon emissions in a reasonable way between producers and consumers, but how to design a reasonable sharing way and avoid double accounting is the core of emission accounting under this principle (Wang et al., 2022). The emission accounting under this principle mainly includes the weighted mean and the input-output methods (Li et al., 2020). The weighted mean method measures carbon emissions by assigning proper weights to the emissions from both production and consumption sides. Its strength is simplicity, but the weaknesses are the relatively low accuracy and insufficient consideration of the production process structure.

As to the monitoring methods of carbon emissions, there are five main types including IPCC inventory accounting, chemical measurement, spectral analysis measurement, carbon satellite remote sensing, and big data methods. The IPCC inventory accounting method estimates the carbon emissions based on statistics of fossil fuel consumption combined with corresponding parameters including net caloric value, carbon content, and oxidation ratio (IPCC, 2006). This method has been widely used in carbon emission accounting at the national and regional levels and is also an important basis for global emission accounting and checking (Liu et al., 2015). The chemical measurement method deduces carbon emissions by measuring the composition of flue gas in the exhaust pipe using a device equipped with chemical reagents (Huisingh et al., 2015; Wang et al., 2022). This method is mostly applied to the continuous emission monitoring system of industrial enterprises, and the emission information can be uploaded through sensors in real time (Frodl and Tille, 2007), so it is mostly suitable for enterprises with relatively concentrated emission processes. The spectral analysis measurement method uses the optical properties of polluting gases to investigate the concentration of CO_2 (Tang et al., 2019). At present, this method mostly serves to monitor various types of pollutant gases at the enterprise level (Bullock et al., 2020; Zhang and Schreifels, 2011). The carbon satellite remote sensing method is a top-down emission monitoring method, which retrieves the global or regional carbon emissions through satellite remote sensing data, and has many advantages such as

[1] As from https://baijiahao.baidu.com/s?id=1733710757695768782&wfr=spider&for=pc, there are 1.8 million companies by the end of year 2021. However, the total number of companies registered to State Grid Beijing Electric Power Company is 0.81 million.

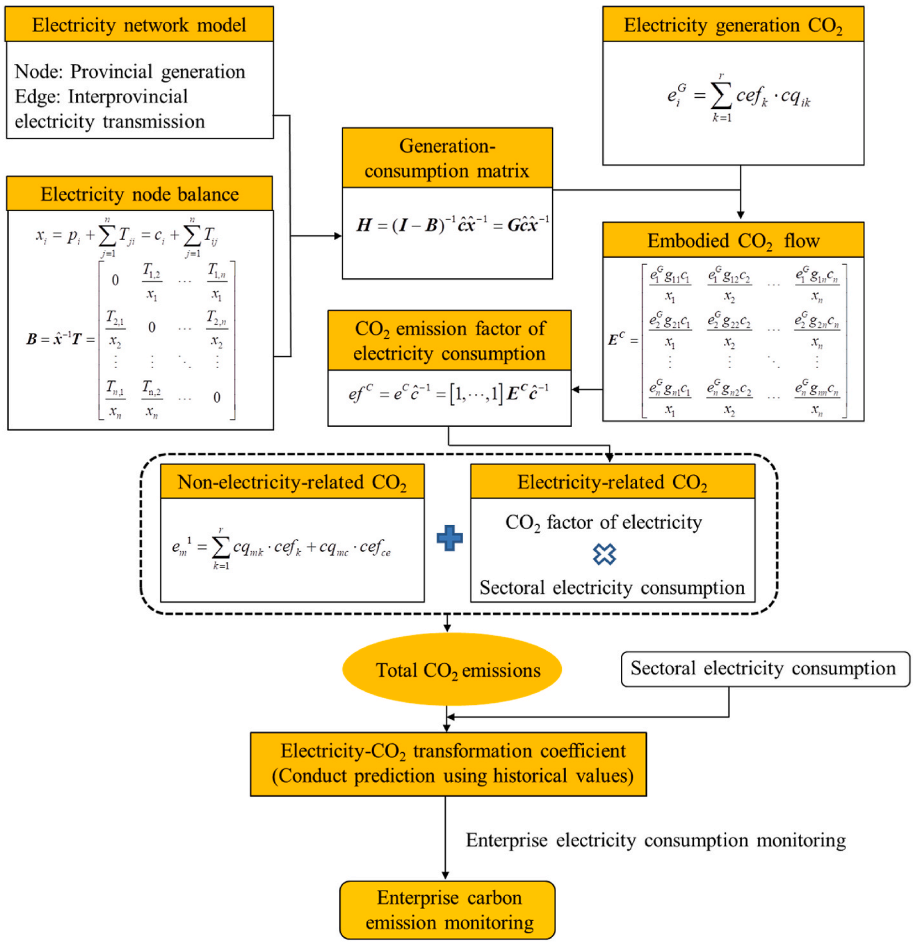

Fig. 1. Framework of enterprise carbon emission monitoring using electricity big data.

stable, continuous, and large-scale observation (Bovensmann et al., 2010; Labzovskii et al., 2019). The big data monitoring method analyzes the correlation mechanism between high-frequency economic data and carbon emissions in different industries by using supercomputers, cloud computing platforms, and machine learning methods to mine massive data and establish emission monitoring methods for different industries and regions (Liu et al., 2020, 2022).

Compared with previous studies, this study makes the following two contributions. First, this study brings a network analysis approach to enterprise-level emissions monitoring under the comprehensive responsibility principle. In previous works, the calculation of electricity-related emissions at the enterprise level or industry level was usually vague. Electricity consumption is directly converted to standard coal equivalent to estimate emissions roughly (Liu et al., 2020, 2022), ignoring that the emission factors of electricity consumption are different among regions. Meanwhile, most accounting principles (IPCC inventory and CEADs inventory) fully account for electricity carbon emissions in the power generation sector. This study takes a comprehensive responsibility principle to divide the total enterprise carbon emissions into electricity-related and non-electricity carbon emissions and redistribute electricity-related emissions with network analysis. This improvement could further clarify the emission responsibilities of different provinces and reflect the heterogeneity of electricity-related emissions in different regions and sectors, thus providing a scientific basis for an equitable sharing of emission reduction responsibilities. Second, existing studies have difficulty in balancing the high data granularity, the wide enterprise coverage, and the low application cost targets in the monitoring of enterprise carbon emissions. This study proposes a monitoring approach using electricity big data, which makes full use of existing data resources of grid companies and achieves all three targets simultaneously.

3. Methodology and data

3.1. Carbon emission monitoring model

The framework of the monitoring model of enterprise carbon emissions based on electricity big data is shown in Fig. 1. The monitored carbon emissions can be obtained as a result of multiplying the real-time enterprise electricity consumption data by the corresponding sectoral electricity-CO_2 transformation coefficient. The real-time enterprise electricity consumption can be obtained from electric power grid companies, while the electricity-CO_2 transformation coefficients are the results of dividing the total sectoral emissions by the total electricity consumption. The total sectoral carbon emissions are classified into two categories and are estimated separately: The electricity-related carbon emissions of different sectors are calculated using the network approach, while non-electricity-related carbon emissions are estimated using the IPCC inventory accounting approach. The details of the model are described below.

The monitored carbon emissions of the *l*-th enterprise in the *m*-th sector in a specific province are shown as Eq. (1):

$$ce_{ml} = ec_{ml} \cdot ecc_m \tag{1}$$

where ce_{ml} represents the carbon emissions caused by energy use of the *l*-th enterprise in the *m*-th sector; ec_{ml} shows the electricity consumption of the *l*-th enterprise and can be obtained from power grid companies; ecc_m denotes the electricity-CO_2 transformation coefficient of sector *m*.

The estimation of the electricity-CO_2 transformation coefficient ecc_m can be divided into two steps. First, the historical results of the electricity-CO_2 transformation coefficient can be calculated. Then, an econometric regression model is constructed to predict the future coefficients.

The historical electricity-CO_2 transformation coefficient of sector m can be calculated by Eq. (2):

$$ecc_m = \left(e_m^1 + e_m^2\right)/z_m \tag{2}$$

where e_m^1 is the non-electricity-related CO_2 emissions (emissions from energy consumption and industrial process); e_m^2 is the electricity-related CO_2 emissions (including CO_2 emissions from both self-generated and inflow electricity). Therefore, e_m^1 and e_m^2 can reflect the emission characteristics from fossil fuel combustion and electricity consumption in different sectors. z_m is the electricity consumption of sector m in a certain region. Finally, the electricity-CO_2 transformation coefficient in Eq. (2) is adopted to establish the correlation between energy consumption, carbon emissions, and electricity consumption, reflecting the different carbon emission characteristics of sectors.

Using the IPCC inventory accounting method, the non-electricity-related CO_2 emissions (e_m^1) of sector m can be calculated by Eq. (3):

$$e_m^1 = \sum_{k=1}^{r} cq_{mk}\cdot cef_k + cq_{mc}\cdot cef_{ce} \tag{3}$$

where cq_{mk} shows the consumption of the k-th type fossil fuel in sector m; cef_k represents the CO_2 emission factor of the k-th type fossil fuel; cq_{mc} denotes the cement production, and cef_{ce} indicates the CO_2 emissions of unitary cement production.

The CO_2 emission factors of various types of fossil fuels can be decomposed by Eq. (4):

$$cef_k = v_k\cdot f_k\cdot o_k\cdot\frac{44}{12} \tag{4}$$

where v_k refers to the net caloric value of fossil fuel k; f_k is the carbon content coefficient of fossil fuel k; o_k shows the oxidation ratio of fossil fuel k; 44/12 is a constant that converts carbon to CO_2.

The electricity-related CO_2 emissions of sector m in region i can be calculated through Eq. (5):

$$e_m^2 = ef_i^C\cdot z_{im} \tag{5}$$

where ef_i^C signifies the CO_2 emission factor of electricity consumed by region i; z_{im} shows the electricity consumption of sector m in region i.

The CO_2 emission factor of electricity consumption of region i can be calculated as a result of dividing the total electricity-related CO_2 emissions by the total electricity consumption, as shown in Eq. (6). Moreover, the total electricity-related CO_2 emissions of a given region are the sum of emissions embodied in the electricity from various regions it consumes.

$$\begin{aligned} ef^C &= \left[ef_1^C, ef_2^C, \dots, ef_n^C\right] \\ &= [1,\cdots,1]\cdot\begin{bmatrix} e_{11}^C & e_{12}^C & \cdots & e_{1n}^C \\ e_{21}^C & e_{22}^C & \cdots & e_{2n}^C \\ \cdots & \cdots & \cdots & \cdots \\ e_{n1}^C & e_{n2}^C & \cdots & e_{nn}^C \end{bmatrix}\cdot\begin{bmatrix} \frac{1}{c_1} & & & \\ & \frac{1}{c_2} & & \\ & & \cdots & \\ & & & \frac{1}{c_n} \end{bmatrix} = [1,\cdots,1]E^C\hat{c}^{-1} \end{aligned} \tag{6}$$

where ef^C is a row vector with its element ef_i^C representing the CO_2 emission factor of electricity consumption from region i; E^C is a matrix of embodied emissions with its (i, j)th element e_{ij}^C showing the CO_2 emissions embodied in the electricity flow from region i that consumed by region j; $\hat{c}$ is a diagonal matrix with c_i denoting the electricity consumption of region i.

This study uses a network approach to estimate the matrix E^C, which can be divided into three steps. First, construct the diagonal matrix of CO_2 emissions from the power generation of each region. The CO_2 emissions e_i^G from thermal power generation of region i can be obtained by Eq. (7):

$$e_i^G = \sum_{k=1}^{r} cef_k\cdot cq_{ik} \tag{7}$$

where cq_{ik} shows the amount of fuel type k used for power generation in region i.

Second, construct a generation-consumption matrix (H) that links power generation and consumption in different regions through the power transmission network. In the network approach, each grid can be treated as a node, and the electricity transmissions among different grids can be considered as edges. In this study, each Chinese province can be considered as a grid as well as a node, and the total inflow and outflow of each node in the transmission network are determined by the electricity flow between different provinces. The sum of local electricity generation and direct inflows equals the sum of local electricity consumption and direct outflows. Suppose there are n regions in this study, the total electricity flow of a region can be shown as Eq. (8):

$$x_i = p_i + \sum_{j=1}^{n} T_{ji} = c_i + \sum_{j=1}^{n} T_{ij} \tag{8}$$

where x_i denotes the total electricity flow of region i; p_i represents the electricity generation of region i; T_{ij} stands for the amount of electricity transmitted from region i to region j; c_i is the electricity consumption of region i.

A $n \times n$ matrix T describes electricity transmissions among regions:

$$T = \begin{bmatrix} 0 & T_{1,2} & \cdots & T_{1,n} \\ T_{2,1} & 0 & \cdots & T_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n,1} & T_{n,2} & \cdots & 0 \end{bmatrix} \tag{9}$$

Based on the total electricity inflow or outflow of each region, a direct outflow matrix B can be defined as:

$$B = \hat{x}^{-1}T = \begin{bmatrix} \frac{1}{x_1} & 0 & \cdots & 0 \\ 0 & \frac{1}{x_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{x_n} \end{bmatrix}\cdot\begin{bmatrix} 0 & T_{1,2} & \cdots & T_{1,n} \\ T_{2,1} & 0 & \cdots & T_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n,1} & T_{n,2} & \cdots & 0 \end{bmatrix} = \begin{bmatrix} 0 & \frac{T_{1,2}}{x_1} & \cdots & \frac{T_{1,n}}{x_1} \\ \frac{T_{2,1}}{x_2} & 0 & \cdots & \frac{T_{2,n}}{x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{T_{n,1}}{x_n} & \frac{T_{n,2}}{x_n} & \cdots & 0 \end{bmatrix} \tag{10}$$

where the (i, j)th element T_{ij}/x_i is the proportion of electricity transmitted from region i to region j in the total electricity flow of region i.

Then, Eq. (8) can be converted to Eq. (11) in matrix form:

$$\begin{aligned} x &= [x_1\ x_2\ \dots\ x_n] = [p_1\ p_2\ \dots\ p_n] + [x_1\ x_2\ \dots\ x_n]\cdot\begin{bmatrix} 0 & \frac{T_{1,2}}{x_1} & \cdots & \frac{T_{1,n}}{x_1} \\ \frac{T_{2,1}}{x_2} & 0 & \cdots & \frac{T_{2,n}}{x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{T_{n,1}}{x_n} & \frac{T_{n,2}}{x_n} & \cdots & 0 \end{bmatrix} = p \\ &\quad + xB \end{aligned} \tag{11}$$

where p is a $1 \times n$ vector denoting the local electricity generation of each region.

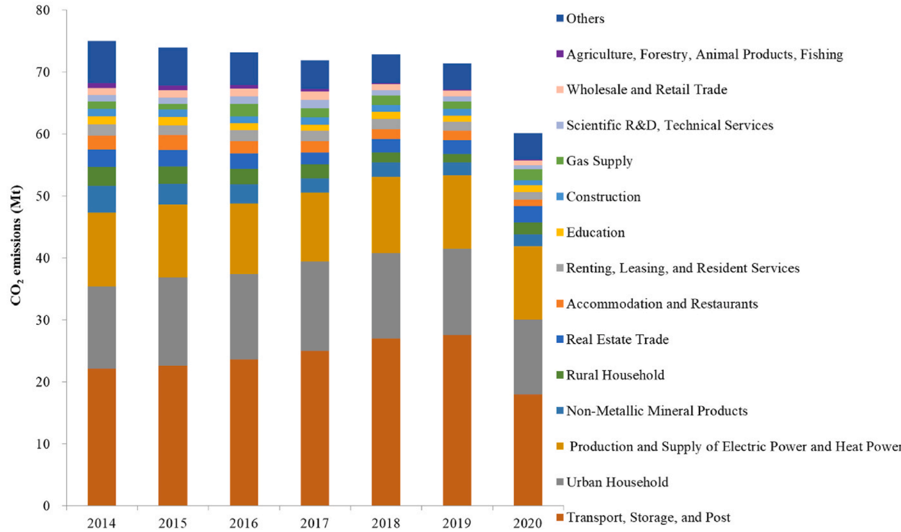

Fig. 2. Non-electricity-related CO_2 emissions of all sectors in Beijing (2014–2020).

Eq. (11) can be rewritten as Eq. (12):

$$x = p(I-B)^{-1} = [p_1 \quad p_2 \quad \dots \quad p_n]\cdot \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nn} \end{bmatrix} = pG \tag{12}$$

where I is the identity matrix denoting the internal electricity flow in a region; $G = (I-B)^{-1} = I + B + B^2 + B^3 + \cdots$ is the total outflow coefficient matrix with its element g_{ij} denoting the ratio of electricity transmitted from region i to region j in the total electricity generation of region i; B represents direct electricity transmission to other regions without passing through a transit region; B^2 is the interregional electricity transmission through one transit region; B^3 means the electricity transmits through two transit regions, and so forth. Therefore, $\sum_{i=1}^{n} p_i \cdot g_{ij}$ denotes the total amount of electricity flowing into region j.

A generation-consumption matrix H is defined to link electricity generation and consumption in different regions, as Eq. (13):

$$H = G\hat{c}\hat{x}^{-1} \tag{13}$$

where the (i, j)th element $H_{ij} = g_{ij}\cdot\frac{c_j}{x_j}$ shows the proportion of unitary electricity generated in region i that is consumed by region j.

Third, calculate the embodied emission flow matrix E^C. The matrix H links the CO_2 emissions from power generation $E^G = (e_i^G)$ to consumption $E^C = (e_i^C)$:

$$E^C = \hat{E}^G H = \begin{bmatrix} e_1^G & & & \\ & e_2^G & & \\ & & \ddots & \\ & & & e_n^G \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nn} \end{bmatrix} \begin{bmatrix} \frac{c_1}{x_1} & & & \\ & \frac{c_2}{x_2} & & \\ & & \ddots & \\ & & & \frac{c_n}{x_n} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{e_1^G g_{11} c_1}{x_1} & \frac{e_1^G g_{12} c_2}{x_2} & \cdots & \frac{e_1^G g_{1n} c_n}{x_n} \\ \frac{e_2^G g_{21} c_1}{x_1} & \frac{e_2^G g_{22} c_2}{x_2} & \cdots & \frac{e_2^G g_{2n} c_n}{x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{e_n^G g_{n1} c_1}{x_1} & \frac{e_n^G g_{n2} c_2}{x_2} & \cdots & \frac{e_n^G g_{nn} c_n}{x_n} \end{bmatrix} \tag{14}$$

where $E^C(i,j) = \frac{e_i^G g_{ij} c_j}{x_j}$ refers to the CO_2 emissions embodied in the electricity transmission from region i to region j.

Then, ef_i^C, the CO_2 emission factor of consumed electricity in region i, can be obtained by Eq. (6). Furthermore, the electricity-related emissions (e_m^2) of sector m can be obtained by multiplying the electricity consumption z_m and the CO_2 emission factor of electricity ef_i^C. The total CO_2 emissions of sector m are the sum of non-electricity-related emissions (e_m^1) and electricity-related emissions (e_m^2). To avoid double accounting, e_m^2 is the reallocation of emissions from power generation to all sectors according to their electricity consumption, which means e_m^1 excludes the emissions from thermal power generation. Finally, the electricity-CO_2 transformation coefficient of sector m (ecc_m) in region i can be calculated through Eq. (2).

Based on historical values of the electricity-CO_2 transformation coefficients, a p-order auto-regression AR(p) model on the electricity-CO_2 transformation coefficient (ecc_m) is constructed as follows:

$$ecc_{m,t} = c + \varphi_1 ecc_{m,t-1} + \varphi_2 ecc_{m,t-2} + \cdots + \varphi_p ecc_{m,t-p} + \varepsilon_t, t = 1, 2, \dots, T \tag{15}$$

Since there is a similarity in the electricity-CO_2 transformation mechanism of different enterprises within the same sector, we can conduct real-time monitoring of enterprise carbon emissions using the estimated electricity-CO_2 transformation coefficient and the monitored electricity consumption obtained by electricity big data.

3.2. Data sources

Beijing, the capital of China, is taken as a case study to illustrate the application of our proposed carbon emission monitoring approach. All the 0.81 million enterprises registered at the State Grid Beijing Electric Power Company are covered in this study. The CO_2 emissions from fossil fuel combustion in Beijing come from the consumption of coal, coke, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas (LPG), liquefied natural gas (LNG), and natural gas. The parameters of net caloric value, carbon content, and oxidation ratio of different fossil fuels are drawn from IPCC (2006) and Liu et al. (2015). Electricity data on local generation and consumption in Chinese provinces are from *China Electric Power Yearbooks* (EBCEPY, 2015–2020) and *China Electric Power Statistical Yearbook* (CEC, 2021). The interprovincial electricity transmissions within China and sectoral electricity consumption are extracted from *Electricity Industry Statistical Data Compilations* (CEC, 2015–2021), and part of the electricity transmissions occur between provinces and

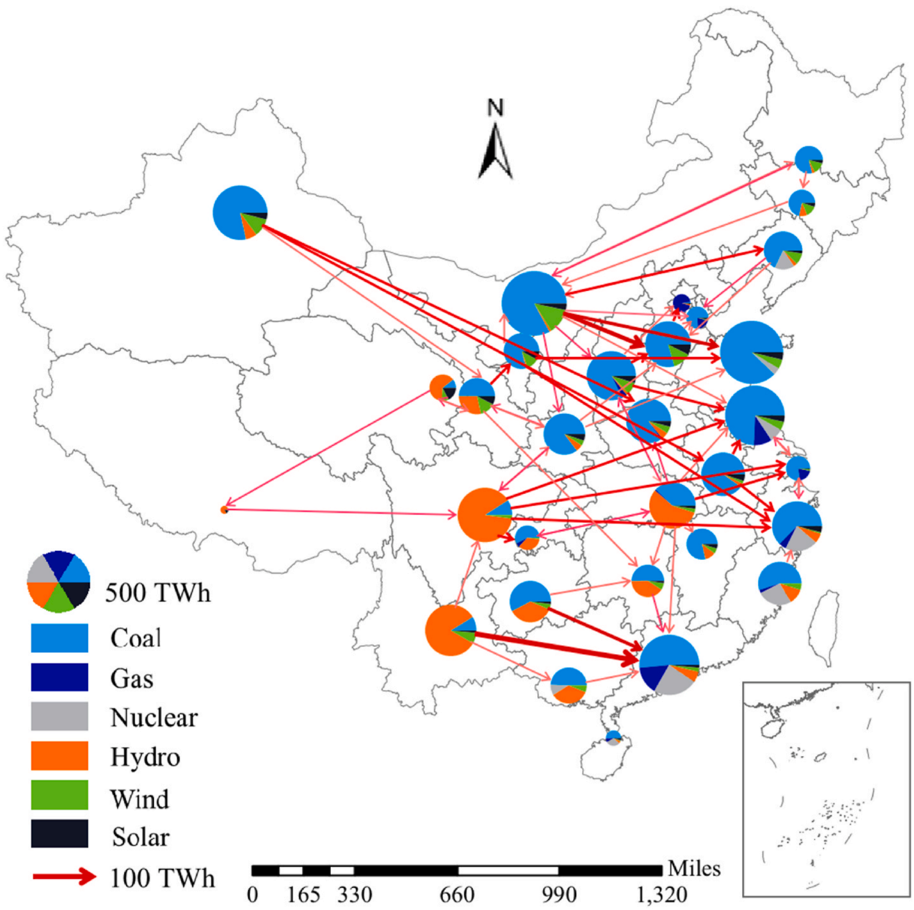

Fig. 3. Electricity generation structure and interprovincial electricity transmissions in 2020.

sub-national grids (such as North China Power Grid), and this part is allocated among internal provinces of the sub-national grid according to each province's power consumption. This operation is proved to have little error through the verification of each province's electricity supply and demand balance. Data on fossil fuels for thermal power generation in each Chinese province are from *China Energy Statistical Yearbooks* (NBSC, 2015–2021). The sectoral consumption data on fossil fuels of various sectors and cement production can be drawn from *Beijing Statistical Yearbooks* (BMBS, 2015–2021). The electricity consumption data of enterprises in Beijing come from State Grid Beijing Electric Power Company. Besides Beijing, any region could be the application object when given the relevant data mentioned above.

4. Results and discussions

4.1. Non-electricity-related CO_2 emissions of Beijing

The non-electricity-related CO_2 emissions of all sectors in Beijing from 2014 to 2020 are estimated based on the IPCC inventory accounting method, as shown in Fig. 2. The total non-electricity-related CO_2 emissions in Beijing showed an overall fluctuating downward trend, from 74.96 million tonnes (Mt) in 2014 to 60.12 Mt in 2020, with an average annual decline rate of 3.43%. The non-electricity-related CO_2 emissions of Beijing account for less than 1% of the total emissions in China since Beijing has a relatively low-carbon industrial structure and most of the carbon-intensive industries have relocated to its neighbor provinces.

As to the emission structure in Beijing, the proportion of CO_2 emissions varies greatly among different sectors. *Transport, Storage, and Post* is the largest source of CO_2 emissions in Beijing. Its proportion has shown an obvious upward trend from 29.49% (22.11 Mt) in 2014 to 38.57% (27.55 Mt) in 2019, but a significant decrease to 29.97% (18.02 Mt) in 2020 possibly due to COVID-19. *Urban Household* is the second largest source of emissions in Beijing, accounting for 19.19% on average from 2014 to 2020. The emission from *Production and Supply of Electric Power and Heat Power* (excluding direct CO_2 emissions from electric power generation) is another important source in Beijing. During the study period, its CO_2 emissions have remained stable at 11–12 Mt, accounting for an average proportion of 16.57%.[2]

4.2. Electricity-related CO_2 emissions of Beijing

Beijing imports large amounts of electricity from other provinces, and its external dependence on electricity in 2020 is 62% (BMBS, 2015–2021).[3] Therefore, electricity-related CO_2 emissions are an important part of the total emissions under the comprehensive responsibility principle (Fan et al., 2021). Electricity-related CO_2 emissions are not only affected by Beijing's power generation, but also by interprovincial electricity transmissions. To explore the CO_2 emissions driven by electricity consumption in Beijing, it is necessary to analyze the characteristics of the electricity generation structure and interprovincial electricity transmission flows within China, as shown in Fig. 3.

[2] If the CO_2 emissions from electric power generation of Beijing is included, the direct CO_2 emissions of Beijing in 2014 were 92.03 Mt, and decline with fluctuation to 75.13 Mt in 2020. Meanwhile, *Production and Supply of Electric Power and Heat Power* has the largest CO_2 emissions among all the sectors, accounting for 31.51% on average during 2014–2020.

[3] In 2020, the total electricity consumption in Beijing is 114.00 TWh, and the electricity generated locally is 43.61 TWh.

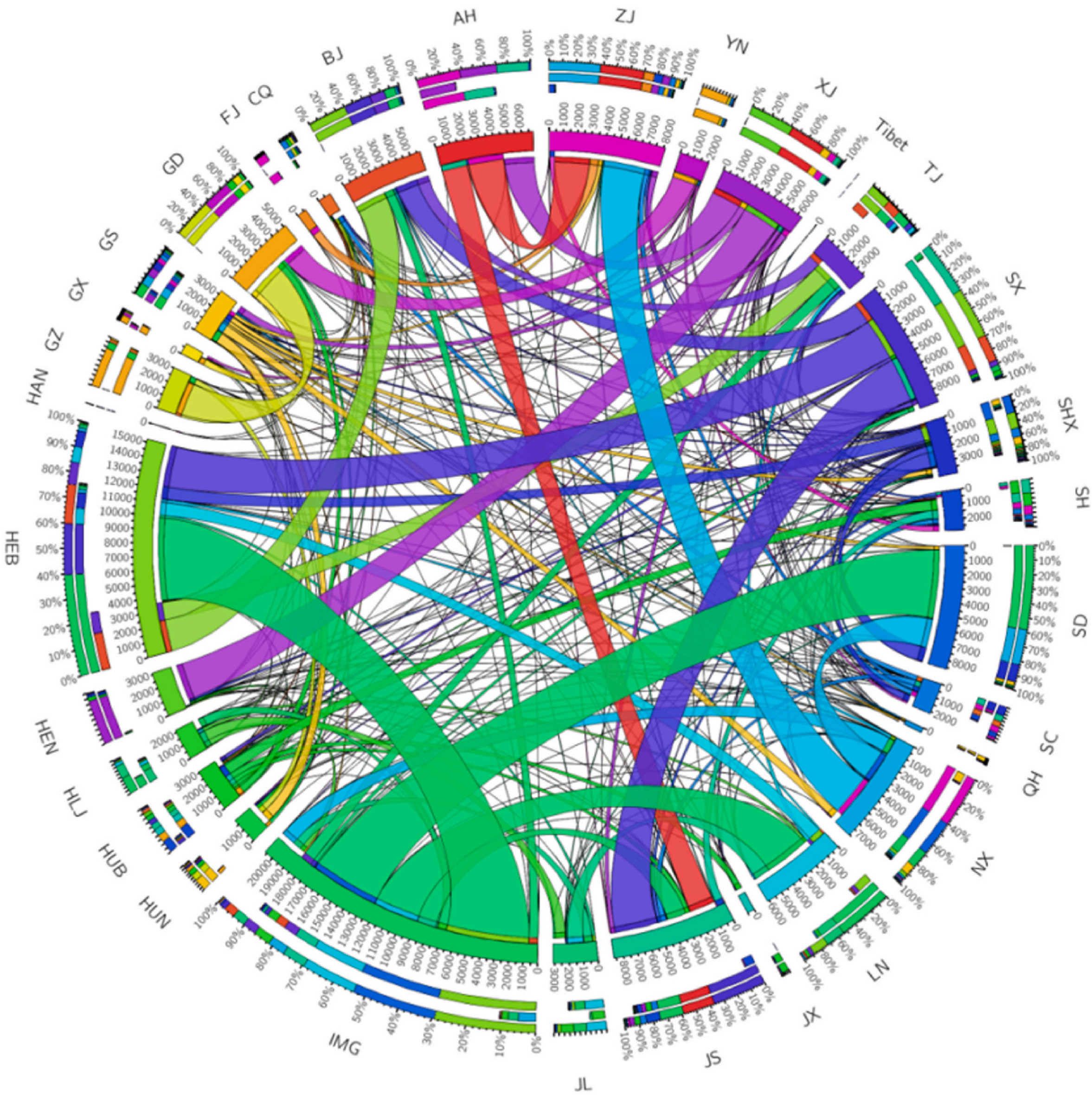

Fig. 4. CO_2 emissions embodied in interprovincial electricity transmissions in 2020
Note: Labels listed are abbreviations for different provinces. BJ (Beijing), AH (Anhui), ZJ (Zhejiang), YN (Yunnan), XJ (Xinjiang), TJ (Tianjin), SX (Shanxi), SHX (Shaanxi), SH (Shanghai), SD (Shandong), SC (Sichuan), QH (Qinghai), NX (Ningxia), LN (Liaoning), JX (Jiangxi), JS (Jiangsu), JL (Jilin), IMG (Inner Mongolia), HUN (Hunan), HUB (Hubei), HLJ (Heilongjiang), HEN (Henan), HEB (Hebei), HAN (Hainan), GZ (Guizhou), GX (Guangxi), GS (Gansu), GD (Guangdong), FJ (Fujian), and CQ (Chongqing).

Significant differences exist in the total amount of power generation in each province due to different resource endowments. In 2020, Inner Mongolia generated the largest amount of electricity, with a share of 7.47% of the national total. Coal-fired power is the main source of power generation in all Chinese provinces, except Sichuan and Yunnan, where hydropower dominates. In addition, there are extensive electricity transactions among provinces. Most eastern provinces are electricity importers, while exporters are mainly in western and northern China. Among all the interprovincial electricity transmissions, Yunnan exported the largest amount of electricity to Guangdong with a volume of 130.88 TWh in 2020.

The CO_2 emission flows embodied in interprovincial electricity transmissions are illustrated in Fig. 4. In 2020, the total CO_2 emissions from electricity generation are 4264.79 Mt in China, of which 17.09% (728.90 Mt) are embodied in interprovincial electricity transmissions. The embodied emissions generally flow from resource-rich but less developed provinces in the central and western regions to developed provinces in the east. The largest embodied emission flow is from Inner Mongolia to Hebei, with a volume of 60.58 Mt. These flows include emissions embodied not only in the direct electricity transmissions but in the indirect electricity transmissions passing through transit provinces (which can be described as high-order flows). In the case of Beijing, the embodied emission inflows cover those not only from Shanxi (15.97 Mt) and Hebei (23.22 Mt) with direct electricity transmissions but from provinces such as Inner Mongolia (6.63 Mt), Shaanxi (0.82 Mt), Liaoning (1.26 Mt) with electricity transferred to Beijing for consumption after passing through one or more intermediate provinces.

The provincial CO_2 emission factors of unitary electricity consumed in different provinces are shown in Fig. 5. The national average value of emission factor is 524.94 gCO_2/kWh, and provinces also show significant differences. From the perspective of spatial pattern, the emission factors are generally higher in the central and northern provinces since their electricity generation structure and electricity exporting provinces are dominated by coal. Hebei, a province where thermal power

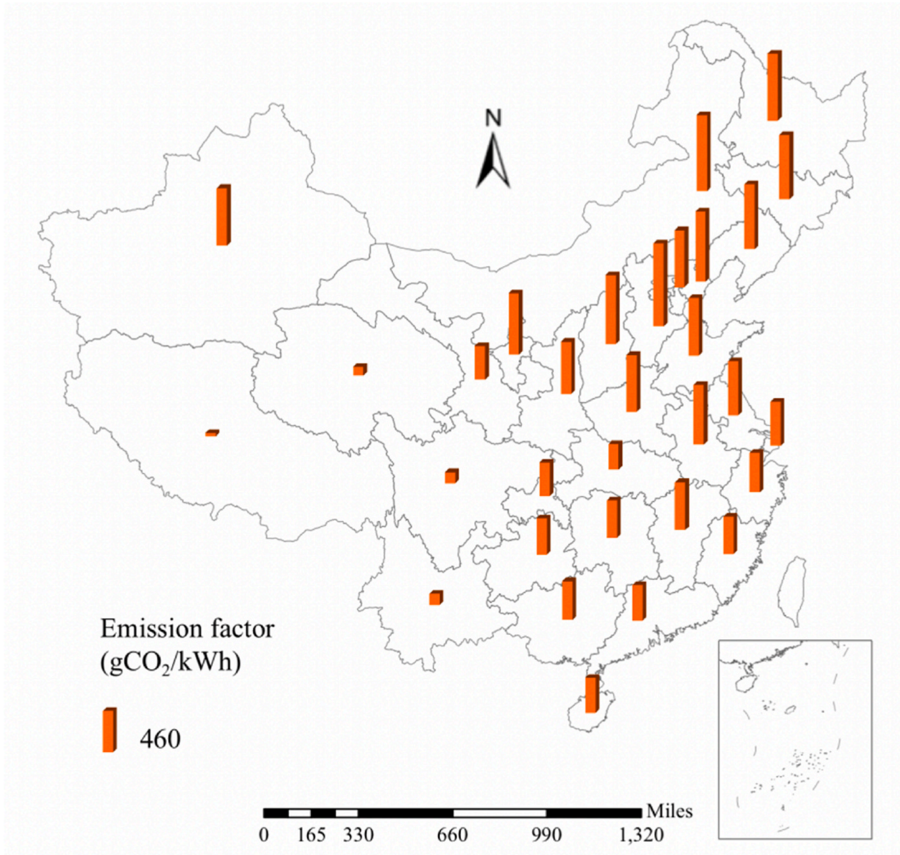

Fig. 5. Provincial CO_2 emission factor of electricity consumption in 2020.

dominates, has the highest CO_2 emission factor and reaches 939.99 gCO_2/kWh, and it imports electricity from Inner Mongolia, Shanxi, Liaoning, etc., where the electricity generation structure is also carbon intensive. The emission factor is generally low in the southeast coastal regions of China. For instance, the emission factor of Guangdong is only 404.21 gCO_2/kWh, which is mainly due to the relatively high proportion of clean energy such as hydropower in its locally generated and inflowed electricity.

The CO_2 emission factor of unitary electricity consumed in Beijing is 645.26 gCO_2/kWh in 2020. The CO_2 emission intensity of local electricity generation is not high, but its main source of electricity inflow includes Hebei and Shanxi, whose proportions of coal in electricity generation are high. Concerning the carbon emission composition of Beijing's unitary electricity consumption, Hebei contributes the largest part with 206.71 gCO_2, followed by Shanxi (142.21 gCO_2) and Beijing (133.07 gCO_2). The total CO_2 emissions driven by electricity consumption in Beijing are 73.57 Mt, accounting for about 55% of Beijing's total emissions (133.7 Mt) under the comprehensive responsibility principle.[4] Therefore, ignoring the CO_2 emissions driven by electricity consumption could seriously underestimate the emission level of Beijing and lead to unequal responsibility-sharing of carbon emissions.

4.3. Monitoring the enterprise carbon emissions using electricity big data

Based on the estimation of electricity-related and non-electricity-related CO_2 emissions from various sectors in Beijing, the sectoral electricity-CO_2 transformation coefficients can be calculated as a result of dividing the sectoral total emissions by their corresponding electricity consumption. Take Beijing as an example, the electricity-CO_2 transformation coefficients of all industrial sectors are shown in Table 1. Great divergence exists in the electricity-CO_2 transformation coefficients among different sectors, with a minimum of 653.62 gCO_2/kWh in *Water supply* and a maximum of 15005.61 gCO_2/kWh in *Gas Supply*, and the average is 1208.33 gCO_2/kWh. The heterogeneity of sectoral emission levels also highlights the necessity of monitoring enterprise carbon emissions based on the individual sector's electricity-CO_2 transformation coefficient.

To realize the function of monitoring enterprise carbon emissions, we use an auto-regression model to forecast the electricity-CO_2 transformation coefficient of each sector based on historical data of coefficients from 2014 to 2020. Then, using the real-time enterprise electricity consumption monitored by grid companies and the electricity-CO_2 transformation coefficient of the corresponding sector to which the enterprise belongs, the hourly or daily CO_2 emissions of 0.81 million enterprises in Beijing in 2022 can be monitored, as illustrated in Fig. 6. It can be seen that most enterprises with high CO_2 emissions in Beijing are concentrated in the central urban area, while enterprises in other areas have relatively low emissions. Through the monitoring heat map of enterprise carbon emissions, timely information on enterprise carbon emissions can be obtained. Moreover, the enterprises, periods, and regions with higher carbon emissions can be precisely identified, thus providing good data support for the formulation of climate policies.

In addition, to check the data accuracy of the established emission monitoring approach in this study, we use the data from 46 sectors of Beijing in 2019 and 2020 as samples to estimate the forecasting errors. The year 2020 is the latest year for which real data are available, while the year 2019 has also been added as a reference with consideration of the potential impact of COVID-19 in 2020. Sectoral-level data are used

[4] The direct CO_2 emissions is 60.12 Mt, excluding the direct emissions from power generation of Beijing's electric power sector.

Table 1
The electricity-CO_2 transformation coefficients of all industrial sectors in Beijing in 2020.

No.	Sector	Electricity consumption (TWh)	e_m^1 (Mt)	e_m^2 (Mt)	TCE (Mt)	Coefficient (gCO_2/kWh)
1	Agriculture, Forestry, Animal Products, Fishing	1.62	15.48	104.40	119.88	740.92
2	Mining and Washing of Coal	0.00	0.00	0.00	0.00	0.00
3	Extraction of Petroleum and Natural Gas	0.00	0.00	0.00	0.00	0.00
4	Mining of Ferrous Metal Ores	0.14	1.26	9.16	10.43	734.34
5	Mining of Non-ferrous Metal Ores	0.00	0.00	0.00	0.00	0.00
6	Mining and Processing of Nonmetal Ores	0.00	0.00	0.00	0.00	0.00
7	Mining Support Service Activities	0.00	0.00	0.00	0.00	0.00
8	Processing of Food from Agricultural Products	0.35	9.99	22.33	32.32	934.00
9	Foods	0.84	35.25	54.40	89.64	1063.37
10	Textile	0.03	0.06	1.94	1.99	664.76
11	Textile Wearing Apparel and Ornament	0.09	2.69	5.94	8.63	937.85
12	Processing and Production of Wood, Bamboo	0.11	1.38	6.84	8.22	775.90
13	Paper and Paper Products	0.16	4.17	10.52	14.68	900.84
14	Printing, Reproduction of Recording Media	0.52	5.26	33.30	38.56	747.23
15	Culture and Entertainment	0.03	0.55	2.19	2.75	807.47
16	Processing of Petroleum and Other Fuels	1.99	70.53	128.08	198.62	1000.59
17	Chemical Raw Materials and Chemical Products	1.27	6.93	81.63	88.55	700.01
18	Medicines	1.06	24.81	68.40	93.21	879.32
19	Chemical Fibers	0.03	0.86	1.81	2.67	954.15
20	Rubber and Plastics Products	0.26	1.28	16.71	17.99	694.58
21	Non-Metallic Mineral Products	0.96	187.75	61.75	249.50	2607.10
22	Manufacture and Pressing of Ferrous Metals	0.32	19.06	20.91	39.96	1233.43
23	Manufacture and Pressing of Non-Ferrous Metals	0.13	0.71	8.58	9.29	698.43
24	Fabricated Metal Products	0.41	5.67	26.33	32.00	784.32
25	General and Special Purpose Machinery	1.01	10.85	65.04	75.89	752.86
26	Railway Locomotives and Other Equipment	2.33	41.59	150.54	192.13	823.51
27	Electrical Machinery Communication Equipment	3.55	10.89	229.33	240.21	675.90
28	Other Manufacturing	0.08	1.08	5.23	6.30	778.13
29	Waste Recycling, Recovery and Repair of Machinery	0.09	4.11	5.87	9.98	1096.95
30	Production and Supply of Electric Power and Heat Power	8.65	1188.06	558.09	1746.15	2018.90
31	Gas Supply	0.12	173.76	7.81	181.57	15005.61
32	Water Supply	2.46	2.05	158.48	160.53	653.62
33	Construction	2.49	77.28	160.35	237.63	956.26
34	Wholesale and Retail Trade	5.70	79.69	367.61	447.29	785.14
35	Transport, Storage, and Post	5.86	1801.64	377.93	2179.57	3721.31
36	Accommodation and Restaurants	3.42	103.16	220.94	324.10	946.54
37	Information Technology Services	9.36	18.53	604.09	622.62	665.05
38	Finance	1.85	7.78	119.57	127.34	687.23
39	Real Estate Trade	9.03	264.28	582.74	847.01	937.90
40	Renting, Leasing and Resident Services	4.21	121.72	271.85	393.57	934.17
41	Scientific R&D, Technical Services	3.29	68.80	212.29	281.10	854.39
42	Municipal Engineering Conservancy	1.98	35.40	127.89	163.29	823.85
43	Education	3.44	114.26	221.84	336.10	977.61
44	Healthcare and Social Works	2.14	35.36	138.28	173.64	810.26
45	Culture, Sports, and Entertainment	1.46	16.86	94.40	111.26	760.49
46	Social Organizations	3.20	39.35	206.55	245.89	768.18

Notes: (1) TCE stands for total CO_2 emissions. (2) The coefficients of five sectors are 0 because they almost disappeared from Beijing's economic system, including *Mining and Washing of Coal*, *Extraction of Petroleum and Natural Gas*, *Mining of Non-ferrous Metal Ores*, *Mining and Processing of Nonmetal Ores*, and *Mining Support Service Activities*.

here for verification due to the deficiency of real data at the enterprise level, and Fig. 7 shows the forecasting errors for 2019 and 2020. The average sectoral forecasting error is 3.61% for 2019 and 6.37% for 2020, respectively, exhibiting the good performances of enterprise carbon emission monitoring using electricity big data. As to the forecasting errors of all sectors in the above two years, 85% of the sectors have a forecasting error of less than 10%, and only two sectors exhibit errors over 20%, namely *Gas Supply* in 2019 and *Transport, Storage, and Post* in 2020. The main reason for the largest monitoring error is their weak coupling relationship with electricity. For *Transport, Storage, and Post* in 2020, the reduction of travel traffic due to COVID-19 leads to a sharp reduction in related CO_2 emissions, making the monitoring error of this sector the largest.

5. Conclusions and policy implications

5.1. Conclusions

Achievement of carbon peak and neutrality targets rely on a good understanding of the enterprise carbon emissions, but the existing data on enterprise carbon emissions cannot provide the necessary support for the climate policies due to the long-time lag, easy human manipulation, and high data collection cost. With this motivation, this study proposes a monitoring approach to enterprise carbon emissions using electricity big data. Moreover, the proposed approach has been applied to 0.81 million enterprises in Beijing to demonstrate its effectiveness. During this process, we have obtained the following conclusions:

(1) Beijing is a major electricity-inflowing province, and ignoring the CO_2 emissions from the inflowed electricity could seriously underestimate its total emissions. Beijing's CO_2 emissions driven by electricity consumption are 73.57 Mt in 2020, contributing 55% of the total emissions under the comprehensive responsibility principle. The non-electricity-related CO_2 emissions of Beijing have shown a downward trend in recent years and decreased from 92.03 Mt in 2014 to 75.13 Mt in 2020. Therefore, the electricity-related CO_2 emissions driven by interprovincial electricity trading cannot be ignored in the emission accounting, otherwise, it could lead to unequal responsibility-sharing of carbon emissions.

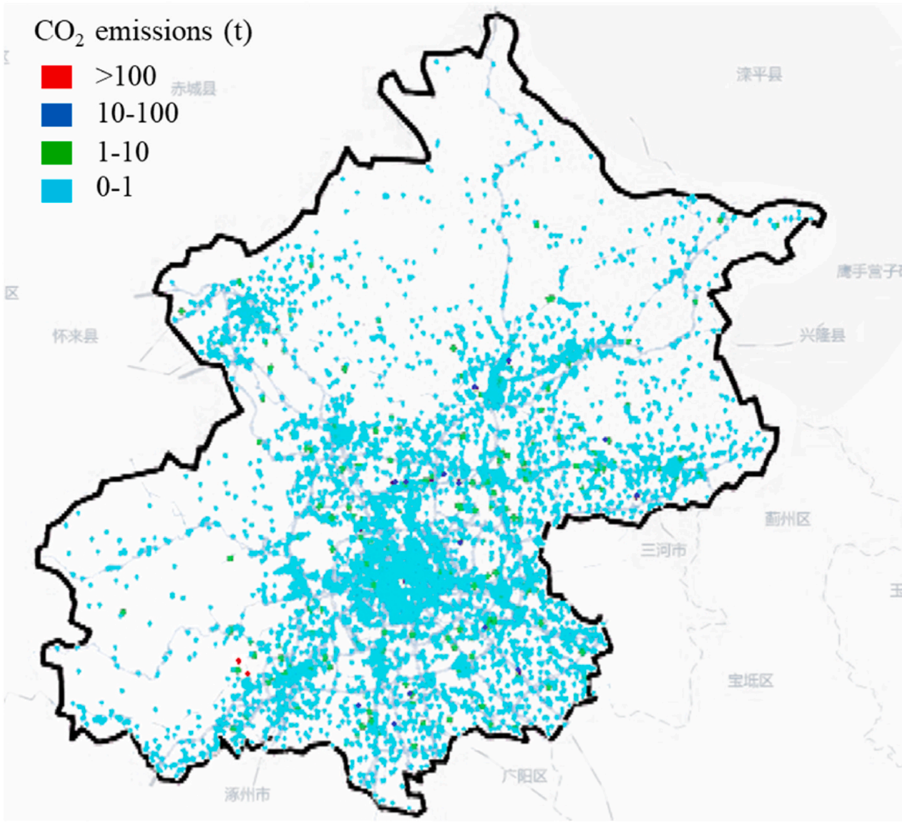

Fig. 6. CO_2 emission monitoring of enterprises in Beijing on a typical day (Sep. 10th, 2022).
Note: The time granularity of monitoring results depends on the time granularity of enterprise electricity consumption data (daily or hourly level). Here, the carbon emission monitoring results at a daily level are used to illustrate the effectiveness of the carbon emission monitoring approach established in this study.

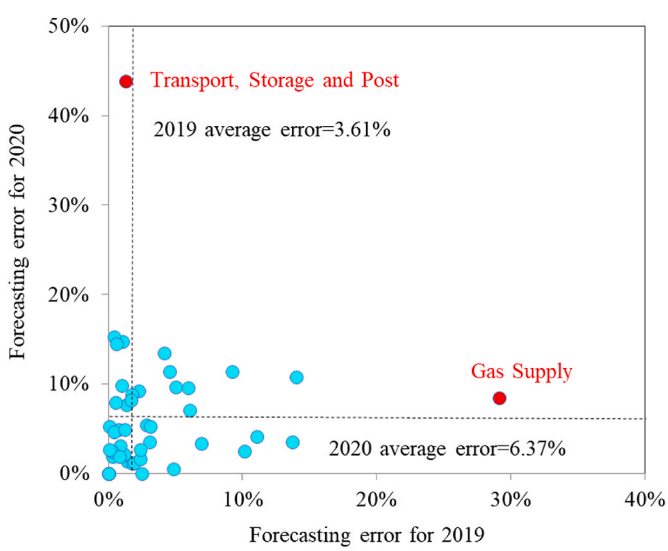

Fig. 7. Forecasting errors of 46 sectors of Beijing based on electricity big data for the year 2019 and 2020.

(2) There are significant differences in the CO_2 emission factors of consumed electricity among Chinese provinces, and they are synthetically affected by the structure of local power generation and interprovincial electricity transmissions. In 2020, the national average CO_2 emission factor of electricity consumption in China is 524.94 gCO_2/kWh. The CO_2 emission factor of Hebei (939.99 gCO_2/kWh) is the highest, mainly due to the relatively high proportion of coal in its power generation. The CO_2 emission factor of Beijing is 645.26 gCO_2/kWh, and the top three contributors to its emission factor are Hebei (206.71 gCO_2), Shanxi (142.21 gCO_2), and Beijing itself (133.07 gCO_2).

(3) Great divergence exists in the electricity-CO_2 transformation coefficients of different sectors in Beijing, so customized emission monitoring and accounting should be carried out for different sectors. In 2020, the comprehensive CO_2 emission factors based on electricity consumption, namely the electricity-CO_2 transformation coefficient, is on average 1208.33 gCO_2/kWh for all 46 industrial sectors in Beijing under the comprehensive responsibility principle. The maximum is 15005.61 gCO_2/kWh in *Gas Supply*, while the minimum is 653.62 gCO_2/kWh in *Water Supply*.

(4) In the applications of our proposed approach to monitoring the carbon emissions of Beijing's enterprises, the comprehensive monitoring error is less than 7%, which proves the effectiveness of the monitoring approach using electricity big data. Apart from the high accuracy, this approach can achieve multiple-time granularity, strong objectivity, and wide enterprise coverage simultaneously. Based on the enterprise carbon emissions monitored, timely information on the carbon-intensive enterprises, periods, and regions can be easily identified, which can be used as important input information for policymakers.

5.2. Policy implications

To provide better support for the climate policies, we put forward the following policy implications based on the above conclusions:

(1) With the continuous increase of interprovincial electricity transactions, provincial carbon emissions are not only impacted by their direct emission level but the indirect emissions embodied in the cross-border electricity transmissions. To ensure the equity of carbon emission accounting and responsibility sharing, the government needs to promote an accounting methodology that includes indirect emissions from electricity consumption. An accurate trace of carbon emissions from electricity consumption could lay a solid data foundation for emission reduction responsibility sharing and emission trading market.
(2) The monitoring approach for enterprise carbon emissions based on electricity big data has the advantages of wide coverage, small-time granularity, and objectivity. Meanwhile, this approach can be promoted and applied at a low cost based on the existing data resource advantages of power grid enterprises. Therefore, the government can assist in building a carbon emission monitoring platform for enterprises based on electricity big data, and conduct data calibration and cross-verification with other emission monitoring methods to improve the objectivity and accuracy of carbon emission data. Monitored emission data could assist carbon emission trading markets in assessing participants' emission reduction implementation and serve as the database for carbon quotas allocation. Furthermore, the carbon emission information of enterprises can be disclosed to the public promptly to increase the transparency of emission information and support the national strategy to cope with climate change.
(3) Significant heterogeneities exist in the carbon emission characteristics among different sectors, and the correlation degree between carbon emissions and electricity consumption varies. To further improve the effectiveness of carbon emission monitoring approaches based on electricity big data, the government can coordinate and establish data-sharing mechanisms for various sectors to break down data barriers among them. By supplementing the high-frequency big data indicators of other sectors and establishing a multi-source big data integration approach, the accuracy of emission monitoring for enterprises in different industries can be greatly improved.

Although a monitoring approach for enterprise carbon emissions has been established and demonstrated good performances in this study, several points can be done in future studies. First, data mining and in-depth analysis can be conducted based on the monitored carbon emission data to better support the construction of the national emission trading market. Second, the current carbon emission path can be compared with the carbon neutrality target to measure the emission gap and to work out better strategies to achieve the carbon targets. Meanwhile, the monitoring model can be optimized by combining multi-source big data from different industries, such as traffic congestion index of the transportation industry, production index of the manufacturing industry, and trading index of the financial industry. These above improvements will make better use of the carbon emission monitoring results and provide new impetus for the development of a digital economy.

CRediT authorship contribution statement

Hao Chen: Conceptualization, Formal analysis, Funding acquisition, Writing – original draft, Methodology. **Renhao Wang:** Methodology, Visualization. **Xinyi Liu:** Software, Data curation. **Yuetong Du:** Software, Data curation. **Yuantao Yang:** Conceptualization, Funding acquisition, Project administration, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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