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Research on high-precision accounting methods for regional carbon emissions under the peak carbon target

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Abstract. In recent years, the level of digitalization and intelligence in the energy sector has profoundly changed the management mode of the energy sector. However, in the process of promoting the digital transformation of the energy sector, we also face some difficulties. One of the main manifestations is the lack of energy data sharing, and the difficulty of realizing the convergence and integration of various types of energy data. In addition, there is insufficient mastery of customer-side energy use data and a lag in the perception of customer demand, which requires the improvement and enhancement of energy efficiency diagnosis and energy saving services. At the same time, we have not yet established advanced digital technology monitoring means to grasp the user's energy use and carbon emissions in real time. Therefore, this paper proposes the study of high-precision accounting methods for regional carbon emissions under the carbon peak goal. Based on the energy consumption and production activities of each region, a greenhouse gas emission inventory is compiled, so that carbon emissions can be accurately calculated. The high-precision accounting method of carbon emissions is analyzed, and by establishing a more complete database and model, and constructing a regional online monitoring system under the peak carbon target, we aim to improve the efficiency of data acquisition and processing, as well as how to combine carbon emission accounting with the peak carbon target, in order to provide support for the formulation of a more effective emission reduction policy. The testing experiments after flow and CO2 concentration measurements show that the accuracy of the experiments on regional carbon emissions is as high as 97.5%.

1 Introduction

In order to actively support the "dual-carbon" goal, we use advanced technologies such as "big cloud, material, mobile and smart chain" to dig deep into the value of energy big data, and promote the cleanliness of energy production, the electrification of energy consumption, and the high efficiency of energy utilization [1]. Many researchers and enterprises utilize real-time monitoring data to dynamically track carbon emission sources and improve the timeliness and accuracy of carbon emission accounting. For example, by installing emission monitoring equipment, real-time monitoring of enterprises' emissions of waste gas, waste water, waste residue, etc., so as to calculate their carbon emissions. In addition, there are some enterprises that process, analyze and mine massive data through big data analysis technology to discover the correlation and law between the data to further improve the precision and reliability of carbon emission accounting. For example, big data analysis technology is used to comprehensively analyze meteorological data, energy consumption data, economic data, etc., to predict future carbon emission trends. As an example, the energy big data innovation practice in Guangzhou City promotes the construction of a clean and low-carbon, safe and reliable, efficient and interactive, intelligent and open energy system [2]. Therefore, we need to use digital technology to empower the power grid, carry out new business practices based on the value utilization of energy big data, change the original management of the energy sector, and realize real-time and effective control of the carbon footprint of key energy-consuming units. By promoting users to reduce carbon emissions, we can expand new energy consumption and improve the efficiency and effectiveness of enterprises to achieve multiple benefits [3].

First, the second power load data of each power consuming sector in the secondary block corresponding to the primary block is obtained based on the time scale. Secondly, the first electricity consumption statistics of each power consumption sector of the first level block are calculated based on the second electricity load data; then the carbon emission data corresponding to the first level block are obtained based on the time scale: The variable coefficient panel data regression model is used to fit the carbon emission data corresponding to the first level block and the corresponding first [4]. Electricity consumption statistics are fitted to obtain the variable coefficients corresponding to the first level block on the time scale, and the variable coefficient matrix is obtained; finally, the

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carbon emission data corresponding to the second level block is calculated through the variable coefficients corresponding to the first level block on the time scale and the second electricity load data corresponding to the second level block [5].

2 Analysis of high-precision accounting methods for carbon emissions

The variable coefficient panel data regression model is used to fit the carbon emissions data corresponding to the first level block and the corresponding first electricity consumption statistics to obtain the variable coefficients corresponding to the first level block on the time scale, and the variable coefficient matrix is obtained [6].

Specifically, the fixed effects panel data variable coefficient model with the following equation.

$$C_{\mathrm{it}} = P_{\mathrm{it}}^{\mathrm{T}}\alpha(Z_{\mathrm{it}}) + \mu_{\mathrm{it}} + \varepsilon_{\mathrm{it}}, i = 1,\cdots,23; t = 1,\cdots,T \quad (1)$$

where P_{it} is a$\lambda \times 1$ dimensional explanatory variable, i.e., electricity consumption data of λ electricity consuming sectors corresponding to the first level blocks, λ is the number of electricity consuming sectors, i is a covariate, μ_{it} is an individual fixed effect, and ε_{it} is an error term; satisfying E（ε_{it}） $= 0$, Var $(\varepsilon_{\mathrm{iit}}) = \sigma_{\chi}^{2} < \infty$ [7].

Further represent (1) as a matrix:

$$\mathrm{C} = \mathrm{B}\{\mathrm{P}, \mathrm{a}(\mathrm{Z})\} + \mathrm{D}_{0}\mu_{0} + \varepsilon \quad (2)$$

Among them:

■(&$P = (P\_1\text{^}\mathrm{T},\cdots,P\_\mathrm{n}\text{^}\mathrm{T})\text{^}\mathrm{T}, P\_i\text{^}\mathrm{T} = (P\_i1,\cdots,P\_iT), P\_it = (P\_in,\cdots,P\_it\lambda)\text{^}\mathrm{T}, C = (C\_1\text{^}\mathrm{T},\cdots,C\_\mathrm{n}\text{^}\mathrm{T})\text{^}\mathrm{T}$@&$C\_i\text{^}\mathrm{T} = (C\_i1,\cdots,C\_iT), \alpha(\cdot) = (\alpha\_1(\cdot),\cdots\alpha\_\lambda(\cdot))\text{^}\mathrm{T}, \varepsilon = (\varepsilon\_1\text{^}\mathrm{T},\cdots,\varepsilon\_n\text{^}\mathrm{T})\text{^}\mathrm{T}, \varepsilon\_i = (\varepsilon\_i1,\cdots,\varepsilon\_iT)\text{^}\mathrm{T}$@&$\mu\_0\text{^}\mathrm{T} = (\mu\_1,\cdots,\mu\_\mathrm{n})\text{^}\mathrm{T}, D\_0 = I\_n \otimes e\_T$) (3)

e_T is a $\mathrm{T} \times 1$ dimensional all-1 vector, where $\mathrm{B}\{\mathrm{X}, \mathrm{a}(Z_{it})\}$ is a stacking function of dimension $(nT) \times 1$, and $\{\mathrm{u}_i\}$ is an independently and identically distributed sequence that satisfies $E(\mu_i) = 0, \mathrm{Var}\,(\mu_i) = \sigma_{\mu}^{2} < \infty$.

Further, if $\sum_{i=1}^{n}\mu_i = 0$, equation (2) can be collapsed into

$$\mathrm{C} = \mathrm{B}\{\mathrm{P}, \mathrm{a}(\mathrm{Z})\} + \mathrm{D}\mu + \varepsilon; \quad (4)$$

Among them. $D = [-e_{n-1}, I_{n-1}]^{\mathrm{T}} \otimes \mathrm{e}_T, \mu = (\mu_2,\cdots,\mu_n)^{\mathrm{T}}$ for the（n − 1）× 1-dimensional vector $D_{\mu} = \mu_0 \otimes e_T$, the where $\mu_0 = (\mu_1,\cdots,\mu_n)^{?}, \mu_1 = -\sum_{\omega=2}^{n}\mu_l$

Estimate a(Z) and μ in equation (3) by weighted least squares. eq:

$$\min_{\alpha(Z),\mu}[C - B\{P,\alpha(Z)\} - D\mu]W_h(\mathrm{z})[C - B\{P,\alpha(Z)\} - D\mu] \quad (5)$$

where the weights $W_h(z) = \mathrm{diag}\,\{K_h(Z_1, z),\cdots,K_h(Z_n, z)\}$ are $\mathrm{nT} \times \mathrm{nT}$ dimensional matrices;

$\mathrm{K_h}(\mathrm{Z_i}, \mathrm{z}) = \mathrm{diag}\,\{\mathrm{K_h}(\mathrm{Z_{i1}}, \mathrm{z}),\cdots,\mathrm{K_h}(\mathrm{Z_{it}}, \mathrm{z})\}$ is a $\mathrm{T} \times \mathrm{T}$ dimensional matrix;

$K_h(Z_{it}, \mathrm{z}) = \frac{1}{\mathrm{h}}K\left\{\frac{(Z_{it},\mathrm{z})}{h}\right\}$, where $K_h(\cdot)$ is the kernel function and h denotes the window width.

The estimation of $\alpha(Z)$ using the local linear method, for $\mathrm{z} \in (0,1)$ and a point Z_{it} in the domain of z, $\alpha(Z_{it})$ is approximated using the first-order Taylor expansion and further processing can be expressed as follows

$$\alpha_m(Z_{it}) \approx \beta_m^{\mathrm{T}}(z)G_{it}(z,h) \quad (6)$$

$$\mathrm{vec}\,(abc) = (c^{\mathrm{T}} \otimes a)\mathrm{vec}\,(b) \quad (7)$$

$$R_i(z,h) = \begin{pmatrix} \left(G_{i,1}(z,h) \otimes P_{i1}\right)^{\mathrm{T}} \\ \vdots \\ \left(G_{i,\tau}(z,h) \otimes P_{iJ}\right)^{\mathrm{T}} \end{pmatrix} \quad (8)$$

$$\mathrm{vec}\,(\tilde{\beta}(z)) = \{R^{\mathrm{T}}(z,h)S_h(z)R(z,h)\}^{-1}R^{\mathrm{T}}(z,h)S_h(z)C \quad (9)$$

The matrix of variable coefficients can be obtained by combining the above equations (6-7). Through the variable coefficients corresponding to the first-level blocks on the time scale and the second electric load data corresponding to the second-level blocks, the carbon emission data corresponding to the second-level blocks are calculated [8]. Specifically, the variable coefficient time series α(Z_it), the individual fixed effects μ_it, and the error term ε_it of each first-level block are separated from the variable coefficient matrix obtained by the fixed-effects panel data variable coefficient model, the fixed-effects panel data variable coefficient model adapted to each first-level block is constructed, and the second electricity load data of the second-level block corresponding to the first-level block is input into the fixed-effects panel data variable coefficient model to obtain the carbon emissions data corresponding to the second-level block. The second electricity load data of the second-level block corresponding to the first-level block is input into the fixed-effects panel data variable coefficient model to obtain the carbon emission data of the corresponding second-level block [9]. Since the variable coefficients of the variables in the same period and the same administrative region have the same values, the variable coefficient time series $\alpha(Z_{it})$, μ_{it} and ε_{it} of each province are separated from the solved variable coefficient matrix, and the electricity data of the prefecture-level cities under the province are substituted into the equations to obtain the carbon emission data of each prefecture-level city in the corresponding province [10].

3 Research on regional online monitoring system under the carbon peak goal

A continuous flue gas monitoring system is a monitoring system used to determine the concentration of various pollutants in the flue gas emitted from stationary pollution sources in real time and continuously. It can monitor by sampling method or direct measurement method. In addition to the function of monitoring pollutant concentrations, CEMS has sampling, instrument calibration, data acquisition and processing functions to provide accurate and reproducible data [11]. A complete CEMS system consists of a particulate matter (soot) monitoring subsystem, a gaseous pollutant (SO2, NOX, CO2) monitoring subsystem, a flue gas emission parameter (humidity, temperature, pressure, flow rate, oxygen content, etc.) monitoring subsystem, a data acquisition subsystem, and a transmission and processing subsystem [12]. The system not only monitors the concentration of pollutants in the flue gas, but also monitors the emission parameters of the flue gas, thus realizing comprehensive monitoring and data analysis. Among them, the emission limits of air pollutants are shown in Table 1:

Table 1. Air pollutant emission limits.

Pollutant type	Emission concentration limits (mg/m3)	Special emission concentration limits (mg/m3)
SO_2	100	50
NO_X	100	100
Soot	30	20

The CEMS sampling system has the capability to simultaneously monitor multiple parameters such as temperature, pressure, flow rate and oxygen content of gaseous pollutants and particulate matter. The data acquisition subsystem is responsible for collecting the sampling data, processing and analyzing them, and finally displaying and printing out the various parameters and graphs. The transmission and processing subsystem is responsible for transmitting the data and graphs to the monitoring system [13]. In this way, the monitoring system is able to acquire and monitor the parameters monitored by the CME system in real time. The continuous flue gas emission monitoring system is shown in Fig. 1:

Fig. 1. Flue gas emission continuous monitoring system.

During the actual working condition testing experiments, we will draw the sampling and measuring point map and use the handheld instrument to test the flue gas parameters. Based on the measured flue gas parameters, we will select, install and debug the carbon emission online monitoring system module to ensure that the instrument can operate normally and effectively monitor the carbon emission data online. Using SQLServer 2000, we created a monitoring database and developed a server using VisualBasic 6.0 programming language for the continuous monitoring system of regional flue gas emissions under the carbon peaking target. This server realizes 24-hour uninterrupted transmission, storage and management of monitoring data [14]. In addition, we have developed a monitoring data analysis and management information system using the VisualBasic 6.0 programming language in combination with the MapObjectsGIS secondary development component for a continuous monitoring system of regional flue gas emissions under the carbon peaking target. This system can realize the deployment of monitoring grids and monitoring points in the global and defined areas of the city, and has the function of evaluating the current status of flue gas emissions in the global and defined areas of the city. Among them, the CEMS sampling point is located in the horizontal flue, where the flue gas runs smoothly and without turbulence, so the measurement results are more accurate [15]. In this location, the flue gas flow is stable and no turbulence occurs, making the measurement data more accurate and reliable. The CEMS sampling points are drawn according to the site conditions as shown in Figure 2:

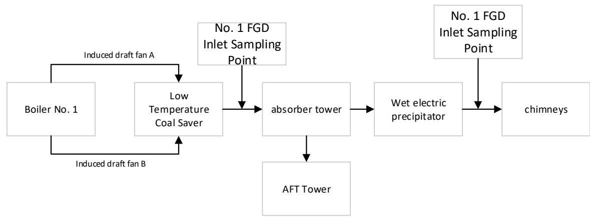

Fig. 2. Site conditions mapping CEMS sampling points.

4 Testing and Analysis

4.1 Testing experiments for flow and CO2 concentration measurements

We conducted a 30-minute test at the selected horizontal flue sampling point of the No. 1 FGD outlet. We used a Testo350XL flue gas analyzer to analyze and measure the CO2 concentration and captured the flue gas flow through the CEMS system already installed in the unit. We chose the most fluctuating time period to analyze the CO2 concentration during the test period as shown in Figure 3:

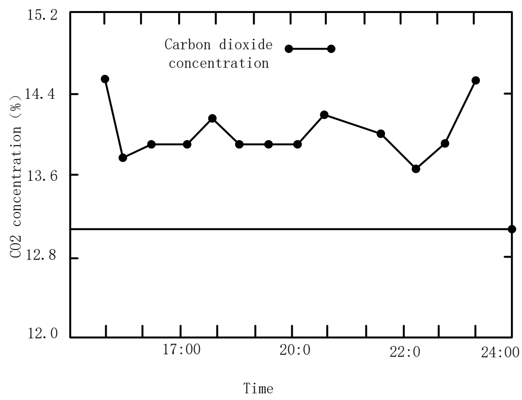

Fig. 3. CO2 concentration during the analyzed test period in actual conditions.

The flue gas flow rate during the analyzed test period for the actual working condition is shown in Fig. 4:

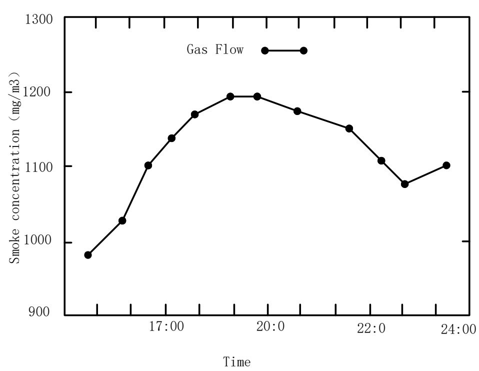

Fig. 4. Flue gas flow rate during the analyzed test period for actual working conditions.

According to the CO2 concentration test results, it shows that the concentration fluctuation range is between 13.6% and 14.6%, and this fluctuation range does not exceed ±5%. This concentration is lower than the national unit average. This indicates that the CO2 concentration remains within a relatively stable range and at a low level.

4.2 Analysis of test results

The CO2 concentration and section flue gas flow during the analytical test of the actual working conditions were subjected to zero-drift drift detection and volume-drift drift detection as shown in Table 2 and Table 3:

Table 2. zero drift drift detection value.

Serial number	Concentration of standard gas (%)	Test value before detection (%)	Zero drift (%)
1	0	0.0097	0.019
2	0	0.0287	0.023
3	0	0.0328	0.029

Table 3. Measurement Drift Detection Values.

Serial number	Concentration of standard gas (%)	Test value before detection (%)	Volume drift (%)
1	15.9	16.23	0.71
2	15.9	16.07	0.66
3	15.9	16.19	0.69

Standard gases with CO2 concentrations of 0 and 15.9 were added to the sample points to conduct experiments, and three sets of quantitative drift and quantitative drift parameters were tested. According to the data in Tables 2 and 3, the experimental error range is less than ±2.5%, and the monitoring module complies with the "75" technical standard, and the monitoring data are valid and can be used for experimental monitoring.

5 Conclusion

In the process of industrialization, the acceleration of economic development and urbanization, environmental pollution and climate change problems are becoming increasingly serious. However, with economic transformation and industrial restructuring, carbon emissions may gradually decline. According to the test results, the monitoring value of emissions obtained from the online monitoring method is lower than the results of the calculation method. The results of the calculation method depend on the values of carbon content per unit calorific value and carbon oxidation rate. The CO2 emissions from the online monitoring technology are affected by the boiler load, and the boiler load affects the flue gas flow, CO2 concentration, and thus CO2 emissions, and the rate of change of the three is positively correlated. The CO2 emission of online monitoring technology is affected by boiler load. In addition, boiler load affects flue gas flow and CO2 concentration, which in turn leads to changes in CO2 emissions. The rate of change between these three factors is positively correlated.

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