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Carbon emission accounting approaches study

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Abstract. In recent years, greenhouse gas (GHG) emissions have become a global focal point, and carbon emission accounting approaches have become even more important in measuring the reliability of data. This paper comprehensively analyzes the principles, reliability and other characteristics of the existing traditional carbon emission accounting approaches and comprehensively compares the application status and realizability of the carbon emission factor approach, the actual measurement approach and the mass balance approach. Additionally, this paper introduces the principle of using the relatively novel satellite remote sensing carbon emission accounting approach and the current status of its application, and proposes a CNN-LSTM model for carbon emission prediction based on electric power big data. Moreover, a kind of ARDL model is constructed for the data of China's Industrial Statistical Yearbook to explore the relationship between total carbon emissions and energy intensity, economic development level, and industrial development level, proving that there is a long-term linear relationship between them. It is concluded that a 1% increase in the level of economic development increases total carbon emissions by about 0.65%–1.31%; a 1% increase in energy intensity increases total carbon emissions by about 1.23%–1.95%; and a 1% increase in industrial development level increases total carbon emissions by about 0.27%–0.43%.

Keywords: Carbon Emission Accounting, Satellite Remote Sensing, ARDL Model, CNN-LSTM Forecast Model

1. Introduction

Since the beginning of the twenty-first century, the trend of global warming has become more and more serious, and the average temperature of the earth's surface has increased by about 0.9 degrees Celsius compared with that of 100 years ago. In the field of carbon emissions, the IPCC put forward the report on global warming. The United Nations and many governments have, for this, many times held a climate change conference, reached the Paris Agreement, and other agreements to cope with the phenomenon of global warming. Zhou et al. also interpreted the structural methodology of traditional carbon emission monitoring systems in the European Union and the United States [1-3]. This article analyzes the characteristics, accuracy, realizability and application of traditional carbon emission accounting approaches on the basis of the predecessors, introduces the principles and specific applications of novel carbon emission accounting approaches, including machine learning approaches and satellite remote sensing approaches, and designs the ARDL model to calculate and analyze the relationship between total carbon emissions and its energy intensity, economic development level and industrial development level. This article provides specific guidance for the implementation of carbon emission accounting, and provides a reference for the promotion of global GHG emissions reduction.

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2. Traditional carbon emission accounting approaches

2.1. Emission factor approach

The general idea of the approach is to multiply the activity data of the emission sources obtained from carbon emission inventories with the corresponding emission factors [4]. Based on the high correlation between emissions sources and carbon emissions, GHG emissions are usually expressed as follows:

$$E = AD \times EF \tag{1}$$

Where EF stands for Emission Factor, which means the amount of greenhouse gases produced by the use of a given source unit; AD stands for Activity Data, which means the amount of inputs used by a single source to produce direct carbon emission; Besides, E is an acronym for emission, which mainly records the emission of greenhouse gases such as CO_2, CO, CH_4. Activity Data for emission sources can usually be collected from relevant statistical websites of individual countries, emission source monitoring organizations or census reports.

2.2. Actual measurement approach

The actual measurement approach is the approach of measuring and summarising the operation directly through the carbon emission base data of the emission source, which is generally categorised into two types: online monitoring and non-online monitoring. Online monitoring, also known as continuous emission monitoring systems (CEMS), is a tool that collects data on carbon emissions during the operation of an emission source for effective environmental monitoring, emission control, and optimization. This monitoring approach targets the measurement of the concentration, flow rate, and velocity of the emitted gases and combines them with the internal piping structure of the emitting stack to obtain the greenhouse gas emissions. It has proven to be a stable and reliable detection approach over the past few decades of industrial practice [5]. Non-online monitoring generally involves sampling the emission source at fixed intervals and sending it to a specialised testing facility for quantitative analysis, which is strongly influenced by factors such as monitoring accuracy and sample selection.

2.3. Mass balance approach

The mass balance approach is an approach of accounting for carbon emissions constructed from a macro perspective that monitors additions or losses based on the chemical substance level. The approach strictly follows the law of conservation of mass and usually requires the measurement of total initial input materials, final product volumes and waste materials in an industrial system. The approach should be based on a fixed industrial system and the difference between the total material and the sum of the product and waste to obtain the GHG emissions from the source [6]. For industrial systems that are constantly being replaced, it is necessary to add the share of emitted chemical substances resulting from the replacement of new equipment.

2.4. Comparison of the different dimensions of the three accounting approaches

The comparison of the three approaches, which is shown in Table 1, reveals that the practical use of each approach has its own characteristics, different levels of accuracy, as well as different requirements for their realizability, and concludes with a statement of the current status of their respective applications.

Table 1. Comparison of three traditional carbon emission accounting approaches

Approaches	Characteristic	Accuracy	Realizability	Application
Emission factor approach	The computational process is straightforward, and well-established databases exist globally, as well as mature technical guidance; it	Relatively imprecise. Emission factor data are heavily estimated when they are determined, and activity data are also affected by sampling	The existence of mature databases, regulatory measures support; the methodology is fully achievable.	Applicable at both micro and macro levels; fully integrated with practical processes; mostly used for

Table 1. (continued).

	does not respond well to changing system environments.	approaches, regional variability, calorific values, and other factors. The product of the two increases the error even further.		monitoring emission sources in structurally stabilized production systems.
Actual measurement approach	Data access is most direct, time-sensitive, and automated; there are regional limitations that make it difficult to obtain data for large-scale production systems, and there is a possibility of data loss.	Most accurate. There are sampling errors due to human factors and monitoring errors due to equipment accuracy. The former can be controlled within acceptable limits by scientifically guiding the testing process, while the latter can be controlled through regular maintenance and upgrading of equipment.	A single manual accounting is realized at a lower cost. Electronic equipment testing module (monitoring CO_2,CO and CH_4) installation requires certain costs. It needs to be combined with the specification of the relevant technical regulatory requirements, suitable for long-term monitoring.	Applicable at the micro level, it has a long history and is mostly used for carbon emission sources with a simple production system structure and the ability to be directly monitored.
Mass balance approach	The higher the quality of the parameters, the more reliable the measurement results, which can distinguish between various types of equipment and their corresponding emission sources. The actual process to be considered is more involved, the data acquisition is more difficult, and the measurement process is relatively cumbersome.	More accurate. There are data acquisition problems and more data with errors; the waste generated during the production process is difficult to calculate accurately; and the rapid replacement of equipment can lead to the accumulation of errors.	It requires a certain level of integrated management and is highly influenced by social economic developments.	Applicable at the macro level, it has emerged in recent years, with more operational approaches, and is mostly used to account for carbon emission sources with large and complex production system.

3. Carbon emission accounting approaches based on satellite remote sensing

In order to cope with the global warming phenomenon, the satellite remote sensing monitoring and carbon emission accounting approach came into being, and the United States, Japan and China have launched satellites for data collection, monitoring of major greenhouse gas parameters and other operations. For the main greenhouse gases, according to the principle of the atmospheric absorption cell, molecules in the near-infrared band and short-infrared band have the ability to absorb and can form unique absorption spectral lines. Based on the depth and shape of these absorption spectral lines recorded by satellite remote sensors, a series of high-precision radiative transfer simulations are combined with algorithms to quantitatively reverse-engineer atmospheric concentrations.

In the twenty-first century, the United States launched two satellites, US Orbiting Carbon Observatory-2 (OCO-2) and US Orbiting Carbon Observatory-3 (OCO-3). OCO-2 carries a three-waveband imaging grating-type hyperspectral sounder, which can measure the concentration of columns in the atmosphere. OCO-2 carries a three-band imaging grating hyperspectral sounder that can measure atmospheric column concentration, aerosol content, and surface albedo, as well as obtaining a map of global CO_2 concentration [7]. OCO-3 is designed to detect mid-latitude regions where emissions are concentrated, and has added snapshot mode scanning technology, which allows for detailed detection of localized carbon emissions within a range of 80*80km.

Japan has the Japanese Greenhouse gases Observatory Satellite (GOSAT) and the Japanese Greenhouse gases Observatory Satellite-2 (GOSAT-2), which is the first high spectral resolution satellite specialized in providing accurate data. GOSAT is the first satellite dedicated to providing accurate data with high spectral resolution, obtaining global column concentrations and concentrations at multiple global pressure levels by ordinary kriging interpolation, while GOSAT-2 is equipped with an upgraded TANSO-FTS-2 sensor with five bands, an optimized spectral range in each band, and 16 levels of gain to increase the dynamic range [8].

The TanSat satellites launched by China are dominated by the Atmospheric Greenhouse Gas Sounder (ACGS), which detects gas concentrations in the near-infrared band using molecular absorption spectra, and the Cloud and Aerosol Polarization Image (CAPI), which is used to monitor interfering substances such as atmospheric particulate matter and clouds to assist in more accurately back-projecting concentrations in the atmosphere [9].

4. Carbon emission accounting approaches based on power big data and machine learning

4.1. ARDL model

Autoregressive Distributed Lag Model (ARDL) is a model estimated using standard least squares, and the advantage of this model is that it can test the cointegration relationship for variables that are not monotonic of the same order such as horizontal smooth, first-order difference smooth, or mixed smooth. According to the selected big data on electric power, studies can be carried out to study the carbon emission reduction path, influencing factors, etc. Generally speaking, it is necessary to determine the energy intensity of a certain area, the level of economic development, the level of industrial development, and other parameters to measure the overall GHG emissions [10]. The benchmark model can refer to the following formula:

$$\ln C_t = \alpha_0 + \alpha_1 \ln EI_t + \alpha_2 \ln GDP_t + \alpha_3 \ln IOV_t + \mu_t \tag{2}$$

Where, C denotes the overall carbon emissions in the region; EI denotes energy intensity, calculated from the total energy consumption ratio GDP; GDP measures the level of economic development, meaning the gross domestic product of a region; IOV denotes the level of industrial development, calculated from the gross domestic product of the secondary industry ratioGDP; μdenotes the stochastic error term; $t$subscripts the year of the record; α_1,α_2,$\alpha_3$denotes the elasticity coefficients of each indicator; and α_0 is the model coefficient.

The research on the ARDL model is generally divided into two steps. Firstly, the F statistic is calculated using the boundary test approach, based on which the stability test is carried out to determine whether there is a long-term cointegration relationship between the variables, and the general law between the variables can be investigated. Secondly, according to the short-term shocks suffered by the model, the error correction model is established to respond to the short-term impact on carbon emissions [11]. The expression of the ARDL model for carbon emissions in a region is as follows:

$$\Delta \ln C_t = \beta_0 + \beta_1 \ln C_{t-1} + \beta_2 \ln EI_{t-1} + \beta_3 \ln GDP_{t-1} + \beta_4 \ln IOV_{t-1} + \sum_{i=0}^{m_1} \gamma_1 \Delta \ln C_{t-i} + \sum_{i=0}^{m_2} \gamma_2 \Delta \ln EI_{t-i} + \sum_{i=0}^{m_3} \gamma_3 \Delta \ln GDP_{t-i} + \sum_{i=0}^{m_4} \gamma_4 \Delta \ln IOV_{t-i} + \varepsilon_t \tag{3}$$

Where, Δ denotes the first-order difference; β_1,β_2,β_3,β_4 denotes the long-term coefficients of the model; γ_1,γ_2,γ_3,γ_4 denotes the short-term coefficients of the model; m_1,m_2,m_3,m_4 denotes the maximum lag order of the variable; ε_t obeys the white noise series. Subsequently, the unit root test,

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boundary test, and long-term and short-term cointegration can be analyzed, and then the effect of each factor on carbon dioxide emissions can be derived to provide corresponding policy recommendations.

4.2. CNN-LSTM forecast model

The CNN-LSTM forecast model is a short-term carbon emission prediction model constructed by mixing two machine learning models, CNN and LSTM, with reference to the historical carbon emission data of each power generation source in a certain region and combining influence factors such as wind and rain [12]. The structure of the model is shown in Figure 1.

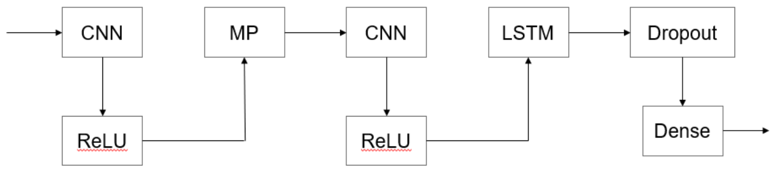

Figure 1. Structure of CNN-LSTM forecast model [12].

The left end of the model inputs the hourly carbon emissions prediction data based on the Artificial Neural Network (ANN) model for each power source, and the right end outputs the return flow of hourly prediction data. The main part consists of two layers of Convolution Neural Networks (CNN), both of which need to keep the output size and input size the same. Rectified Linear Unit (ReLU) is the rectified linear function used for activation, MP is the maximum pooling layer, and the Long Short-Term Memory (LSTM) layer of 24 units is used for time series prediction. The Dropout and Dense layers provide prediction data in the form of line graphs. The two-layer design allows for multi-day iterative prediction data overlays to stabilise the prediction results. If the number of forecast days is too large, the deviation of the forecast curve from the actual curve will increase.

5. Empirical results

This research was based on the data of total value of secondary industry, energy consumption, and GDP in China Industrial Statistical Yearbook. The four variable pairs of EI, GDP, IOV and C were tested for cointegration by using EViews10 software [13]. The positive correlation between total carbon emissions and the level of economic development reaches up to 91%, the positive correlation with energy intensity reaches up to 90%, and the positive correlation with the level of industrial development reaches down to 81%. What's more, the regression coefficients with the three parameters are 0.7, 2.1, and 3.9, respectively, which indicate that the 1% significance test has been passed. The results of the relationship coefficients analyzed by the long-run bounds test obtained by the Constant model are shown in Table 2.

Table 2. Results of long-term correlation analysis.

Variant	Growth Factors	Error Value	P Value	t Value
$\ln IOV_t$	0.98	0.33	<5%	<5%
$\ln EI_t$	1.59	0.36	<1%	<5%
$\ln GDP_t$	0.35	0.08	<1%	<5%

According to the above table, the probability P value of the t-test statistics corresponding to the coefficients of the level of economic development and energy intensity is less than 1% significance level, and the probability P value of the t-test statistics corresponding to the coefficients of the level of industrialization is less than 5% significance level, which indicates that all the explanatory variables are significant. Moreover, it can be concluded that total carbon emissions have a long-term linear relationship with the level of economic development, energy intensity and industrialization, respectively. Specifically, it is concluded that a 1% increase in the level of economic development increases total carbon emissions by about 0.65%-1.31%; a 1% increase in energy intensity increases total carbon emissions by about 1.23%-1.95%; and a 1% increase in the level of industrialization increases total carbon emissions by about 0.27%-0.43%. This suggests that energy intensity has the greatest impact on total carbon emissions, followed by the level of industrialization, with the level of economic development having the least impact.

6. Conclusion

Through this paper, it is easy to summarise that the actual measurement approach has the highest accuracy because of its good error control ability, and it has more applications at the micro measurement level; the emission factor approach has the simplest calculation process and is highly achievable at both the micro and macro measurement levels, but with larger errors; the mass balance method has a good measurement effect for the stable and complex system at the macro level, and it has high accuracy. The satellite remote sensing method can provide dynamic monitoring of carbon emissions at the global level as well as macroscopic analysis of carbon emissions in local areas, which is of great significance in promoting global energy conservation and emission reduction. The advantages and disadvantages of traditional carbon emission accounting approaches are more obvious, and novel measurement approaches are more combined with power big data and machine learning, so it is necessary to increase theoretical innovation and explore the possibility of combining multiple fields to account for carbon emissions. The carbon emission prediction of each link of production can be refined, and the emission sources can be monitored in real time so as to improve the production link.

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