

Article

Research on Carbon Emissions Estimation in Key Industries Based on the Electricity–Energy–Carbon Model: A Case Study of Henan Province

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Abstract: This study focuses on the carbon emissions of key industries in Henan Province, employing techniques of seasonal adjustment, frequency transformation, and statistical modeling to construct an industry-level “Electricity–Energy–Carbon” model to aid in the high-frequency monitoring of carbon emissions in the province’s industries. Based on relevant data, this research performs high-frequency calculations of carbon emissions from energy consumption in 34 typical industries and from the production processes of 53 typical sub-categories in the industrial sector of Henan. The findings reveal the following: Firstly, industrial energy consumption in Henan accounts for over half of the total provincial energy consumption, with most months seeing proportions around 60%. Industries such as energy, non-ferrous metals, building materials, steel, chemicals, petrochemicals, and paper making contribute to over 80% of the industrial energy consumption’s carbon emissions, often nearing 90% in most months. Secondly, among the major industries, such as non-ferrous metals, chemicals, building materials, and steel, there is a dual challenge of being restricted under the “high energy consumption and high emissions” project while also being required to build key industrial bases, leading to fluctuating trends in historical annual carbon emissions data. Thirdly, six sub-categories, namely plastic products, cement, flat glass, steel, ten types of non-ferrous metals, and alumina, have significant carbon emissions in their production processes, accounting for about 72.3% of the total production-related emissions.

Keywords: electricity-energy-carbon model; key industries; carbon emissions; high frequency monitoring



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1. Introduction

In September 2020, General Secretary Xi Jinping formally announced at the United Nations General Assembly that “China will enhance its national commitments, adopt more robust policies and measures, and strive to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060”. To date, provinces including Beijing, Tianjin, Shanxi, Shandong, Hainan, Chongqing, Yunnan, Gansu, and Xinjiang have all set explicit targets for peaking carbon emissions. On 30 April 2021, during the 29th collective study session of the Political Bureau of the CPC Central Committee, the General Secretary emphasized that achieving these carbon peak and neutrality targets represents a solemn pledge to the world and involves a broad and profound transformation of the economic and social systems, which cannot be achieved easily. The first plenary meeting of the carbon peaking and carbon neutrality work leadership group convened on 26 May 2021, to discuss and deploy relevant efforts. By December 2022, the Central Economic Work Conference put forth new demands on carbon peaking and neutrality, calling for the development of new industrial competitive advantages through the implementation of these targets and promoting a virtuous cycle of “technology–industry–finance.”

Clearly, to achieve the targets of carbon peaking and neutrality set by the General Secretary, we must first accurately calculate our carbon emissions, especially through high-frequency estimations for various specific industries, which will provide critical data support for fostering the virtuous cycle of “technology–industry–finance.” Globally, seven developed country institutions, including the International Energy Agency (IEA), the Emissions Database for Global Atmospheric Research (EDGAR), the Energy Information Administration (EIA), the World Resources Institute’s Climate Analysis Indicators Tool (CAIT of WRI), British Petroleum (BP), the World Bank (WB), and the Carbon Dioxide Information Analysis Centre (CDIAC), have established authoritative carbon emission estimation databases that cover all nations, forming a significant international voice. Although these institutions provide trends that are reference-worthy for China’s carbon emission estimations, such as those by CDIAC and EDGAR, they generally tend to overestimate China’s carbon emissions [1].

From a theoretical perspective, the main methods for carbon emission estimation include inventory methods, direct measurements, material balance methods, and model-based approaches [2], with the inventory method being the most commonly used. Typically, this method is applied at the macro level to estimate emissions by region or industry. This paper, drawing on this approach, focuses on constructing and selecting “Electricity–Energy–Carbon” models based on electricity consumption data for Henan Province’s major industries and key sub-sectors within industries, to calculate carbon emissions for the province and its major industries.

This paper’s contributions are threefold: First, comparing with the electricity–carbon model [3], we build a model capacity database for our “Electricity–Energy–Carbon” model, and consider various types of models including linear, nonlinear, original, and TC series in the database. Second, in addition to commonly used criteria such as the Akaike information criterion (AIC) and mean squared error (MSE), the model selection criteria also consider the maximum generalization error. Third, it performs high-frequency carbon emission calculations for key industries and sub-sectors in Henan Province from the perspectives of energy consumption and production processes, providing data support for establishing a high-frequency carbon emission calculation service system in Henan Province.

2. Literature Review

In terms of carbon emission estimation methods, inventory methods, direct measurement methods, material balance methods, and model-based approaches are currently the main techniques used both domestically and internationally [2], with the inventory method being the most common (specific methodologies can be referred to in Shi Junyi (2017) [4]. Internationally authoritative organizations, such as the IEA, CDIAC, EDGAR, and EIA, though employing different specific methods for carbon emission calculation, generally use the inventory method based on the IPCC calculation formulas [5]. Based on the inventory method of IPCC, and with power big data, some researchers apply techniques such as frequency conversion and statistical modeling to construct the electricity–carbon model to realize the high-frequency and multi-dimensional measurement of provincial carbon emissions [3].

In terms of the scope of estimation, the setting of China’s carbon emission boundaries generally only considers carbon emissions caused by the combustion of fossil fuels and the production of cement [5]. As estimation research has deepened, international institutions have gradually refined the carbon emissions from industrial production processes. The 2021 “Global Energy Review” proposed that the scope of carbon emissions includes energy consumption as well as emissions from the chemical processes of cement, steel, and other chemicals, with the IEA using this standard to calculate carbon emissions and greenhouse gas emissions related to energy combustion (IEA, 2021).

Regarding the frequency of estimation, the existing literature on low-frequency (annual or quarterly) estimates is plentiful, while high-frequency (monthly or daily) studies are scarce. Due to the limitations in obtaining high-frequency data, existing carbon emission

estimation studies are mostly based on annual data, such as the global annual carbon emission data from 1970 to 2018 released by EDGAR, the 2019 global carbon emission grid data based on geographic information systems released by the Tsinghua University GID team (2021), and the annual carbon emission data for China and its provinces released by CEADs [CEADs is a third-party carbon emission accounting data platform supported by institutions like the National Natural Science Foundation of China, the Ministry of Science and Technology, the Chinese Academy of Sciences, and the British Research Council, which gathers scholars from China, the UK, Europe, and the USA]. Other annual estimates by scholars include those by Dong Huijuan (2015), Zhao Hongyan (2012), and Shan et al. (2016) [6–8]. Some scholars have conducted quarterly carbon emission estimates [9]. The existing high-frequency estimates include the daily data on China's national-level carbon emissions released by CEADs (2022). Monthly and daily carbon emission estimates for China's provinces, cities, and industries are rare.

In terms of carbon reduction research, the existing literature is predominantly qualitative rather than quantitative. Qualitative research primarily focuses on the analysis and discussion of emission reduction policies. For example, internationally, from the “United Nations Framework Convention on Climate Change” (1992) to the “Paris Agreement” (2015), after multiple consultations and discussions among countries, the post-2020 global greenhouse gas emission reduction process was formally initiated [10]. Other scholars have comparatively analyzed various countermeasures for emission reduction from an international perspective [11,12]. Domestically, due to significant regional differences, the existing literature mostly discusses various potential emission reduction policies and their impacts from the perspectives of regional economic development levels and industrial structures [13,14]. On the quantitative side, the existing literature primarily focuses on simulations of various emission reduction scenarios [15,16] and evaluations of emission reduction effects [17], with very few studies on the actual measurement of emission reductions.

Regarding the results of carbon emission estimation, existing studies still exhibit certain uncertainties. These uncertainties are primarily reflected in four aspects: First, there is inconsistency in emission inventory standards. For example, standards from institutions such as the IPCC, the U.S. Energy Information Administration, the Japanese Energy Research Institute, the Chinese National Science and Technology Commission's Climate Change Project, and the Chinese National Development and Reform Commission's Energy Research Institute all have certain differences [18]. Second, there are discrepancies in the results of estimations between authoritative institutions. For instance, the results of estimations by seven international authoritative institutions compared with the results submitted by China to the international community in the “National Communications” over 22 years were overestimated in 19 years, with the highest reaching 7%, and the results of the “Third National Communication” differed by 19.3% and 12.3% compared to the results of the Chinese Academy of Sciences [1]. Third, macro-statistical data used in China's carbon emission estimates contain certain errors. For example, although the national and provincial energy consumption statistical data in China had large discrepancies historically, and although adjustments were made in 2015, differences still exist [1]. Fourth, the results of estimates given by the same institution in different years also exhibit significant errors. For example, the results of China's carbon emissions for 2017 downloaded from the CEADs official website by the authors in 2021 and 2022 showed underestimations of approximately 9% and overestimations of approximately 10%, respectively, with a nearly 20% difference between the two (authors downloaded the data for China's 2017 carbon emissions from the CEADs official website in 2021 and 2022, finding that the results of the two releases differed by nearly 20%).

In practical application, to implement the central government's “dual carbon” strategic targets and reflect the social responsibility of state-owned enterprises, provinces such as Guangdong, Fujian, Zhejiang, Qinghai, and Jiangsu have actively conducted high-frequency carbon emission estimation studies based on big data from the electric power sector. On 24 May, the China News Service reported under the title “China's First ‘Electric

Power High-Frequency Data Carbon Emission' Intelligent Monitoring and Analysis Platform Officially Launched" that the Qinghai Provincial Electric Power Company of the State Grid, based on big data, conducted new high-frequency carbon emission estimation studies. In June 2022, the National Development and Reform Commission commissioned a joint research team from the State Grid, Beijing University of Posts and Telecommunications, and other institutions to study "Electric Power Big Data Carbon Emission Monitoring Research." In June 2023, the National Development and Reform Commission organized the acceptance meeting for the "National Carbon Emission Monitoring and Analysis Service Platform," which is capable of calculating, monitoring, and analyzing national carbon emissions by month, region, and industry (agriculture, industry, construction, transportation, etc.). However, there are currently no carbon emission assessment and monitoring analysis platforms for key emission industries and enterprises in the industrial sector.

In May 2023, the Ministry of Industry and Information Technology released the "Industrial Field Carbon Peaking and Carbon Neutrality Standard System Construction Guide (2023 Edition)" (draft for comments). On one hand, this guide proposes monitoring technical standards for many sub-industries in the industrial field, but these standards lack generality, economic applicability, and timeliness; on the other hand, the guide does not involve monitoring standards for sub-industry carbon emissions.

3. Materials and Methods

3.1. Data and Variable Description

3.1.1. Industry Categorization and Correspondence

Consistent with the national statistical department and the State Grid Data Center, the classification includes seven major industry categories: agriculture, forestry, fishing and hunting; industry; construction; transportation and storage; wholesale and retail trade, accommodation and food services; residential life; and others.

Specific to Henan Province, distinct classifications such as petroleum and petrochemicals, non-ferrous metals, building materials, chemicals, electricity, steel, energy, and paper industries are aligned with the 2017 National Economic Industry Classification (GB/T 4754—2017) and the National Development and Reform Commission's "Guidance Catalog for Industrial Structure Adjustment (2019 Edition)".

3.1.2. Electricity Consumption Data Explanation

Electricity consumption data for all major and minor industry categories have been analyzed statistically. For six specific subcategories, the data begin in 2017, while for other industries, the data start from 2009. To calculate carbon emissions during production processes, products within subcategories vary depending on the industry. In cases where no specific sub-subcategory product data are available, the electricity consumption data of the broader subcategory is used as a substitute, which may introduce some data inaccuracies. Due to changes in the classification standards of subcategories around 2011, the electricity consumption data for all industries have been uniformly used from January 2012 to December 2022, excluding the six subcategories mentioned in Table A1 (given in Appendix A).

Energy consumption data for various industries: The energy consumption data for all major and minor industry categories are annual figures, sourced from the "China Energy Statistical Yearbook" and the "Henan Statistical Yearbook." Due to changes in the classification standards of subcategories around 2011, which mainly involved the addition and removal of certain subcategories, data from 2012 onwards are used for analysis.

Production data for industry products: The count of minor category products is extensive, totaling 240. Our statistical analysis shows that within the industrial categories needing calculations, there are 20 sub-industries (excluding the 7 major industry categories). However, among these sub-industries, there are 240 subcategory products, but due to data availability, only 53 of these products have sufficient data for calculation.

3.2. Construction of the “Electricity–Energy–Carbon” Model

The construction of the electricity–carbon models for Henan Province’s key industries is based on the inventory method, referring to the IPCC guidelines from 2006 and 2019. We categorize the electricity–carbon models of Henan’s key industries into two types: one for energy use within the industries and another for the production processes. Both types consist of three groups of models: data preprocessing models, data verification models, and core electricity–carbon models.

The difference between the electricity–carbon model method and the inventory method of IPCC is that the former applies the power consumption to compute the energy consumption and the amount of the industry product based on the model at first and then compute the carbon emission by multiplying the corresponding emission factors, the latter applies directly the official annual statistical data of the energy consumption and production of industries to compute the carbon emission by multiplying the corresponding emission factors. Because of the high-frequency and inexpensive power data, the advantage of electricity–carbon model method is that the measurement results are timely and high frequency (monthly) and the implementation of measurement is cheap.

3.2.1. Electricity–Energy–Carbon Model Construction

Based on the electricity–carbon model [3], we construct the electricity–energy–carbon model from the following three aspects: the data preprocessing model group, data verification model group, and core model group. There are three new contents of our model compared with the electricity–carbon model. The first is that in order to ensure that analysis logic is rigorous, we add the data verification model in our model construction comparing with the electricity–carbon model. The second is that we build a model capacity database which includes various types of models including linear, non-linear, original, and TC series, but the electricity–carbon model only included linear model. The third is that in addition to commonly used criteria such as the Akaike information criterion (AIC) and mean squared error (MSE) which were used in the electricity–carbon model, our model selection criteria also consider the maximum generalization error which is more important for the monthly carbon emission forecast.

Data preprocessing model group: This includes interpolation models such as linear interpolation and geometric mean interpolation, frequency conversion models like the Litterman model and cubic interpolation model, and time series decomposition models such as the X-12-ARIMA model and TRAMO-SEATS model.

Data verification model group: This group includes the unit root test models such as the augmented Dickey–Fuller (ADF) test and Phillips–Perron (PP) test, cointegration test models such as the Engle–Granger two-step test and Johansen test, and causality test models like the Granger causality test.

Core model group: Includes models such as the autoregressive distributed lag (ADL) (p,q) model, long-term equilibrium model, ADL-TC (p,q) model for trend-cycle (TC) series, and non-linear Copula models.

3.2.2. Calculation Steps for the Electricity–Energy–Carbon Model in Energy Use

Step one, data imputation. Estimate the annual total energy consumption ($E1$) for each industry. Let E represent the annual total energy consumption for all major industry categories in the province, G represent the annual added value for all major industry categories, and $G1$ represent the annual production value for minor industry categories.

$$E1 = (E/G) * G1 \quad (1)$$

Step two, frequency conversion and series decomposition. Utilize frequency conversion models to transform annual energy consumption data into monthly series. Concurrently, employ the X-12-ARIMA model to decompose the original series of energy

consumption and electricity usage into trend-cycle (TCI), trend (TC), seasonal (S), and irregular (I) components.

Step three, model selection. After data imputation, frequency conversion, seasonal adjustment, and pre-modeling tests such as unit root, cointegration, and causality tests, estimate and select the monthly electricity–carbon models that relate total energy consumption to electricity usage for each industry. The specific types of models used include the following:

$$B(L)(\ln y_t) = \alpha_0 + A(L)(\ln x_t) + \varepsilon_t, B(L) = 1 - \gamma_1 L - \dots - \gamma_p L^p, A(L) = 1 + \alpha_1 L + \dots + \alpha_q L^q. \quad (2)$$

$$B(L)(y_{TCt}) = \alpha_0 + A(L)(x_{TCt}) + \varepsilon_t, B(L) = 1 - \gamma_1 L - \dots - \gamma_p L^p, A(L) = 1 + \alpha_1 L + \dots + \alpha_q L^q. \quad (3)$$

$$B(L)(\ln(y_{TCI_t})) = \alpha_0 + A(L)(\ln(x_{TCI_t})) + \varepsilon_t, B(L) = 1 - \gamma_1 L - \dots - \gamma_p L^p, A(L) = 1 + \alpha_1 L + \dots + \alpha_q L^q. \quad (4)$$

Gumbel–Copula:

$$F(y, x; \theta) = C(u, v) = \exp(-((- \ln u)^{1/\theta} + (- \ln v)^{1/\theta})^\theta), (\theta \geq 1); u = F_1(y), v = F_2(x). \quad (5)$$

Clayton–Copula:

$$F(y, x; \theta) = C(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}, (\theta > 0); u = F_1(y), v = F_2(x). \quad (6)$$

Gaussian–Copula:

$$F(y, x; \theta) = C(u, v) = \frac{1}{2\pi\sqrt{1-\theta^2}} \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \exp\left[\frac{-(\xi_1^2 - 2\theta\xi_1\xi_2 + \xi_2^2)}{2(1-\theta^2)}\right] d\xi_1 d\xi_2, (-1 \leq \theta \leq 1); \\ u = F_1(y), v = F_2(x). \quad (7)$$

In the context of the model setup, y represents the monthly energy consumption, while x stands for the monthly electricity consumption.

Step four, model selection criteria. The general criteria for model selection include adjusted R^2 , mean squared error (MSE), Akaike information criterion (AIC), Schwarz criterion (SC), and Hannan–Quinn criterion (HQ). Considering that the statistical bureau usually releases annual statistics in October of the following year, we employ a criterion that controls for generalization prediction error. Specifically, we select the optimal model based on maximizing the minimum generalization error, $\max(\min(E_i))$, where E represents the generalization error and i represents the observed individual.

Step five, calculation of adjustment factor F . Using the models described and monthly electricity consumption data, calculate the annual total monthly energy consumption for each industry. This total is denoted as $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_{12}$, which serves as the adjustment factor for the annual major industry categories across the province. The formula for calculating F is as follows:

$$F = \frac{E}{\sum_{t=1}^{12} \hat{y}_t} \quad (8)$$

Step six, calculation of monthly carbon emissions in energy usage. With the adjustment factor F and the carbon emission coefficient h for standard coal, calculate the monthly carbon emissions C_t for each industry. The formula is as follows:

$$C_t = \hat{E}_t \times F \times h \quad (9)$$

3.2.3. Calculation Steps for Electricity–Energy–Carbon Model of the Production Process

Step one, data imputation and frequency conversion: Utilize interpolation models to fill in missing monthly data for each industry based on historical monthly production data.

For industries with only annual production data available, apply frequency conversion models to transform these into monthly data.

Step two, series decomposition: Employ the X-12-ARIMA model to perform seasonal adjustments on the original series of industry production and electricity consumption. This adjustment isolates the seasonal factors (S) of each series, while also extracting the trend-cycle (TCI) components (production TCI series denoted as Y, and electricity consumption TCI series as X).

Step three, model selection: After conducting unit root tests, cointegration tests, and causality tests, estimate and select the monthly electricity–carbon models for each industry’s total energy consumption relative to electricity usage. The specific types of models used are similar to those mentioned in step three of the “Electricity–Energy–Carbon” model calculation steps for energy usage.

Step four, model selection criteria: Apply the same selection criteria as used in step four of the energy usage model calculation steps. These criteria typically include adjusted R^2 , MSE, AIC, SC, and HQ, focusing on minimizing generalization errors.

Step five, calculation of adjustment factor F : Calculate the adjustment factor F based on annual data of products and the estimated monthly production data derived from the models. Here, Y represents annual production data, and the derived monthly production data are denoted as $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_{12}$.

$$F = \frac{Y}{\sum_{t=1}^{12} \hat{y}_t} \quad (10)$$

Step six, calculation of carbon emissions in the production process: Assuming that the carbon emission coefficient for industry products is w , use the production data $\hat{y}_t$ obtained from the electricity–carbon model, along with the adjustment factor F , to calculate the monthly carbon emissions C_t for each industry’s production process. The formula can be expressed as follows:

$$C_t = \hat{y}_t \times w \times F \quad (11)$$

4. Results and Discussions

4.1. Carbon Emissions from Energy Use in Various Industries

Before results are formally introduced, the relationship between the energy consumption and carbon emission of various industries should be described first. According to the inventory method of the IPCC calculation formulas [5], the carbon emission of the industry includes two parts. One part is released from energy consumption which is calculated to CO_2 by the amount of energy consumption transformed to standard coal multiplied by the emission factor of standard coal. Another part is released from the production process of the products which is calculated to CO_2 by the amount of the industry product multiplied by the emission factor of this product.

Based on the “Electricity–Energy–Carbon” model design and calculation steps previously described, models were constructed using total energy consumption data for electricity usage across 34 industries. Using these optimal models and referring to the carbon emission parameter for standard coal released by the National Development and Reform Commission—2.66 tons CO_2 per ton of standard coal—the monthly carbon emissions for each industry were calculated. The results of monthly carbon emissions caused by energy use across 34 industries are shown in Table A2 (given in Appendix B).

From these results, several observations can be made:

Industrial Energy Consumption: Carbon emissions from industrial energy consumption in Henan Province account for more than half of the province’s total energy carbon emissions, with most months averaging around 60%.

Sub-industry emissions: The cumulative carbon emissions from 20 sub-industries account for approximately 50% of the total. Since 2023, there has been a significant increase to about 70%, exceeding the proportion of industrial energy carbon emissions. This phenomenon could be attributed to two factors:

Error propagation: A combination of data inaccuracies and model errors may lead to significant positive errors in individual months.

Energy conversion in the electricity sector: There may be an underestimation of the green electricity component in the energy conversion, leading to an overly high conversion factor, which results in the total carbon emissions from these 20 sub-industries surpassing those from the broader industrial sector.

Key industrial sectors: The petroleum chemical, non-ferrous, building materials, chemical, electricity, and steel sectors collectively contribute approximately 50% to the energy carbon emissions, with recent monthly proportions rising to about 65%.

Other significant industries: Industries such as transportation, storage and postal services, urban and rural residential life, manufacture of chemical raw materials and chemical products, and electricity have high proportions of provincial energy carbon emissions, nearly 10%. Among these, urban and rural residential life and the electricity sector have the highest shares, each accounting for about 15%.

The carbon emissions from energy consumption of industries with higher carbon emission shares are shown in Figure 1 as follows. The figure depicts the trend of monthly carbon emissions from the past two years for these main industries of carbon emissions.

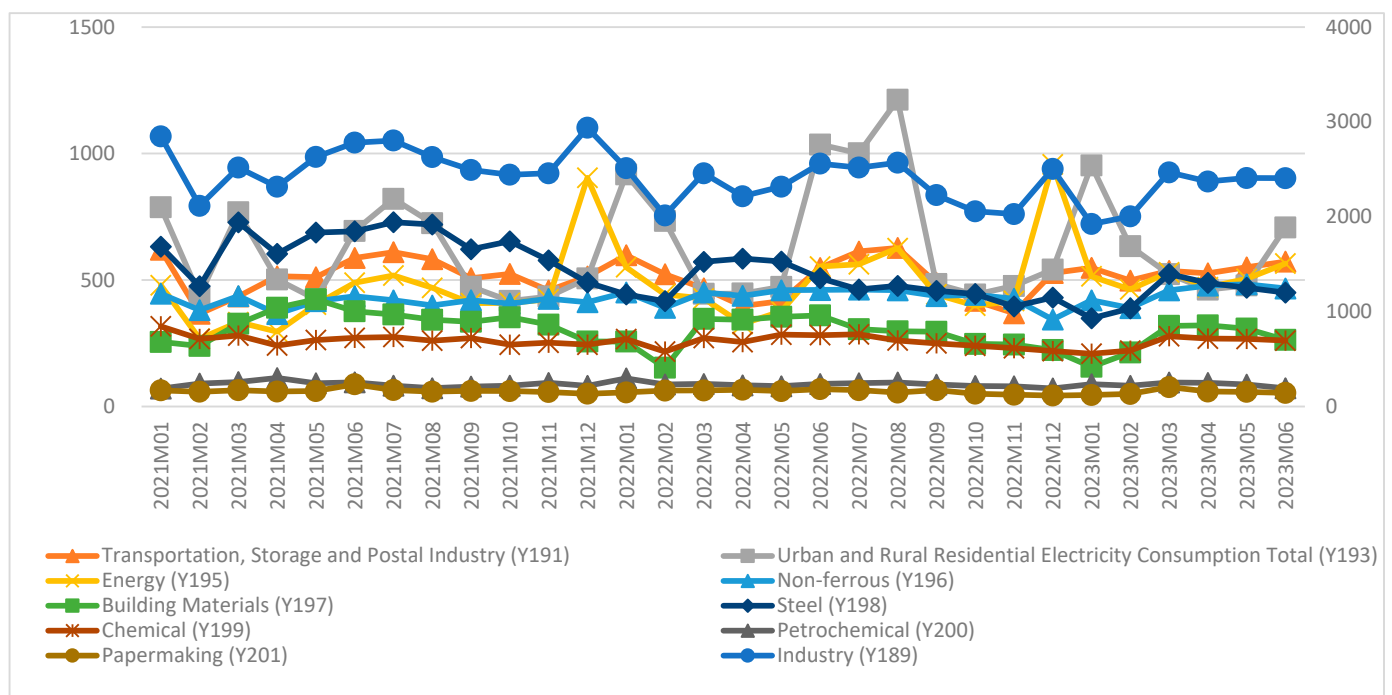


Figure 1. Sequence diagram of carbon emissions from industries with high proportions of energy consumption based on energy consumption data (unit: 10,000 tons CO₂). (Note: right axis: industrial (Y189); left axis: all other categories (Y191, Y193, Y195~Y201)).

As shown in Figure 1, aside from a significant upward trend in the electricity sector, other series—including the total provincial energy carbon emissions series—show stable development. Notably, the total provincial energy carbon emissions and the energy carbon emissions from urban and rural residential sectors exhibit clear seasonal fluctuations. Trend analysis indicates that the significant growth in the electricity sector is a fundamental cause of the observations noted in points two and three.

These insights highlight the dynamic interplay of industry-specific factors affecting carbon emissions in Henan Province, underscoring the need for targeted policies that address the specific needs and challenges of different sectors. This detailed analysis also aids in understanding the broader implications of energy use and carbon emissions within regional economic and environmental frameworks.

4.2. Carbon Emissions during Production Processes of Various Industries

Following the design and calculation steps of the “Electricity–Energy–Carbon” model for production processes, models were built using product output data from various sub-industries. Optimal models were achieved for 53 industries. With these models, monthly product output data across various industries was computed. To estimate the carbon emissions during the production processes of these products, carbon emission parameters for 53 industry products were collected, all based on the publicly available literature and data sources. By combining the product carbon emission parameters with the production data, the carbon emissions for each industry’s production process were calculated, as shown in Table A3 (given in Appendix C).

From these results, several observations can be made:

Total emissions: In 2022, the total carbon emissions from industrial production processes in Henan Province amounted to approximately 227 million tons of CO₂.

Major contributors: Six sub-industries accounted for a significant share of emissions: plastic products, cement, flat glass, steel, ten types of non-ferrous metals, and alumina. Combined, these industries emitted around 164 million tons of CO₂ in 2022, representing 72.3% of the total calculated emissions of 227 million tons.

Sub-industry breakdown: Within the high-emission sub-industries, cement was the largest contributor, accounting for 21.51% of emissions, followed by steel at 17.57%, flat glass and alumina at 11.51% and 10.6%, respectively, ten types of non-ferrous metals at 6.97%, and plastic products at 4.13%.

The carbon emissions of production processes of the six major sub-categories of industries in Henan Province are shown in Figure 2 as follows. The figure depicts the trend of monthly carbon emissions from the past two years for these six major sub-industries.

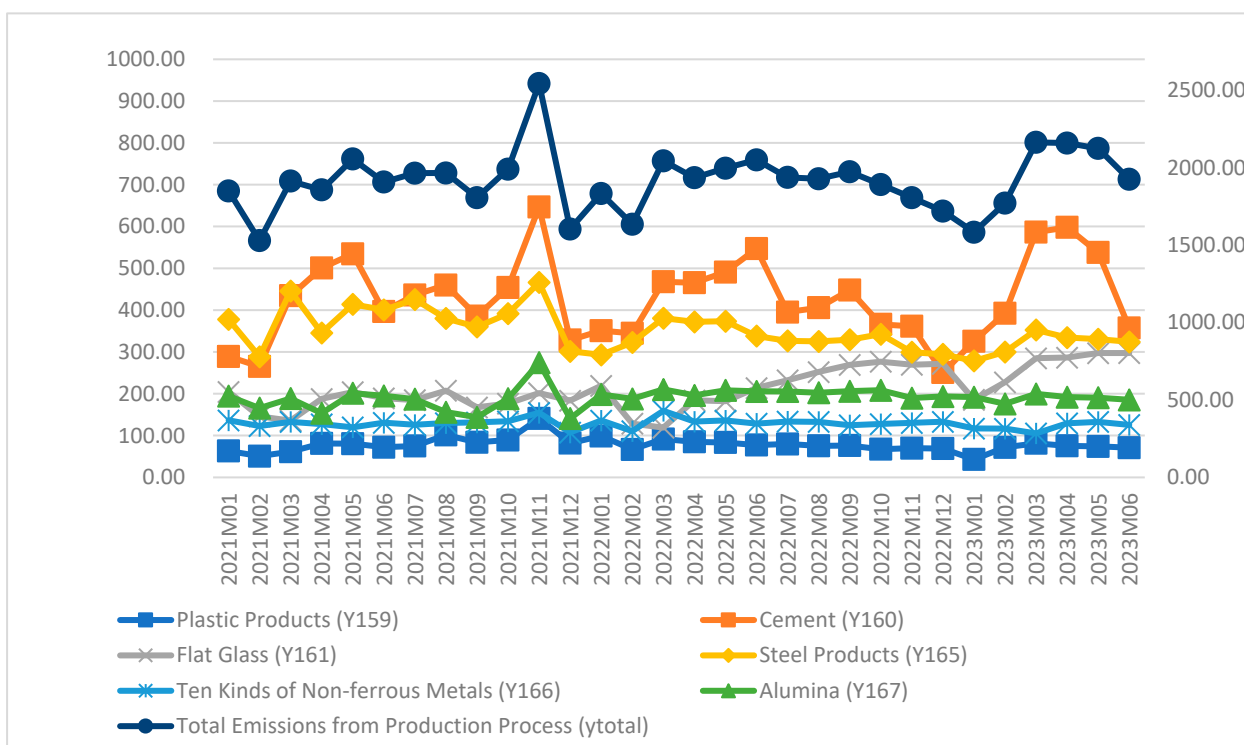


Figure 2. Monthly trend chart of carbon emissions for products of six major subcategories in Henan Province and the provincial production process (unit: 10,000 tons CO₂). (Note: right axis: total emissions from production process (Ytotal); left axis: all other categories (Y159~Y161, Y165~Y167)).

Key observations from the figure include the following:

Overall trends: The total carbon emissions from production processes (YTOTAL) and cement production emissions show strong volatility. An anomaly was noted in November

2021, where the total production emissions spiked. An analysis of Henan's economic performance in November 2021 indicated that despite the pandemic's impact, the province's industrial added value grew by 2.7%, with strategic emerging industries and high-tech manufacturing growing by 5.3% and 10.7% year-over-year, respectively. Electricity consumption for the month stood at 275.95 billion kWh, up by 11.22% year-over-year, with industrial electricity consumption increasing by 10.59%. The steady recovery in traditional energy-intensive industries like building materials, black and non-ferrous metals, and chemicals, along with high growth in emerging manufacturing sectors such as general equipment, electrical machinery, and automobiles, significantly boosted electricity consumption. These factors contributed to the monthly spike in carbon emissions, highlighting the rapid industrial growth during this period.

Flat glass emissions: The carbon emissions from the flat glass production process showed a clear upward trend, while other industries maintained a more stable emission trend.

This detailed analysis provides insights into the factors influencing carbon emissions across various industries, emphasizing the significant impact of industrial activity and energy consumption on the province's overall carbon footprint. Such data are crucial for developing targeted environmental policies and strategies to mitigate the impact of industrial production on climate change.

5. Conclusions and Future Prospects

This study developed and applied an "Electricity–Energy–Carbon" model for key industries in Henan Province based on external statistical data to estimate carbon emissions from energy consumption and production processes. The preliminary conclusions are as follows:

Industrial carbon emissions: Carbon emissions from industrial energy consumption in Henan Province account for more than half of the province's total energy-related carbon emissions, with most months around 60%. The 20 main sub-industries within the industrial sector nearly account for about 50% of the total provincial energy carbon emissions. Among these, the energy, non-ferrous metals, building materials, steel, chemical, petrochemical, and paper industries alone contribute over 80% of the industrial sector's emissions, with many months nearing 90%. The petroleum chemical, non-ferrous, building materials, chemical, electricity, and steel sectors together account for about 50% of the total provincial energy carbon emissions.

Stability and trends in carbon emissions: Most industries show a stable trend in energy consumption carbon emissions, except for a few that exhibit noticeable seasonal fluctuations. The overall production processes and cement production specifically display strong volatility in carbon emissions, while flat glass production shows a significant upward trend in monthly carbon emissions. Other industries' production-related emissions trends are relatively stable.

Total production-related carbon emissions: The total carbon emissions from production processes in Henan Province are approximately 227 million tons. Six sub-industries contribute significantly to this total, namely plastic products, cement, flat glass, steel, ten types of non-ferrous metals, and alumina, accounting for about 72.3% of the total emissions from production processes.

Future Prospects:

Application level: One of the main areas for future work involves collecting data at the corporate level to apply the "Electricity–Energy–Carbon" model for enterprise carbon emission calculations. The results can then be validated against annual corporate audits. This will potentially provide a case study for widespread, low-cost carbon emission calculations across enterprises.

Methodological and theoretical enhancements: Building on the current research, there is an opportunity to integrate machine learning theories to automate the optimization and selection of models, thereby enhancing the intelligence level of future industrial carbon emission calculations.

Combining with the above future prospects, there are obviously two limitations of our present work. The first is that our method cannot be directly used to measure the enterprises' carbon emission, so we cannot ensure the effectiveness of our method when it faces the high volatility of enterprises' data. The second is that our whole work including model selection, data preprocess, and result computation takes a long time, so our work cannot be widely spread due to the lack of automatic selection and automatic computation.

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Appendix A

Table A1. Starting statistics table for industrial electricity consumption data.

Industry	Electricity Consumption Period
Other Subcategories Industries	January 2009–December 2022
General Equipment Manufacturing Industry	
Automobile Manufacturing Industry	
Railway, Shipbuilding, Aerospace, and Other Transport Equipment Manufacturing Industry	
Electrical Machinery and Equipment Manufacturing Industry	January 2017–December 2022
Computer, Communication, and Other Electronic Equipment Manufacturing Industry	
Instrument and Apparatus Manufacturing Industry	
Computer, Communication, and Other Electronic Equipment Manufacturing Industry	
Instrument and Apparatus Manufacturing Industry	

Appendix B

Table A2. Monthly carbon emissions results for 34 industries calculated based on the electricity–energy–carbon model (unit: 10,000 tons CO₂).

Major Category	Industry Name	ID	2022 (Monthly)													2023 (Monthly)					
			January	February	March	April	May	June	July	August	September	October	November	December	Total	January	February	March	April	May	June
Province-wide	Total Energy Consumption of the Province	Y101	5937.93	4856.16	5040.74	4613.14	4885.54	6643.75	6483.63	7064.76	5077.76	4560.60	4501.61	5621.18	65,286.78	5475.30	5069.74	4925.13	4537.75	4655.19	5231.79
	I. Agriculture, Forestry, Animal Husbandry, and Fishery	Y102	131.41	118.91	158.13	185.87	191.22	370.35	212.03	325.83	187.53	157.79	140.95	160.08	2331.38	169.75	174.40	217.11	151.13	166.13	241.98
7 Major Industries	II. Industry	Y103	3509.75	2644.75	3199.90	2972.53	3144.99	3532.18	3518.85	3632.84	3140.24	2921.84	2884.02	3135.37	38,288.31	2794.28	2870.90	3055.45	2878.36	2887.25	2924.37
	III. Construction	Y104	138.35	100.29	63.47	90.25	94.59	134.95	135.18	145.30	99.11	86.65	96.32	138.65	1322.48	97.91	102.86	95.09	84.06	85.66	102.65
	IV. Transportation, Warehousing, and Postal Services	Y105	533.68	561.09	286.56	360.47	380.57	508.69	576.75	600.29	468.21	405.29	360.75	528.61	5574.20	557.79	505.51	475.68	463.68	484.85	517.36
	V. Wholesale and Retail Trade, Accommodation and Catering	Y106	364.76	324.11	232.98	245.87	271.55	463.78	477.83	512.44	354.98	267.47	245.14	369.86	4122.78	411.02	370.05	312.82	291.43	321.34	413.79
	Urban and Rural Resident Life	Y107	914.65	776.01	986.57	559.32	588.49	1289.48	1243.25	1506.23	591.81	538.17	575.53	1012.31	10,543.00	1164.14	762.61	544.32	473.04	486.55	734.41
	Other	Y108	345.32	331.00	113.13	198.83	214.12	344.32	319.74	341.83	235.87	183.39	198.91	276.29	3104.63	280.42	283.40	224.65	196.06	223.41	297.22
	3. Mining of Ferrous Metals (Iron and Steel 1)	Y109	1.88	2.32	2.28	1.93	2.05	1.94	1.94	1.83	1.82	1.75	1.87	2.02	23.62	1.45	1.54	1.76	1.76	1.87	1.80
	4. Mining of Non-ferrous Metals (Non-ferrous 1)	Y110	5.91	3.86	5.83	5.31	5.64	5.38	5.50	5.71	5.40	5.66	5.79	6.29	66.28	5.47	5.36	5.95	5.65	5.81	5.55
	5. Mining of Non-metallic Minerals (Building Materials)	Y111	1.30	1.30	1.37	1.09	1.16	1.13	1.14	1.13	1.17	0.96	1.17	1.35	14.28	0.63	0.96	1.31	1.35	1.28	1.22
	5. Textile Industry	Y112	18.39	14.11	18.61	15.57	15.75	15.47	14.75	14.89	16.12	14.97	14.72	13.44	186.79	11.49	16.28	18.51	17.97	18.70	17.70
	6. Textile and Apparel Industry	Y113	2.35	2.20	2.71	1.98	2.12	2.55	2.63	2.68	2.31	2.10	1.96	2.15	27.74	1.39	2.28	2.52	2.38	2.44	2.58
	13. Petroleum, Coal, and Other Fuel Processing Industries	Y114	90.56	77.11	103.76	84.47	82.74	89.60	92.30	94.21	89.99	86.30	86.46	108.35	1085.86	99.47	95.59	99.58	97.75	90.35	74.95
	14. Manufacture of Chemical Raw Materials and Chemical Products	Y115	468.81	485.57	598.31	479.13	548.62	532.20	541.35	488.95	486.85	482.16	449.31	476.24	6037.50	431.59	429.65	487.10	476.82	477.05	468.21
	16. Manufacture of Chemical Fibers (Chemical Industry 2)	Y116	11.41	11.40	15.18	13.54	12.41	13.48	12.79	10.82	13.22	10.40	9.45	9.13	143.23	9.02	10.03	13.84	11.08	11.35	11.17
	17. Rubber and Plastic Products Industry (Chemical Industry 3)	Y117	9.87	6.91	9.89	9.20	9.45	9.10	9.76	9.51	9.63	8.61	8.97	8.87	109.77	5.73	9.35	10.47	9.61	9.39	8.89
20 Selected Subcategories in Industry	18. Non-metallic Mineral Products Industry (Building Materials)	Y118	228.28	187.73	262.43	310.04	326.87	329.62	287.50	285.06	301.38	259.90	257.28	211.02	3247.11	169.74	239.26	325.50	331.23	321.73	277.04
	19. Smelting and Rolling Processing Industry of Ferrous Metals	Y119	311.88	329.61	411.18	422.01	419.41	365.33	341.34	357.79	362.50	360.53	318.42	318.47	4318.48	284.39	327.27	400.87	375.12	360.66	346.80
	20. Smelting and Rolling Processing Industry of Non-ferrous Metals	Y120	332.51	299.94	366.45	329.86	346.85	339.08	344.85	342.62	341.54	348.75	332.25	341.33	4066.03	327.02	310.50	329.28	345.75	349.89	338.97
	22. General Equipment Manufacturing Industry	Y121	7.59	5.47	8.13	7.11	6.03	6.26	6.53	6.31	5.89	5.22	5.11	5.09	74.75	3.81	5.21	5.65	5.28	4.97	4.79
	24. Automobile Manufacturing Industry	Y122	12.00	10.07	10.30	8.53	8.94	10.49	11.59	11.53	10.55	9.80	9.92	9.89	123.61	7.24	9.91	11.06	10.18	10.82	11.84
	25. Railway, Shipbuilding, Aerospace, and Other Transport Equipment	Y123	1.56	1.48	1.92	1.45	1.35	1.48	1.54	1.40	1.14	0.91	0.81	0.64	15.69	0.36	0.34	0.29	0.18	0.16	0.15
	Manufacturing Industry																				
	26. Electrical Machinery and Equipment	Y124	12.82	9.14	13.96	12.03	11.25	12.59	15.64	17.04	18.30	20.71	24.94	31.02	199.46	30.14	51.44	81.40	108.43	156.55	289.86
	Manufacturing Industry																				
	27. Computer, Communication, and Other Electronic Equipment	Y125	9.39	8.64	12.96	9.81	10.52	11.35	12.67	13.37	12.14	11.27	9.51	10.37	132.00	9.04	8.33	8.27	6.96	7.36	7.64
	Manufacturing Industry																				
	28. Instrument and Apparatus	Y126	1.00	0.81	0.72	0.82	0.87	0.98	1.03	0.99	0.85	0.70	0.74	0.80	10.31	0.54	0.73	0.82	0.76	0.80	0.91
	Manufacturing Industry																				
	1. Production and Supply of Electricity and Heat	Y127	1105.87	990.53	1007.68	821.57	909.78	1241.23	1265.63	1363.79	1052.57	953.13	976.61	1176.21	12,864.61	1897.70	1712.92	1735.39	1500.97	1602.55	1805.13
	3. Production and Supply of Water	Y128	4.04	3.87	4.70	4.04	4.35	4.30	4.30	4.33	4.02	3.92	3.83	4.06	49.76	4.17	4.01	4.48	4.61	4.85	4.73

Table A2. Cont.

Major Category	Industry Name	ID	2022 (Monthly)												2023 (Monthly)						
			January	February	March	April	May	June	July	August	September	October	November	December	Total	January	February	March	April	May	June
Total of 20 Subcategories			2637.41	2452.06	2858.39	2539.49	2726.19	2993.56	2974.80	3033.96	2737.40	2587.76	2519.12	2736.74	32,796.88	3300.40	3240.96	3544.05	3313.84	3438.60	3679.93
6 Major Sector Industries	Petroleum Petrochemical	Y129	99.47	90.80	120.74	96.40	99.40	102.54	105.78	106.75	100.06	96.53	93.80	112.40	1224.68	104.36	98.46	102.44	103.30	99.74	87.03
	Non-ferrous Building Materials	Y130	339.93	300.78	372.15	335.42	353.14	344.96	351.23	350.32	348.36	356.71	341.89	353.04	4147.93	336.36	320.43	341.34	356.34	361.43	350.21
	Chemical	Y131	229.53	190.71	262.65	305.72	322.25	324.33	283.83	281.05	296.49	254.84	253.48	210.39	3215.28	165.58	233.53	317.18	322.31	312.39	269.44
	Electricity	Y132	490.74	475.26	601.90	497.92	553.71	540.16	553.12	505.55	510.83	491.67	467.49	487.88	6176.24	421.34	458.52	524.63	502.02	500.91	488.67
	Steel	Y134	1105.87	990.53	1007.68	821.57	909.78	1241.23	1265.63	1363.79	1052.57	953.13	976.61	1176.21	12,864.61	1897.70	1712.92	1735.39	1500.97	1602.55	1805.13
Total of Six Major Sectors			3155.04	3353.39	4147.70	4230.01	4210.06	3675.53	3439.96	3590.05	3632.26	3605.53	3201.12	3207.70	43442.82	2839.79	3252.24	3969.95	3716.62	3578.86	3436.63
			2581.04	2383.47	2779.83	2480.04	2659.33	2920.75	2903.56	2966.51	2671.58	2513.41	2453.39	2660.62	31,973.54	3209.13	3149.10	3417.94	3156.56	3234.87	3344.11

Appendix C

Table A3. Monthly carbon emission results list during the production process of 53 subcategories of industries (unit: 10,000 tons).

Subcategory Industry Names	Production Categories	ID	2022 (Monthly)													2023 (Monthly)					
			January	February	March	April	May	June	July	August	September	October	November	December	Total	January	February	March	April	May	June
Raw Coal Production	Raw Coal Production	Y135	44.60	37.55	64.38	41.78	43.80	46.50	43.93	43.67	39.11	37.20	37.09	38.94	518.55	38.10	38.24	40.76	39.37	38.59	39.09
Oil and Natural Gas Extraction	Crude Oil Production	Y136	0.95	1.15	1.51	1.15	1.43	1.30	1.39	1.40	1.28	1.30	1.19	1.26	15.31	1.26	1.15	1.23	1.40	1.57	1.58
	Natural Gas Production	Y137	0.09	0.10	0.14	0.10	0.13	0.12	0.12	0.12	0.11	0.11	0.10	0.11	1.34	0.10	0.09	0.10	0.11	0.12	0.12
Ferrous Metal Mining and Dressing Industry	Iron Ore Raw Ore Production	Y138	3.03	3.79	3.79	3.25	3.53	3.42	3.51	3.40	3.48	3.43	3.78	4.19	42.61	3.09	3.35	3.91	4.00	4.33	4.24
Non-metallic Mineral Mining and Dressing Industry	Phosphate Rock (Equivalent to 30% P ₂ O ₅) Production	Y139	4.34	4.35	4.57	3.65	3.94	3.85	3.93	4.01	4.26	3.61	4.57	5.49	50.57	2.67	4.29	6.13	6.48	6.36	6.23
	Raw Salt Production	Y140	0.15	0.22	0.22	0.29	0.34	0.33	0.30	0.57	0.56	0.62	0.69	0.84	5.12	0.75	1.26	1.45	2.17	2.69	2.71
Textile Industry	Yarn Production	Y141	16.31	12.51	16.47	13.76	13.91	13.65	13.02	13.15	14.25	13.26	13.06	11.96	165.29	10.25	14.57	16.62	16.19	16.93	16.10
	Cloth Production	Y142	4.95	3.78	4.95	4.11	4.11	3.99	3.75	3.73	3.99	3.65	3.54	3.19	47.73	2.70	3.79	4.28	4.12	4.27	4.02
Textile and Apparel Industry	Apparel Production	Y143	4.11	3.84	4.76	3.51	3.84	4.72	5.02	5.34	4.86	4.72	4.77	5.77	55.25	4.16	7.59	9.31	9.75	11.11	12.94
Petroleum Processing, Coking, and Nuclear Fuel Processing Industry	Crude Oil Processing Capacity	Y144	4.79	3.20	6.89	4.98	4.84	4.94	4.89	4.94	5.09	4.70	4.38	4.57	58.20	4.59	4.58	4.66	4.92	3.93	2.04
	Gasoline Production	Y145	1.17	0.78	1.68	1.20	1.15	1.13	1.07	1.02	0.97	0.81	0.66	0.59	12.24	0.49	0.40	0.31	0.26	0.16	0.06
	Kerosene Production	Y146	0.29	0.20	0.42	0.31	0.30	0.30	0.30	0.31	0.31	0.29	0.27	0.28	3.59	0.28	0.28	0.29	0.30	0.24	0.13
	Diesel Production	Y147	1.20	0.82	1.80	1.34	1.35	1.43	1.48	1.56	1.69	1.65	1.63	1.81	17.76	1.94	2.07	2.25	2.54	2.16	1.20
	Coke Production	Y148	7.71	7.36	7.34	6.48	6.27	6.95	7.19	7.24	6.42	6.20	6.41	8.77	84.34	7.55	7.00	7.33	6.81	6.89	6.92
Chemical Raw Materials and Chemical Products Manufacturing Industry	Sulfuric Acid (100% Basis) Production	Y149	35.95	38.99	40.49	37.26	43.18	42.56	42.86	38.65	37.93	36.75	34.58	35.06	464.27	29.12	30.11	34.12	33.85	35.98	33.10
	Caustic Soda (100% Basis) Production	Y150	13.90	9.11	17.95	12.86	14.16	13.51	14.97	13.19	12.27	11.77	10.62	10.93	155.22	11.42	10.85	11.32	10.96	9.79	9.78
	Soda Ash (Sodium Carbonate) Production	Y151	33.52	22.00	43.50	31.30	34.65	33.28	37.12	32.98	30.91	29.90	27.20	28.21	384.57	29.74	28.46	29.93	29.17	26.19	26.30
	Ethylene Production	Y152	10.03	8.44	9.30	7.50	8.73	9.35	8.46	7.10	7.09	6.15	5.74	5.10	92.98	5.14	3.96	4.15	3.26	3.79	4.15
	Synthetic Ammonia Production	Y153	40.38	44.23	46.82	44.32	53.28	54.89	58.21	55.60	58.10	60.16	60.63	65.91	642.53	58.66	64.87	78.37	82.53	92.69	89.62

Table A3. Cont.

Subcategory Industry Names	Production Categories	ID	2022 (Monthly)														2023 (Monthly)					
			January	February	March	April	May	June	July	August	September	October	November	December	Total	January	February	March	April	May	June	
Chemical Raw Materials and Chemical Products Manufacturing Industry	Agricultural Nitrogen, Phosphorus, and Potassium Fertilizer (Pure Basis) Production	Y154	24.61	32.49	36.93	26.27	30.01	28.17	26.40	23.81	25.09	25.65	23.35	26.32	329.11	23.66	22.42	26.27	24.69	23.49	24.75	
	Chemical Pesticide Production	Y155	4.35	4.75	5.00	4.70	5.58	5.68	5.95	5.62	5.82	5.96	5.95	6.41	65.79	5.66	6.20	7.42	7.75	8.66	8.37	
	Primary Form Plastic Production	Y156	43.84	47.49	49.20	45.13	52.05	50.98	50.93	45.49	44.18	42.35	39.47	39.72	550.84	32.85	33.97	38.69	38.76	41.81	39.18	
	Synthetic Detergent Production	Y157	4.64	5.10	5.41	5.14	6.20	6.40	6.79	6.48	6.76	6.95	6.93	7.41	74.21	6.45	6.92	8.06	8.12	8.68	7.97	
Chemical Fiber Manufacturing Industry	Chemical Fiber Production	Y158	9.34	9.32	12.40	11.05	10.10	10.94	10.34	8.70	10.57	8.26	7.44	7.14	115.59	7.00	7.73	10.61	8.46	8.63	8.47	
Rubber and Plastic Products Industry	Plastic Products Production	Y159	98.86	66.71	91.64	84.98	83.33	77.34	79.74	75.39	76.17	67.36	69.86	68.84	940.22	42.87	71.75	81.46	75.32	74.01	71.06	
Non-metallic Mineral Products Industry	Cement Production	Y160	350.82	344.52	467.82	465.46	490.93	547.04	395.15	405.69	447.77	365.90	361.27	250.80	4893.18	325.57	392.58	586.49	598.02	537.73	357.28	
	Flat Glass Production	Y161	219.11	128.60	119.25	184.30	181.91	213.81	232.24	251.96	269.16	276.82	269.44	271.69	2618.30	185.71	227.60	284.92	286.59	297.19	297.66	
Ferrous Metals Smelting and Rolling Processing Industry	Pig Iron Production	Y162	234.88	258.77	305.37	298.48	300.00	271.56	262.25	261.21	264.35	274.71	240.10	235.72	3207.39	223.17	239.94	281.94	267.17	264.03	258.65	
	Crude Steel Production	Y163	219.31	243.51	290.58	288.16	294.67	272.40	269.56	274.90	285.98	305.43	273.98	276.45	3294.91	267.75	294.47	352.33	339.17	338.64	334.44	
	Finished Steel Products Production	Y164	293.39	323.43	381.68	373.19	375.21	339.88	328.46	327.16	331.42	344.55	301.26	296.07	4015.70	280.39	301.82	354.79	336.66	333.02	326.72	
	Steel Products Production	Y165	293.00	322.72	380.63	371.78	373.39	337.94	326.50	325.07	329.22	342.35	299.38	294.33	3996.31	278.80	299.96	352.56	334.36	330.48	323.95	
Non-ferrous Metals Smelting and Rolling Processing Industry	Ten Kinds of Non-ferrous Metals Production	Y166	136.10	110.51	159.42	133.35	136.02	128.62	133.63	132.85	124.82	127.64	130.25	133.01	1586.23	116.87	116.57	105.39	129.33	132.82	125.58	
	Alumina Production	Y167	198.32	187.76	210.27	196.09	208.27	205.66	205.54	202.52	206.07	208.40	189.74	193.49	2412.12	191.92	175.79	199.54	192.01	190.62	185.40	
	Primary Aluminum (Electrolytic Aluminum) Production	Y168	24.37	23.15	26.06	24.47	26.20	26.10	26.34	26.22	26.95	27.54	25.32	26.06	308.79	26.08	24.06	27.49	26.58	26.47	25.80	
	Copper Products Production	Y169	13.98	11.37	16.46	13.85	14.23	13.59	14.28	14.38	13.72	14.26	14.81	15.41	170.32	13.81	14.06	12.99	16.29	17.11	16.55	
	Aluminum Products Production	Y170	144.76	137.47	154.70	145.28	155.62	155.17	156.69	156.04	160.43	163.83	150.48	154.61	1835.08	154.29	141.97	161.65	155.82	154.75	150.40	
General Equipment Manufacturing Industry	Industrial Boilers Production	Y171	1.66	1.20	1.82	1.59	1.36	1.42	1.49	1.44	1.34	1.19	1.17	1.17	16.85	0.86	1.16	1.23	1.14	1.07	1.03	
	Engine Production	Y172	5.02	3.64	5.58	4.91	4.30	4.52	4.94	4.81	4.78	4.25	4.57	4.44	55.78	3.76	4.74	6.18	4.86	6.13	4.24	
	Metal Cutting Machine Tool Production	Y173	0.02	0.02	0.03	0.03	0.02	0.03	0.03	0.04	0.04	0.04	0.05	0.05	0.40	0.04	0.07	0.08	0.08	0.07	0.07	
	Crane Production	Y174	3.86	2.82	4.32	3.88	3.43	3.74	4.16	4.33	4.41	4.36	4.85	5.55	49.71	4.82	7.77	10.03	11.31	12.89	15.04	
	Packaging Equipment Production	Y175	0.06	0.04	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.60	0.04	0.05	0.06	0.06	0.06	0.06	
Automobile Manufacturing Industry	Automobile Production	Y176	37.22	31.39	32.36	27.12	28.85	34.50	39.02	39.85	37.53	35.93	37.61	38.83	420.20	29.48	41.87	48.47	46.33	51.02	57.65	
Railway, Shipbuilding, Aerospace, and Other Transport Equipment Manufacturing Industry	Civil Steel Ship Production	Y177	2.14	2.19	2.91	2.26	2.11	2.41	2.74	2.94	2.74	2.51	2.77	2.63	30.36	1.90	2.60	3.07	2.48	2.63	2.63	

Table A3. Cont.

Subcategory Industry Names	Production Categories	ID	2022 (Monthly)													2023 (Monthly)					
			January	February	March	April	May	June	July	August	September	October	November	December	Total	January	February	March	April	May	June
Electrical Machinery and Equipment Manufacturing Industry	Generator Set (Power Generation Equipment) Production	Y178	10.59	7.57	11.64	9.88	9.01	9.70	11.39	11.47	11.14	11.03	11.29	11.41	126.12	8.68	11.32	13.17	12.25	11.38	12.47
	AC Motor Production	Y179	29.08	20.92	32.05	27.28	24.83	26.59	30.93	30.75	29.34	28.53	28.54	28.20	337.06	20.98	26.59	30.19	27.27	24.85	26.73
	Lithium Ion Battery Production	Y180	6.34	4.51	6.78	5.72	5.19	5.55	6.50	6.56	6.40	6.43	6.69	6.98	73.66	5.57	7.62	9.37	9.15	9.02	10.48
	Domestic Refrigerator Production	Y181	4.70	3.32	4.95	4.07	3.55	3.65	4.07	3.89	3.61	3.43	3.39	3.33	45.96	2.49	3.21	3.68	3.40	3.16	3.46
	Domestic Freezer (Home Freezer) Production	Y182	1.38	0.97	1.44	1.18	1.03	1.06	1.18	1.13	1.03	0.97	0.93	0.89	13.17	0.65	0.81	0.91	0.81	0.74	0.80
	Room Air Conditioner Production	Y183	14.66	10.49	16.04	13.62	12.41	13.35	15.66	15.75	15.25	15.07	15.34	15.49	173.14	11.77	15.32	17.85	16.58	15.53	17.14
	Domestic Washing Machine Production	Y184	0.84	0.60	0.91	0.78	0.72	0.78	0.92	0.93	0.90	0.89	0.90	0.90	10.07	0.69	0.89	1.03	0.95	0.88	0.96
Computer, Communication, and Other Electronic Equipment Manufacturing Industry	Mobile Communication Handset (Mobile Phone) Production	Y185	64.19	46.65	63.91	45.15	36.34	42.12	46.04	39.89	33.55	28.81	21.52	24.11	492.27	20.64	18.12	18.04	16.09	17.54	17.35
	Color TV Production	Y186	0.89	0.83	1.25	0.95	1.04	1.12	1.26	1.35	1.24	1.17	1.00	1.11	13.21	0.98	0.93	0.96	0.83	0.90	0.98
Instrument and Apparatus Manufacturing Industry	Electrical Instrument Production	Y187	0.82	0.67	0.60	0.69	0.73	0.83	0.89	0.86	0.75	0.63	0.67	0.73	8.89	0.50	0.69	0.78	0.73	0.78	0.90

Explanation 1: When calculating the total, Y162, Y163, Y164 are excluded because there is double counting with Y165. Explanation 2: When calculating the total, Y167 and Y170 are double counted, so we can take Y167 here.

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