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Provincial allocation of carbon emission reduction targets in China: An approach based on improved fuzzy cluster and Shapley value decomposition

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Abstract: An approach to determine carbon emission reduction target allocation based on the particle swarm optimization (PSO) algorithm, fuzzy c-means (FCM) clustering algorithm, and Shapley decomposition (PSO-FCM-Shapley) is proposed in this study. The method decomposes total carbon emissions into an interaction result of four components (i.e., emissions from primary, secondary, and tertiary industries, and from residential areas) which composed totally by 13 macro influential factors according to the KAYA identity. Then, 30 provinces in China are clustered into four classes according to the influential factors via the PSO-FCM clustering method. The key factors that determine emission growth in the provinces representing each cluster are investigated by applying Shapley value decomposition. Finally, based on guaranteed survival emissions, the reduction burden is allocated by controlling the key factors that decelerate CO_2 emission growth rate according to the present economic development level, energy endowments, living standards,

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and the emission intensity of each province. A case study of the allocation of CO_2 intensity reduction targets in China by 2020 is then conducted via the proposed method. The per capita added value of the secondary industry is the primary factor for the increasing carbon emissions in provinces. Therefore, China should limit the growth rate of its secondary industry to mitigate emission growth. Provinces with high cardinality of emissions have to shoulder the largest reduction, whereas provinces with low emission intensity met the minimum requirements for emission in 2010. Fifteen provinces are expected to exceed the national average decrease rates from 2011 to 2020.

Keywords: carbon emission reduction; targets allocation; Shapley decomposition

1. Introduction

Global warming is one of the most important environmental issues that needs to be addressed. Thus, numerous countries are exerting continuous effort to reduce their greenhouse gas (GHG) emissions (Zhang and Cheng, 2009; Soytas and Sari, 2009). In late 2009, the Chinese government has committed to reduce its CO_2 emission per unit gross domestic product (GDP) by 40% to 45% from the 2005 levels by 2020. This commitment has been declared as a restrictive target in the 12th Year Plan of China's Economic Development. This initiative is a response to global climate changes and an action that embodies the responsibility of the State. Moreover, it is an opportunity to change the pattern of development in the country. China, as the second largest economy and the biggest contributor of carbon emissions in the world (IEA, 2011), must implement its national commitment by apportioning tasks to different major responsible bodies, such as sectors, provinces, and industries. Allocation, implementation, monitoring, and evaluation are effective when they are apportioned to provincial administrative areas under the Chinese centralized management system. However, the energy-saving target allocation in the 11th Five-year Plan is arbitrary[1]. Therefore, to achieve the 2020 carbon intensity abatement target successfully, the goal must be delegated among different provinces under the principle of "common but differentiated responsibility" and according to economic development level, economic structure, and emission growth factors.

Several scholars have conducted in-depth studies on the permitted emission allocation for countries before and after the signing of the Kyoto Protocol. All countries have a consistent emission reduction rate (Grübler, 1994). This view is generally accepted previously but is now opposed by emerging industrialized countries. The per capita emission-based allocation scheme, which reflects the concept that everyone possesses equal emission rights, has received considerable attention(Grubb, 1990; Gupta and Bhandari, 1999). However, this concept has been contradicted by several developed countries with high per capita emissions. This view is an important consideration in the latter part of the multistage and multi-index distribution model or scheme. The per unit GDP-based emission allocation method, in which all countries are assumed to have similar emissions per unit GDP, is considered as an efficient solution (Phylipsen et al., 1998). This concept remains controversial and is opposed by both large developing countries and countries with a small GDP although it reflects the importance of emission reduction potential in the economic structure. Nevertheless, this idea remains an important reference for integrated

[1]The provincial allocation of energy-saving targets in the 11th Five-year Plan relies on the proposal of each province to realize the 20% national government target. However, several provinces did not achieve the annual 4.3% energy-saving rate at the beginning of 2006 because of lack of proper understanding regarding the target (Zhou, 2011). As a result, allocating energy-saving targets in subsequent years has become difficult, and these provinces have requested for a reduction in the pre-allocated goals. For example, Shanxi, Inner Mongolia, and Jilin have requested for a reduction from the original targets of 25%, 25%, and 30%, respectively, to 22%.

models that have been developed later because the cost and efficiency of carbon reduction must be considered.

A number of comprehensive and complex allocation models and schemes have been developed based on these early allocation methods. The recent models consider both the characteristics and shortcomings of the previous schemes. The rationality and acceptability of these models have been significantly improved. However, the complexity of their operation has also increased significantly. Phylipsen *et al*. (1998) propose an equal-weighted sum model that integrates three indices: per capita CO_2 emissions, per capita GDP, and CO_2 emissions per unit GDP. Baumert (1999) argues that emission reduction obligations should be determined by considering historical GHG emission trends. Different allocation plans are available based on abatement costs. For example, Edwards and Hutton (2001) study abatement costs among different industries in the United Kingdom based on the computable general equilibrium model. Elzen (2005) compares and analyzes the abatement costs of three types of allocation plans based on the FAIR 2.0 model. The Swedish Stockholm Environment Institute proposes the Greenhouse Development Rights plan (Baer, 2007), which includes a comprehensive analysis index to quantify the ability and responsibility of a country to allocate global emission reduction. This index is calculated by multiplying the per capita accumulated CO2 emissions of a country by its income. The Triptych sectoral approach (Phylipsen, 1998), which is a bottom-up and sector-based allocation model that considers the energy structure, efficiency, and welfare of a sector, has been subjected to a fair amount of attention and has become the primary emission allocation method of the European Union. The Triptych approach has improved significantly since its introduction. A number of improved Triptych methods have been proposed, such as the global Triptych permit allocation

(Groenenberg, 2004) and the Triptych-based multistaged commitment (Den et al., 2008). Several influential models or schemes have been proposed recently, such as the multistage approach (Michel et al., 2009), the contraction and convergence approach (Böhringer and Welsch, 2004; Persson et al., 2006), the per capita cumulative emission-based scheme (Ding et al., 2009), and the high-income group proportion-based plan (Ekholm, 2010). However, these methods or schemes mainly focus on addressing the discrepancies between the emission reductions of developed and developing countries.

To allocate the national emission reduction burden rationally across Chinese provinces, the scholars have participated in a number of significant discussions and have learned from the allocation models of different countries. Chen (2010) analyzes the region allocation results in China by using the grandfather principle, equality, and willingness to pay, which are commonly discussed in international carbon emission permit allocation. Yi et al. (2011) study the 40% to 45% of emission reduction target allocation in terms of capacity, potential, and responsibility. Four preferred scenarios are set by these previous researchers; and they argue that provinces with high per capita GDP, accumulated CO_2 emission, and energy consumption per unit of industrial value added may shoulder high proportions in the final intensity reduction allocation. Wei and Ni (2011) construct an abatement capacity index based on weighted equity and efficiency indices. They suggest that the eastern region has the least inefficient emission and the highest marginal abatement cost, whereas the western region has the largest potential capability for reduction. This allocated scheme does not consider the needs of the Chinese national energy strategy. Provinces with high carbon intensity in western China, such as Shanxi, Ningxia, and Inner Mongolia, bear most of the carbon emissions transferred from eastern provinces, including Beijing and Shanghai

(Yu *et al.*, 2012). A significant emission reduction in western provinces may result in energy supply security in eastern provinces, which lack energy resources but have a huge energy demands. Li *et al.* (2010) obtained the optimal CO_2 abatement allocations of Chinese provinces using a nonlinear programming model with a minimum total abatement cost. However, the abatement marginal costs obtained from different provinces are similar in the model, which does not consider the regional differences in economic development and marginal emission reduction costs. Wang *et al.* (2012) use an improved zero sum gains data envelopment analysis (ZSG-DEA) model to allocate the CO_2 emission allowance of China to its provinces. This method is primarily based on DEA efficiency, and only five indices, namely, GDP, population, total energy consumption, non-fossil energy consumption, and emission, are utilized to allocate the reduction target. According to IPAT identity (Ekins, 2000), many factors should be considered in the allocation of targets for reducing carbon emission. Based on the principle of feasibility, such allocation should consider different energy structures, industrial structures, and the per capita resident income of provinces.

Gao (2011) allocates emissions in a target year by setting an emission benchmark based on the decomposition of total carbon emissions into survival and development emissions. This approach effectively reflects the allocation principle of “common but differentiated responsibility” by considering the differences in regional economic development in China. Based on this concept, the present study has decomposed total carbon emissions into four components (i.e., emissions from primary, secondary, and tertiary industries, and from residential areas) to allocate the target rationally and to obtain a result of the interaction among 13 macro influential factors according to the KAYA identity. Then, 30 provinces in China are clustered into several classes according to the influential factors by using the particle swarm optimization (PSO) algorithm and the fuzzy C-means (FCM) clustering algorithm (PSO–FCM). Shapley value decomposition is applied to investigate the key factors in emission growth in the provinces that represent each cluster. Finally, the reduction burden is allocated by controlling the key factors to decelerate the growth rate of CO_2 emissions according to the current economic development level, energy endowments, living standards, and emission intensity of each province based on guaranteed survival emissions. Furthermore, a case study of the allocation of CO_2 intensity reduction targets in China by 2020 is conducted by applying the proposed method.

2. Methodology and data

2.1 Framework of carbon intensity reduction allocation

The current mainstream allocation models mainly calculate emission reductions. However, CO_2 emissions in China in 2020 are expected to be higher than those in 2005 because China is a developing country that is currently undergoing industrialization and urbanization. Therefore, emission growth rates in China must be strictly controlled to achieve CO_2 emission intensity reduction targets, i.e., to control the emissions in 2020 by using the proposed benchmark. The approach of China allows provincial allocation based on the predicted GDP growth rate to change the emission intensity control target into the total control target. This goal may be realized by controlling emission growth rates, thereby achieving the emission intensity reduction targets (Wang et al., 2011). Gao (2011) argues that total energy-related CO_2 emissions can be decomposed into two parts to illustrate the “common but differentiated responsibility” principle in different regions: basic survival and developmental emissions. Survival emissions are necessary to maintain basic human living standards and production. Development emissions are necessary to pursue a high quality of life and to obtain material wealth beyond that needed for basic survival. This latter type requires reasonable guidance. Several factors resulting in the rapid increase in emissions must be controlled properly to achieve the objective requirements of low carbon emissions and sustainable development after ensuring that survival emissions are sufficient. Therefore, the total emissions for the target year should be reasonably allocated among regions according to regional economic development, energy structure, residential living standards, and actual CO_2 emissions to realize the emission intensity reduction target. The basic allocation framework is illustrated in Fig. 1.

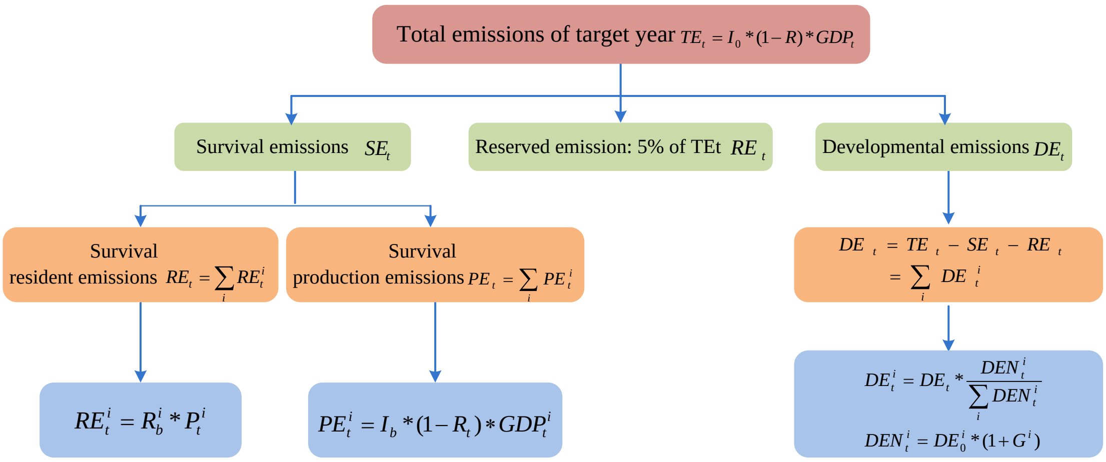

Fig. 1. Basic framework of regional allocation.

The total CO_2 emissions TE_t of target year t is calculated using the carbon intensity I_0 of the benchmark year, the intensity reduction requirement R in the target year t, and the predicted GDP (GDP_t) in the corresponding t year. The result is then decomposed into survival emissions (SE_t), developmental emissions (DE_t), and reserved emissions (RE_t, which can be used as reward or trade emissions). SE_t can be further decomposed into survival emissions for living (RE_t) and for production (PE_t). The RE_t^i of region i depends on the per capita emissions for living for the benchmark R_b^i and the expected population P_t^i in the target year t. PE_t^t is calculated using the emission intensity of benchmark I_b, the emission reduction target R, and the expected GDP_t^i in region i. Therefore, $DE_t = TE_t - (SE_t + RE_t)$. The initial DE_t of region i in target year t (DEN_t^i) depends on the product of the DE_t of the base year (DE_0^i) and its growth rate G^i (regulated growth rates). The ultimate DE_t of region i depends on the share of the national total initial developmental emissions $\frac{DEN_t^i}{\sum_i DEN_t^i}$ and the DE_t to be allocated in target year *t*.

Therefore, this study first decomposes carbon emissions into four components (i.e., emissions from primary, secondary, and tertiary industries, and from residential areas) to obtain a result of the interaction among 13 macro influential factors according to the KAYA identity. Second, 30 provinces in China are classified into several categories via a PSO–FCM algorithm based on the historical data of the 13 factors and according to influential carbon emission factors. A typical province from each category is then selected and decomposed via Shapley value decomposition to identify the key factors affecting the carbon emission growth of each representative province. Finally, the benchmarks of survival emissions (R_b^i and I_b) in each category are determined according to the decomposition results. Meanwhile, the growth rates of development emissions are decelerated by setting a policy control factor to adjust key emission growth factors. The process is depicted in Fig. 2.

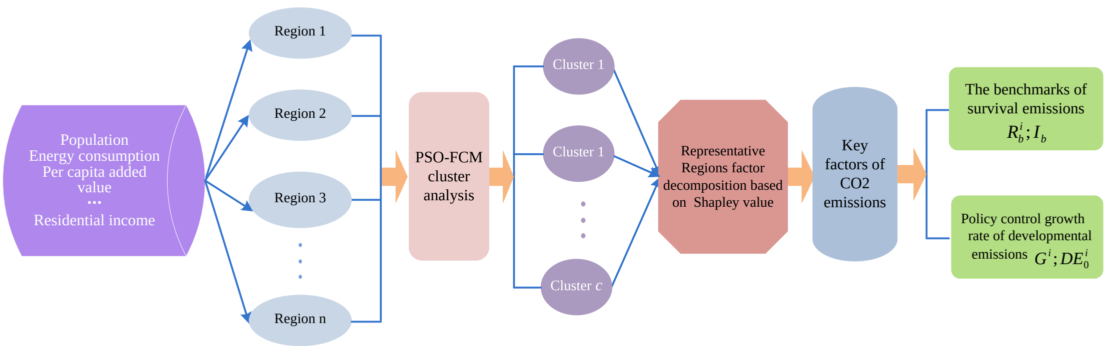

Fig. 2 Solution for the regional emission intensity reduction target allocation.

2.2 Selection of influencing factors

A special IPAT identity case (Ekins, 2000), which is often called KAKY identity (Kaya,1990), reveals the importance of distinct components or factors in the historical data of energy-related CO_2 emissions. The identity decomposes total national CO_2 emissions into four components, namely population (P), per capita GDP (economic activity A), energy intensity of economic activity (technical level T_1), and carbon intensity of energy use (technical level T_2), as follows:

$$CO_2 = P \cdot \frac{GDP}{p} \cdot \frac{E}{GDP} \cdot \frac{CO_2}{E} \quad \text{or} \quad I = P \cdot A \cdot T_1 \cdot T_2 . \tag{1}$$

The KAYA identity is often extended to investigate special components for different objectives. Total energy-related CO_2 emissions have been divided into two parts: the production emissions of three industries (C_S) and the living standard energy consumption emissions of residents (C_R).

$$TC = C_s + C_R , \tag{2}$$

where $C_s = C_1 + C_2 + C_3$.

The emissions of the aforementioned parts can be decomposed further according to Eq. (1) into Eqs. (3) and (4), as follows:

$$C_S = \sum_{i=1}^{3} C_i = P \cdot \sum_{i=1}^{3} \frac{Y_i}{P} \cdot \frac{ES_i}{Y_i} \cdot \frac{C_i}{ES_i} = P \sum_{i=1}^{3} A_i * T_i * F_i , \tag{3}$$

$$C_R = P \cdot (\frac{Y_R}{P} \cdot \frac{ER}{Y_R} \cdot \frac{C_R}{ER}) = P \cdot (A_r \cdot T_r * I_r) . \tag{4}$$

Based on Eqs. (2) to (4), Eq. (5) can be derived as follows:

$$TC = P \cdot (\sum_{i=1}^{3} A_i * T_i * F_i + A_r \cdot T_r * I_r) , \tag{5}$$

where P is the total population; Y_i is the per capita added value of the i^{th} industry; ES_i is the energy consumption of the i^{th} industry; C_i is the energy-related CO_2 emissions of the i^{th} industry; Y_R is resident income; ER is residential energy consumption; C_R represents the CO_2 emissions of the living standard energy consumption of residents; A_i is the per capita added value of the i^{th} industry, which represents the industrial structure and the economies of scale; T_i is the i^{th} industry energy consumption of the per-unit added value that denotes energy efficiency; F_i represents the CO_2 emissions of the i^{th} industry per-unit energy consumption, which, in turn, represents the energy consumption structure; A_r is the per capita income, which represents the living standard of residents; T_r is the energy consumption of per-unit resident income, which represents the energy consumption level of residents; I_r represents the CO_2 emission of per-unit energy consumption of residents, which, in turn, represents the energy consumption structure of residents.

2.3 PSO-FCM cluster method

Socioeconomic development and standard of living are different among Chinese people. The beginning of industrialization is also dissimilar. Provinces with similar influential emission factors are clustered into one group by using an intelligent clustering algorithm to embody the principle of "common but differentiated responsibility" in this study. The provinces in the same class have the same abatement control policy that reflects "common responsibilities." However, the direction and degree of policy control is dissimilar for different classes, thereby reflecting "differentiated responsibilities."

An improved PSO-FCM clustering algorithm is proposed in this study. The main feature of this algorithm is the addition of distances between centers to the objective function and the optimization of the number of clusters via discrete PSO based on the classic FCM algorithm, which can be expressed by the following mathematical formulas:

$$\min V_{zs} = \sum_{k=1}^{c}\sum_{i=1}^{n}\mu_{ki}^{2}\left\|x_i - Z_k\right\| + \frac{c}{\sum_{p,q=1}^{c}\left\|Z_p - Z_q\right\|^2}\ , \tag{6}$$

$$\text{s.t} \quad \begin{cases} \sum_{k=1}^{c}\mu_{ki} = 1, 1 \le i \le N \\ 0 \le \mu_{ki} \le 1, 1 \le k \le c; 1 \le i \le N\ . \\ 0 < \sum_{i=1}^{N}\mu_{ki} < N \quad 1 \le k \le c. \end{cases} \tag{7}$$

In Eq. (6), $\|Z_p - Z_q\|^2$ is the Euclidean distance of two center vectors belonging to classes p and q; $p,q \in c$. $X = \{X_1, X_2, \cdots, X_n\} \subset R^n$, where R^n denotes a vector space with real n dimensions; $\forall i$; $1 \le i \le N$; and $X_i = (x_{i1}, x_{i2}, \cdots, x_{im})^T \in R^n$. $x_{ij}\,(j = 1,2,\cdots m)$ is the j^{th} attribute of sample $X_i\,(i = 1,2,\cdots N)$. $Z^T = (Z_1, Z_2, \cdots Z_c)$ is the central clustering vector, and μ_{ki} is the membership grade of the i^{th} sample belonging to the k^{th} class. Detailed descriptions are found in the literature (Yu *et al.*, 2012).

The PSO-FCM clustering method partitions samples effectively by considering inter-category and within-category distances. Moreover, PSO-FCM determines the global optimal number of clusters and membership grade values. Compared with the results of other traditional clustering methods, such as *K*-means clustering (Gao, 2011), and meta-frontier clustering of DEA (Zhang *et al.*, 2013), those of the fuzzy c-means algorithm based on particle swarm optimization, an intelligent soft clustering method, are self-explanatory and rational (Yu *et al.*, 2012).

2.4 Shapley value decomposition of carbon emissions

Emission growth rates must be strictly controlled in China to achieve the carbon intensity reduction targets. Several policies oriented toward different key factors that affect carbon emissions must be implemented. Therefore, the total emissions must be decomposed over a number of factors to identify the key factors. More than 100 energy and environmental studies on decomposition are listed in the survey conducted by Ang and Zhang (2000). Decomposition analysis techniques are classified into two broad categories: input–output and disaggregation techniques. The former mainly focuses on structural decomposition analysis (Alcántara and Padilla, 2009; Zhang et al., 2009; Su and Ang, 2012). The latter includes Laspeyres index decomposition (Feng, 2011), Divisia index decomposition (Shrestha and Timilsina, 1996; He, 2010) and its improved version, and the logarithmic mean weight Divisia index decomposition (Ang et al., 2003; Ang, 2005). Albrecht et al. (2002) apply Shapley value decomposition to the factor decomposition of carbon emissions based on the fairest allocation of collectively gained profits among several collaborative agents in a cooperative game with n players. Unlike other decomposition methods, Shapley value decomposition, which is symmetric (or anonymous), does not require any assumption or extra effort to allocate residual. Furthermore, Shapley decomposition enables complex decompositions (Albrecht et al., 2002). The basic idea of the Shapley value is introduced briefly in the subsequent paragraphs.

Players in a coalition cooperate with one another and obtain a certain overall gain from their cooperation. Given that several players may contribute more to the coalition than others or may possess different bargaining powers (for example, threatening to destroy the entire surplus), the importance of each player to overall cooperation and the reasonable expected payoff is questioned. The Shapley value provides a possible answer to this question (Shapley, 1953).

Assuming that $N = \{1, 2, \cdots, n\}$, where n is the total number of players. Any coalition in set N corresponds to a real characteristic function $v(s)$ for any subset s of N. x_i denotes the deserved income of the i_{th} player in N based on the value of the coalition $v(n)$. The Shapley value of a coalitional game (N, v) is an allocation rule that assigns a value $\phi_i(v)$ to player i, where

$$\phi_i(v) = \sum_{s \in N \setminus \{i\}} \frac{|s|! * (n - |s| - 1)!}{n!} \cdot [v(s \cup \{i\}) - v(s)], \quad i = 1, 2, ..., n, \tag{9}$$

where $N \setminus \{i\}$ is the set of all players except i. Eq. (9) is considered as the Shapley value of player i, which can be justified if one assumes that player i joins the game in random order.

Player i receives an extra amount, which he/she contributes to the existing coalition of players $s \backslash \{i\}$, i.e., $v(s \cup \{i\}) - v(s)$. This contribution must be averaged over all possible orders in which player i can enter the game. $|s|$ is the number of players in subset s. $\frac{|s|!*(n-|s|-1)!}{n!}$ is the weight, that is, the contribution probability that player i makes to all coalitions. $v(s)$ denotes the best value that can be achieved by coalition s.

After the original Shapley value decomposition, several improved methods have been proposed, specifically for income inequality decomposition (Shorrocks, 1982, 1999). Sastre and Trannoy (2002) examine Shapley inequality decomposition by factor components that focus particularly on several methodological issues that cannot be solved from a theoretical perspective. At least two calculations seem sensible in relation to the definition of Shapley decomposition. In the first calculation, defined as zero income inequality decomposition, the components excluded from S are removed. In the second calculation, which leads to what is called equalized income inequality decomposition (Chantreuil and Trannoy, 1999), the inequality from all components not in S is removed. These two calculations differ in the treatment of the components excluded from the considered subset. However, they are both index decomposition and not income decomposition. First, an index used to measure income inequality (e.g., Gini, Fisher, and Theil indices) should be calculated. Thereafter, the index should be decomposed, and the contribution of each component should be computed. In the present study, Shapley value decomposition is employed to measure the effects of different factors on CO_2 emission growth. The amount of carbon emission growth, an absolute rather than relative variable, is required for decomposition. This decomposition is more likely the classic question of cost or profit allocation among a set of agents than index decomposition. Therefore, the initial Shapley value decomposition can be suitably used despite its several drawbacks.

2.5 Data management

(1) CO_2 emission computation for China

The combustion of fossil fuels is the main source of GHGs according to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2007). Approximately 95% of global carbon emissions in 2004 are ascribed to fossil fuel combustion. We calculate the CO_2 emissions of 30 provinces in China using fossil energy consumption data.

$$Tco_{2ij} = \sum_{i=1}^{n} \left\{ (A_{ij} - S_{ij}) e_i c_i \times 10^{-3} \right\} \cdot O_i \times \frac{44}{12} , \tag{10}$$

where A_{ij} is the real consumption of the i^{th} fuel in the j^{th} province. The sum of the energy consumption conservation sectors (the heating supply and thermal power industries) and the final consumption sectors (farming, forestry, and animal husbandry; fisheries and water conservation; the construction industry; transportation, storage, and postal services; wholesale and retail trades; hotels and restaurants; and residential consumption. S_{ij} is the noncombustion consumption of the i^{th} fuel in the j^{th} province. e_i is the net calorific value of the i^{th} fuel. c_i is the carbon content of the i^{th} fuel. O_i is the carbon oxidation rate of the i^{th} fuel. $n = 30$; $i = 1,2,\cdots,17$; and $j = 1,2,\cdots,30$. The coefficients of various types of energy are found in the literature (IPCC, 2007).

(2) Definition of the influencing factors of carbon emissions

Farming, forestry, animal husbandry, and fishery and water conservancy is the primary industry in the present study. The energy consumption of the secondary industry is the total consumption of the construction and energy conversion industries (i.e., the thermal power and heating supply industries). The tertiary industry is represented by the transportation, storage, postal, wholesale trade, retail trade, hotel, restaurant, and other industries. The disposable income of residents is the calculated weighted average of the disposable incomes of urban residents and the net income of rural residents. The weights represent the proportions of the population in rural and urban areas.

(3) Data sources

Fossil energy consumption data on the 30 Chinese provinces are obtained from the *China Energy Statistical Yearbook 2006–2011.* Hong Kong, Macao, Taiwan, and Tibet are not included because of lack of data, and data on Ningxia are obtained from 2002. GDP and population data are obtained from the 2011 edition of the *China Statistical Yearbook*. The GDP and added value data of the three industries are obtained from the 2011 edition of the *China Statistical Yearbook.* The GDP is converted into the constant price for 2005. Data regarding population as well as rural and urban population proportion are obtained from the *China Population Statistical Yearbook 2006–2011*[2].The data can be found in Table A1 of the Appendix.

3. Case allocated study on the intensity reduction target of China by 2020

3.1 Provincial total CO_2 emissions and intensity

The total CO_2 emissions and growth rates obtained from Eq. (10) are shown in Fig. 3.

[2]Given the different statistical levels, several differences exist between the total national data and the sum of the data for all provinces in China. Therefore, the national data comprise the sum of the data for all provinces in this study.

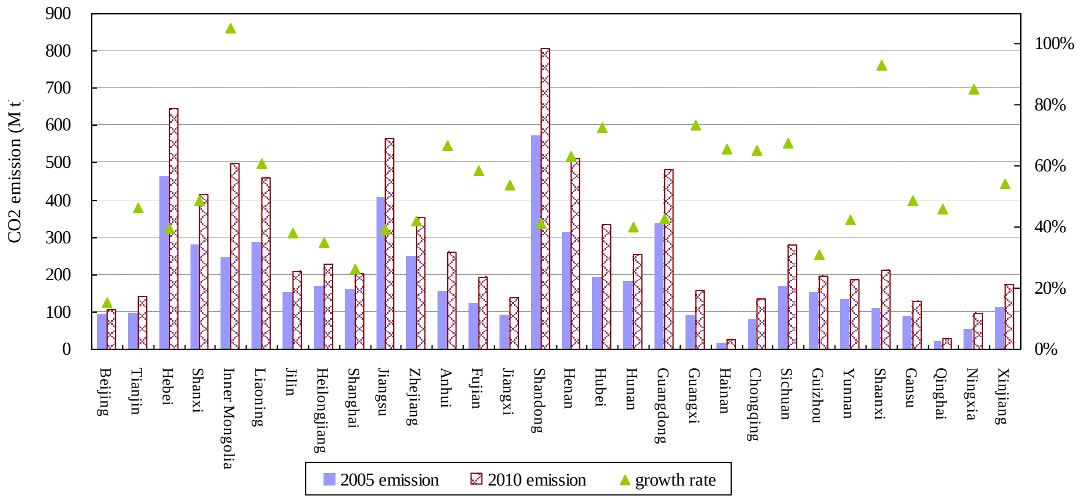

Fig. 3. CO_2 emissions and growth rates of the 30 provinces in China.

The amounts and growth rates of CO_2 emissions are different among the 30 provinces in China (Fig. 3). Shandong and Hebei emitted the most CO_2 in China in both 2005 and 2010. The listed emission in Shandong ranged from 572 million tons in 2005 to 808 million tons in 2010. The emission in Hebei ranged from 463 million tons in 2005 to 647 million tons in 2010. By contrast, Hainan recorded the lowest emission, emitting only 16 million tons of CO_2 in 2005, which is 2.8% that of Shandong. The growth rates of different provinces vary from one another even though the emissions of all provinces in 2010 are higher than those in 2005. The emissions of Inner Mongolia and Shaanxi have the fastest growth rates at 105.3% and 93.2%, respectively. Beijing has the lowest growth rate at 15.3%, followed by Shanghai with a growth rate of 26.2%. These results imply that the latter two provinces have the best emission reduction control.

The CO_2 emission intensities of each province in 2005 and 2010, as well as their growth rates, were obtained by using data on CO_2 emissions and GDP (Fig. 4).

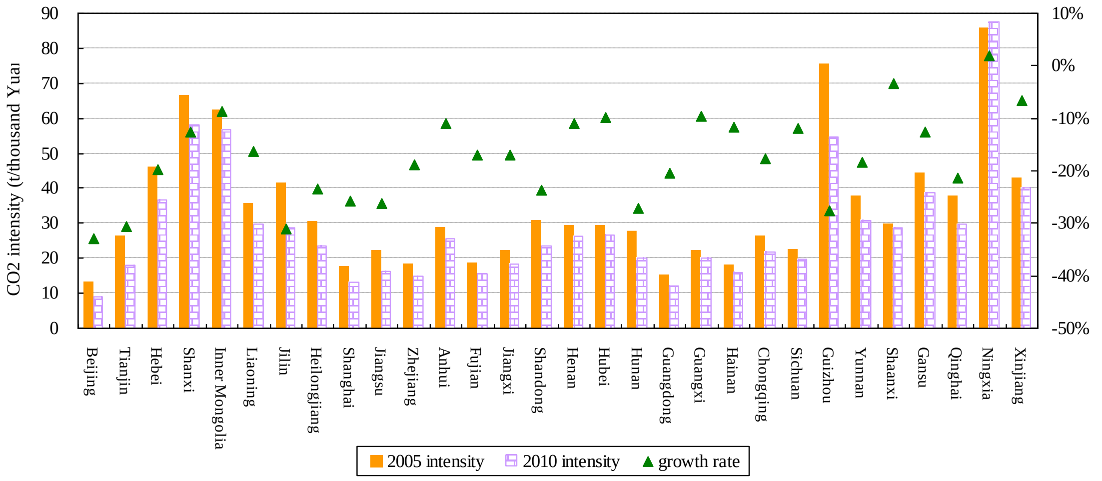

Fig. 4. CO_2 emission intensities and growth rates of the 30 provinces in China.

The CO_2 intensities and the degrees of CO_2 reduction in the provinces have exhibited significant differences in recent years (Fig. 4). According to the 2005 and 2010 data, energy-intensive provinces, such as Ningxia, Shanxi, Inner Mongolia, and Guizhou, exhibit the highest CO_2 intensities; whereas developed provinces, such as Beijing, Shanghai, Guangdong, and tourist-heavy Hainan, display the lowest CO_2 intensities. The highest CO_2 intensity in Ningxia was 6.3 times that in Beijing in 2005 and increased to 9.8 times in 2010. The CO_2 intensities of all Chinese provinces decreased from 2005 to 2010 in various degrees. Beijing exhibits the highest decrease (32.8%), followed by Jilin (31.1%).

3.2 PSO-FCM cluster results and analysis

The size of particles is $n=15$ and the length of each particle is $d=5$ (because only 30 provinces are considered in the study, $2^5>30$) in the PSO–FCM method employed in the present study. The convergent threshold of ISODATA is $\varepsilon=10^{-4}$. Particle iterations are expressed as $\max\_gen=100$. The changes in fitness values after the influencing factors of carbon emission data normalization are selected and PSO–FCM is implemented are shown in Fig. 5. PSO–FCM obtains the optimal cluster number $c = 4$ in both 2005 and 2010 at approximately 70 and 20 iterations, respectively. The best fitness values obtained are 9.9823 and 12.6595.The provinces that belong to 4 categories are shown in Table 1 and Fig 6.

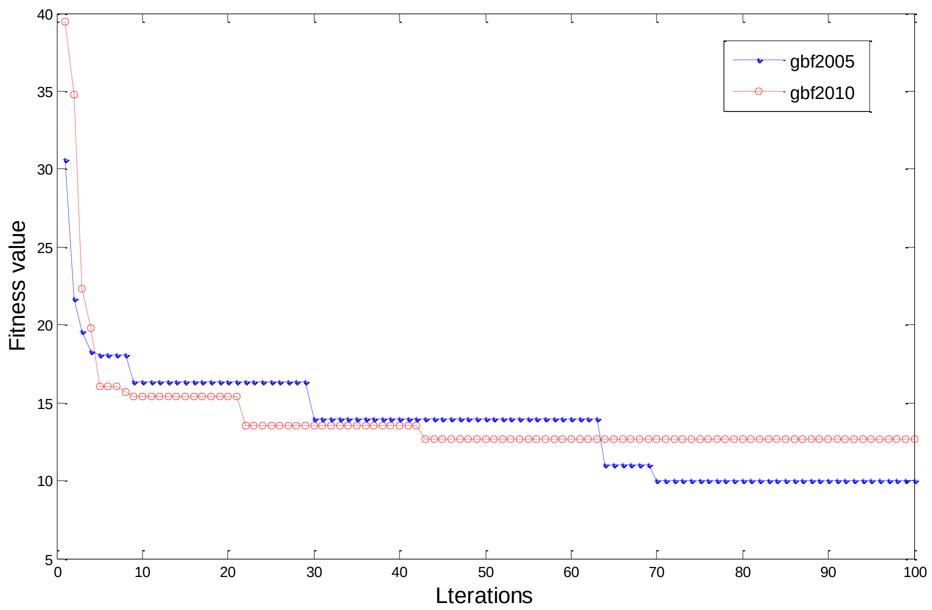

Fig. 5. Fitness value evolution of the PSO–FCM algorithm.

Table 1.

The clustering results of macroeconomic affecting factors of emissions

Classes	2005 Year	2010 Year
Class 1	Beijing Shanghai Tianjin	Beijing Shanghai Tianjin
Class 2	Shanxi Inner Mongolia Ningxia Guizhou Qinghai Ningxia Xinjiang	Shanxi Inner Mongolia Ningxia Guizhou Qinghai
Class 3	Jiangsu Zhejiang Shandong Henan Guangdong Sichuan	Jiangsu Zhejiang Fujian Shandong Henan Guangdong
Class 4	Hebei Liaoning Jilin Heilongjiang Anhui Fujian Jiangxi Hebei Hunan Guangxi Hainan Chongqing Yunnan Shaanxi Gansu	Hebei Liaoning Jilin Heilongjiang Anhui Jiangxi Hebei Hunan Guangxi Hainan Chongqing Sichuan Yunnan Shaanxi Gansu Qinghai Xining

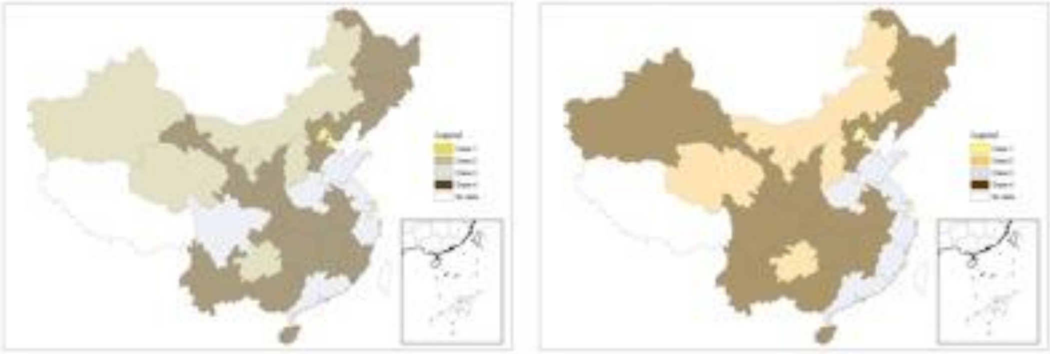

Fig. 6.   PSO-FCM clustering results in 2005(Left) and 2010(Right)

According to Table 1 and Fig 6., the 30 provinces in China are classified into four categories based on data from 2005 and 2010. The samples in each category are generally stable and have significant category features. The category attributions of most provinces are relatively stable. For example, the attributions of Qinghai and Xinjiang have changed from second class in 2005 to fourth class in 2010. Meanwhile, Sichuan changed from third class to fourth class, whereas Fujian changed from fourth class to third class. These characteristics indicate that factors affecting province-wise carbon emissions have not changed significantly. The features of the four categories of Chinese cities are obvious. For example, Beijing, Tianjin, and Shanghai are always in class one, with a low-emission intensity resulting from the high development of tertiary industry. Resource-based provinces constitute class two, which represents the highest emission intensity. Economically developed coastal provinces, along with Henan, constitute class three, whereas most underdeveloped mid-west provinces belong to class four.

3.3 Shapley decomposition results

According to the partitioning results in Section 3.2, the characteristics of the factors that affect the carbon intensity of each category are generally the same. We conduct factor decomposition of the Shapley value in each category by choosing representative provinces to investigate various factors in each type of carbon emission.

As indicated in Eqs. (3) to (5), province-wise carbon emissions consist of four components, namely, emissions from primary, secondary, and tertiary industries, as well as residential areas. Each component consists of four factors: population (P), per capita production added value or residential per capita disposable income (A_i), energy consumption of industrial per-unit added value or residential per-unit income (T_i), and industrial or residential emissions per unit of energy consumption (F_i). Based on Eq. (5), the CO_2 emissions of the primary industry can be expressed as

$$C_1 = P \cdot A_1 \cdot T_1 \cdot F_1 . \tag{11}$$

Based on Eq. (9), if $n = 4$, then $v(s)$ is the amount of CO_2 increase from subset s of the influential factors, whereas $v(s \setminus i)$ is the amount of CO_2 increase without factor i. Therefore, the contribution of P to C_1 can be expressed as

$$\begin{aligned}
&\phi_P(C_1) = \sum_{s \in 4} \frac{(4-|s|)! \cdot (|s|-1)!}{4!} \cdot [C_1(s) - C_1(s \setminus i)] \\
&= \frac{1}{4}(P^t A_1^0 T_1^0 F_1^0 - P^0 A_1^0 T_1^0 F_1^0) + \frac{1}{12}(P^t A_1^t T_1^0 F_1^0 - P A_1^t T_1^0 F_1^0) + \frac{1}{12}(P^t A_1^0 T_1^t F_1^0 - P A_1^0 T_1^t F_1^0) + \\
&\frac{1}{12}(P^t A_1^0 T_1^0 F_1^t - P A_1^0 T_1^0 F_1^t) + \frac{1}{12}(P^t A_1^t T_1^t F_1^0 - P A_1^t T_1^t F_1^0) + \frac{1}{12}(P^t A_1^t T_1^0 F_1^t - P A_1^t T_1^0 F_1^t) + \\
&\frac{1}{12}(P^t A_1^0 T_1^t F_1^t - P A_1^0 T_1^t F_1^t) + \frac{1}{4}(P^t A_1^t T_1^t F_1^t - P A_1^t T_1^t F_1^t)
\end{aligned} . \tag{12}$$

where P^0 represents the population of the base year, and P^t denotes the population of the statistical year. The rest of the factors may be deduced by analogy. Given that population is a common contributing factor in energy-related CO_2 emissions of primary, secondary, and tertiary industries, as well as of residential areas, all the contributions of these sectors can be summed up to obtain the overall contribution of the population to total CO_2 emissions.

In this study, Beijing, Shanxi, Jiangsu, and Hubei are chosen as the representative provinces in their respective categories because their stable position within the category system indicates their typicality. The contributions of various factors to the CO_2 emissions in these four provinces in 2005 and 2010 are obtained via Shapley decomposition. The results are shown in Table 2.

Table 2

Contribution rates of different factors to the CO2 emissions of representative provinces.

Indexes	Beijing	Shanxi	Jiangsu	Hubei
Population	175.7%	16.5%	16.4%	0.7%
Per capita added value of the primary industry	-1.6%	0.4%	0.6%	1.1%
Primary industry energy consumption of the per-unit added value	-0.8%	0.4%	0.5%	0.1%
Primary industry carbon emission of the per-unit energy consumption	0.1%	-0.2%	-0.1%	0.0%
Per capita added value of the secondary industry	95.8%	110.4%	170.8%	114.8%
Secondary industry energy consumption of the per-unit added value	-179.0%	-45.2%	-88.7%	-36.4%
Secondary industry carbon emission of the per-unit energy consumption	-12.6%	4.5%	-8.0%	-4.7%
Per capita added value of the tertiary industry	60.6%	5.5%	9.7%	14.5%
Tertiary industry energy consumption of the per-unit added value	-47.1%	4.9%	-3.5%	3.4%
Tertiary industry carbon emission of the per-unit energy consumption	-5.1%	-0.2%	-0.3%	0.5%
Per capita resident income	50.8%	10.3%	4.4%	7.0%
Energy consumption of the per-unit resident income	-34.6%	-7.0%	-1.6%	-0.4%
Carbon emission of the per-unit resident energy consumption	-2.1%	-0.4%	-0.3%	-0.8%

The ratio of the contribution of the primary industry to the total negative or positive contribution, as well as the ratio of the total positive contribution to the total negative contribution can be calculated further by using the contribution rates listed in Table 2. The ratio of the primary positive or negative contribution to the total contribution can also be calculated further by using these contribution rates. The ratio of the primary positive or negative contribution represents the ratio of the largest positive or negative contribution of all factors to the total positive or negative contribution. These ratios represent the position of the factor with the largest contribution among all factors with the same effect. To a certain extent, these ratios can also indicate balance among all factors with the same effect. The ratio of the total positive contribution to the total negative contribution is the absolute value of the ratio of the total positive contribution to the total negative contribution. In addition, it represents the comparison of the strengths of increased and decreased emissions. The results of the comparison are shown in Table 3.

Table 3.
Comparison of the adding and reducing strengths of energy-related CO_2 emissions.

Representative provinces	Beijing	Shanxi	Jiangsu	Hubei
Primary positive factor	Population	Per capita added value of the secondary industry	Per capita added value of the secondary industry	Per capita added value of the secondary industry
Total positive contributions	383.0%	152.9%	202.5%	142.2%
Ratio of the primary to the total positive contributions	45.9%	72.2%	84.4%	80.7%
Primary negative factor	Secondary industry energy consumption of per-unit added value	Secondary industry energy consumption of per-unit added value	Secondary industry energy consumption of per-unit added value	Secondary industry energy consumption of per-unit added value
Total negative contributions	-283.0%	-52.9%	-102.5%	-42.2%
Ratio of the primary to the total negative contributions	63.3%	85.5%	86.5%	86.3%
Ratio of the total positive to the negative contributions	1.35	2.89	1.98	3.37

The following conclusions can be drawn from Tables 2 and 3:

(1) Although Beijing, Shanxi, Jiangsu, and Hubei represent different types of provinces, the primary factor that affects their carbon emissions is generally the same. Except for Beijing, the primary factor that increases carbon emissions in the remaining three provinces is per capita added value of the secondary industry, the contributions of which exceed 100%. The primary factor that increases carbon emissions in Beijing is population growth[3], followed by per capita added value of the secondary industry. The primary factor that decreases carbon emissions, without exception, is

[3]The population of Beijing in 2010 has increased by 27.7% compared with that in 2005. This increase is not caused by a high birth rate. A large number of highly skilled and educated people have been moving to Beijing in recent years because of its geographic advantage. Another important reason is that China conducted the fifth population survey in 2010, during which many children have not been registered previously in the census, thus resulting in the increase in the population of Beijing from 15.10 million in 2009 to 19.62 million in 2010.

the energy consumption of per-unit added value of the secondary industry. Therefore, the primary influential factor of carbon emissions is consistent in the 30 provinces in China.

(2) Although the primary positive and negative factors related to emission changes are similar, the ratio of the contribution of the biggest factor to the total contribution differs for each province type, that is, the strength of the contribution of the primary factor significantly differs in each province. The ratio of the positive primary factors to total emission in Beijing is 45.9%, whereas those in the other three provinces exceed 72%. The impact strength of emission reduction in Beijing is slightly different from those in the other three provinces. Shanxi, Jiangsu, and Hubei exhibit similar primary emission reduction factors that range from 85% to 87%, thus indicating that the energy consumption of per-unit added value of the secondary industry is the most influential emission reduction factor, whereas the rest of the factors exert insignificant influence. The ratio of the negative primary factors to total emission is only 63.3%, thus indicating that all factors, except for the energy consumption of the per-unit added value of the secondary industry, have remarkable effects on emission reduction. The contributions of the energy consumption per-unit added value of the tertiary industry and the energy consumption per-unit resident income are 16.7 % and 12.2%, respectively.

(3) The ratio of the total positive contribution to the negative contribution is greater than 1 for each province, thus indicating that the influences of emission growth factors are stronger than those of emission reduction factors. The ratio of the total positive contribution to the negative contribution in Hubei is 3.37, which is the highest among the four provinces. In particular, this value is significantly higher than those in Beijing and Jiangsu, thus indicating that the influences of emission growth factors are three times stronger than those of emission reduction factors.

However, the index values of Beijing and Jiangsu are lower than 2, which indicates that the influences of emission growth factors and emission reduction factors are balanced in these two provinces, especially in Beijing.

3.4 Design of abatement and control policies

The decomposition of the factors that influence CO_2 emissions in the representative provinces shows that the main factors that affect emission growth include population, growth in the added value of the tertiary industry, and per capita income increase. Meanwhile, the factors that reduce emissions include reduction in the energy consumption per-unit industrial value growth cost, per-unit national income cost, and changes in the industrial and residential energy structures. The decomposition scheme shown in Fig. 1 illustrates that implementing scientific regulations on the increase in emissions from various regional developments by regulating the fundamental emissions is essential to achieving the emission reduction targets, maintaining or enhancing the factors that lead to decreased carbon emissions, and strictly controlling several factors that lead to excessive increase in emissions. Therefore, the following policy control design is considered.

(1) The pulling effect is allowed on emissions from population growth and per capita income, but is strictly limited on emissions that exceed per capita income. Both factors lead to a certain degree of emission growth, and such growth should be allowed. The population of China will continue increasing slowly for a long period given that population growth is strictly controlled under the birth control plan. Therefore, further control on emission growth caused by demographic factors via an emission limit policy is unnecessary. In addition, the increase in per capita income is not only an important indicator of improved quality of life, but is also one of the goals of national

development. Thus, this factor should not be used to impose restrictions to limit emission growth. These two factors have been realized in survival emissions. Therefore, strict limitation should be imposed on emissions that exceed per capita income.

(2) The added value contribution of the primary industry to emissions in most provinces should be stabilized. The production growth of the agricultural industry, which is the basis of national stability, is stagnating at present. Therefore, emissions from agriculture should be allowed. However, the added value contribution of provinces with agricultural recession (e.g., Beijing, Tianjin, and Shanghai) to emission growth should not be considered.

(3) In general, the growth of the secondary industry should be limited to mitigating emission increase caused by the added value from this industry. However, various policies should be implemented for different classes of provinces. More stringent restrictions should be implemented in the two classes of developed provinces represented by Beijing and Jiangsu. Moreover, strict restrictions should be applied to heavy and chemical industries' development on the premise of guaranteeing a sufficient energy supply and demand for provinces with rich resources, such as Shanxi. The opportunity to develop the secondary industry should be provided to underdeveloped provinces, which is represented by Hubei, with appropriate limitations on emissions from the secondary industry.

(4) Appropriate guidance should be provided to emissions from the tertiary industry. Except for the provinces in the category of Beijing, the contribution of the tertiary industry to emission growth in the remaining provinces is not high (i.e., less than 15%). The development of the tertiary industry is the target direction of the industrial structural adjustment of the country.

Therefore, emissions caused by the increase in value growth of the tertiary industry should be tolerated in most provinces, with the exception of provinces belonging to the first category.

(5) The factors that reduce carbon emissions should be maintained and strengthened. The energy consumption per unit of value added of the secondary industry is the key contributor to emission reduction. Therefore, to meet the emission reduction target, China should reduce the energy consumption per unit of value added of the secondary industry. Thus, based on the present effect, the migrating effect of reducing energy intensity, particularly in the secondary industry, should be enhanced. The energy consumption structure of industries and residential areas also contribute significantly to emission reduction. Therefore, China should improve the energy consumption structure and promote the development of clean energy technologies to substantially reduce CO_2 emission.

The regulation on the growth rate of various factors of development of emissions (G^i) is shown in Table 4. In the table, "0" indicates that the contribution should be limited completely, "1" indicates that the current contribution should be maintained, values between 0 and 1 (e.g., 0.2, 0.5, and 0.8) denotes the different degrees of control from largest to smallest, and values exceeding 1 indicates the need to strengthen the contribution further (accelerate or decelerate) on the emission growth along the direction of action during the 11th Five-Year-Plan period.

The other twenty six provinces' controlled growth rates of developmental emissions (G^i) is calculated by multiplying the trend growth rates of each province to the control coefficients of category which the province belongs to.

Table 4.
Controlled growth rates of developmental emissions of typical provinces between 2011 and 2020.

	Beijing			Shanxi			Jiangsu			Hubei		
	Trend growth rates	Control coefficients	Control growth rates	Trend growth rates	Control coefficients	Control growth rates	Trend growth rates	Control coefficients	Control growth rates	Trend growth rates	Control coefficients	Control growth rates
Population	60.8%	0.0	0.0%	16.8%	0.0	0.0%	13.3%	0.0	0.0%	1.0%	0.0	0.0%
Per capita added value of the primary industry	-0.5%	0.0	0.0%	0.4%	1.0	0.4%	0.5%	1.0	0.5%	1.6%	1.0	1.6%
Primary industry energy consumption of per-unit added value	-0.2%	0.0	0.0%	0.3%	0.0	0.0%	0.4%	0.0	0.0%	0.2%	1.0	0.2%
Primary industry carbon emission of the per-unit energy consumption	0.0%	1.0	0.0%	-0.1%	1.0	-0.1%	-0.1%	0.0	0.0%	0.1%	1.0	0.1%
Per capita added value of the secondary industry	31.4%	0.4	12.6%	136.5%	0.5	68.3%	178.1%	0.2	35.6%	237.1%	0.5	118.5%
Secondary industry energy consumption of the per-unit added value	-47.2%	0.8	-37.8%	-39.2%	0.8	-31.4%	-57.3%	1.0	-57.3%	-46.0%	1.0	-46.0%
Secondary industry carbon emission of the per-unit energy consumption	-3.8%	1.0	-3.8%	4.5%	0.0	0.0%	-6.2%	1.0	-6.2%	-6.7%	0.0	0.0%
Per capita added value of the tertiary industry	19.4%	1.0	19.4%	5.4%	1.0	5.4%	7.8%	1.0	7.8%	22.3%	1.2	26.8%
Tertiary industry energy consumption of the per-unit added value	-13.9%	0.8	-11.1%	4.9%	0.0	0.0%	-2.7%	1.0	-2.7%	5.1%	0.2	1.0%
Tertiary industry carbon emission of the per-unit energy consumption	-1.6%	1.0	-1.6%	-0.2%	0.0	0.0%	-0.2%	1.0	-0.2%	0.7%	1.0	0.7%
Per capita resident income	16.1%	0.2	3.2%	10.2%	0.2	2.0%	3.5%	0.8	2.8%	10.5%	0.4	4.2%
Energy consumption of the per-unit resident income	-10.3%	0.0	0.0%	-6.7%	0.0	0.0%	-1.3%	0.0	0.0%	-0.5%	0.0	0.0%
Carbon emission of the per-unit resident energy consumption	-0.6%	1.0	-0.6%	-0.4%	1.0	-0.4%	-0.2%	1.0	-0.2%	-1.1%	1.0	-1.1%
Total trend growth	49.6%			132.5%			135.5%			224.1%		
Total control growth			-19.7%			44.2%			-20.0%			105.9%

As shown in Table 4, the growth trend of development emission in Beijing has been regulated from 49.6% to -19.6% and that of Shanxi, from 132.5% to 44.2%. The growth trend in the provinces belonging to the third category is regulated from 135.5% to -20.0%. The growth trend in Hubei, as the representative of the fourth category, decreased from 224.1% to 105.9%. These results show a reduction in the growth of development emission in all categories of provinces. In addition, the provinces in the third category exhibit the greatest decline among all categories of provinces. This decline can be attributed to the strict limitation of the pulling effect of the per capita added value of the secondary industry on emissions, thus forcing provinces with high GDPs and high CO_2 emissions to change their economic structures and to improve their level of energy efficiency.

3.5 Provincial allocation results of the intensity reduction target

(1) Related indices in key years

The related indexes calculated from relevant data are shown in Table 5. The annual GDP growth rate is estimated at 7% during the period of 2011 to 2020. The total GDP of China is predicted to reach 71.68 trillion yuan in 2020 (based on the 2005 rate).

Table 5.
GDP and emission indices.

Year	Constant GDP (trillion Yuan)	Total CO_2 emissions (million ton))	Per capita emissions (ton CO_2/person)	Emission intensity (ton CO_2/thousand Yuan)
2005	19.75	5573	4.35	28.21
2010	36.44	8420	6.33	23.11
2020	71.68	11462	8.02	15.99

To achieve the carbon intensity reduction target of 42.5 median of % in 2020, the reduction target for the period of 2011 to 2020 is set to 30.8%. This target indicates that the emission intensity in China should be decreased from 23.1 ton CO2/thousand yuan in 2010 to 15.99 ton CO2/thousand yuan in 2020. Thus, the total CO2 emissions in 2020 should be limited to 11.462 billion tons, as shown in Fig. 1, i.e., $TE_{2020} = 11.462$.

(2) Calculation of the survival emissions SE_t

SE_t is the basic energy consumption emission from the current essential demand of the residents. As stated earlier, this value is divided further into basic survival emissions (RE_t) and development emissions (DE_t). RE_t is determined by R_b^i, which is the benchmark of per capita survival emissions and the expected population P_t^i in year t. Given the vast territory of China, several provinces have demand for heating supplies during winter. Therefore, the benchmark of per capita survival emissions should be determined separately. The 30 provinces in China are classified into two groups, namely, the heating supply and the nonheating supply groups[4], by using the highest per capita residential emission as the benchmark for the survival emission of each group. The benchmarks should also be adjusted to maintain the emission levels of major developed countries by considering the per capita residential emissions of these countries. The benchmarks for the per capita survival emissions in 2020 are set to 0.7641 tons CO_2/person and 0.3858 tons CO_2/person for the heating and nonheating supply groups, respectively. These values are the per capita emissions of Beijing and Yunnan in 2010, respectively. The expected population of the provinces in 2020 is estimated based on their average annual growth rates from 2005 to 2010. The benchmark for basic production I_b is equal to the lowest emission per unit GDP in 2020. This benchmark does not indicate the most basic emission intensity of production for survival, but instead represents the lowest emission intensity levels required for economic production. Beijing is projected to have the lowest emission intensity in 2020, and thus, $I_b = 0.8952$. GDP_{2020}^i is calculated using the assumed growth rate of 7%.

(3) Calculation of the developmental emission DE_t

The initial development emission of region i in target year t, i.e., DEN_t^i, depends on the development emission of base year DE_0^i and its growth rate G^i (regulated growth rates). DE_0^i is calculated by using the actual development emissions of each province, the value of which is equal to the difference in total emissions in 2010 and survival emissions.

[4]According to heating, airiness, and air-conditioning design standards in China, 15 provinces need central heating supplies. These provinces include Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Tibet, Qinghai, Ningxia, Xinjiang, Henan (north of Xuchang), Shanxi (north of Xi'an), and Gansu (north of Tianshui). The other 15 provinces comprise the nonheating supply group, which are not or are only a small part of the heating supply group.

The survival emission in 2020 is calculated by multiplying the benchmarks of the per capita residential emission R_b^i and population P_{2010}^t, which is given by $RE_{2010}^i = R_b^i \times P_{2010}^t$. The survival emission for daily living is determined by the per capita residential emissions in 2010 (if the calculated emission is higher than the actual residential emissions in 2010, then the development emission is no longer calculated). The benchmarks for the per capita residential emission are set to 0.4680 tons CO_2/person and 0.2039 tons CO_2/person for the heating and nonheating supply groups, respectively. These benchmarks represent the per capita emissions of Xinjiang and Fujian, respectively, in 2010, and are the second largest values of the two groups. The survival emission for production is calculated by multiplying the lowest emission intensity of the 30 provinces in 2005 and the GDP obtained under the national planning growth rate. Hence, the excess emission generated by the GDP, which is the growth rate, is higher than that of the national plan for development emissions. The provincial planning GDP in 2010 is calculated by multiplying the actual GDP of each province in 2005 and the national planning GDP growth rate, which has an annual average of 7.5% from 2006 to 2010. The calculated results show the lowest carbon intensity of 8.9520 tons CO_2/thousand yuan in 2010, which is recorded in Beijing. Survival and development emissions are presented in Fig. 7.

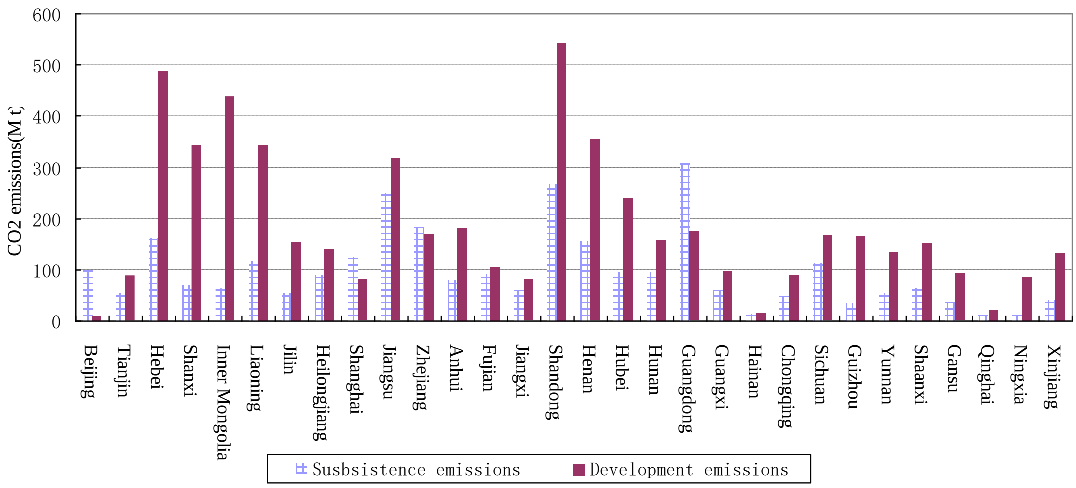

Fig. 7. Survival and developmental emissions for the 30 provinces in 2010.

The initial development emissions and the respective proportions of the national total by 2010 are calculated according to the initial development emissions and their regulated growth rates (G^i). The total development emissions DE_t in 2020 is allocated as follows: $\frac{DEN_t^i}{\sum_i DEN_t^i} * DE_t$.

(4) Allocation results in 2020

The final results of the carbon intensity reduction based on the calculations of the survival and developmental emissions by 2020 are shown in Table 6. A comparison of the decreases in intensity from 2010 to 2020 is shown in Fig. 8.

Table 6.
Allocation results of CO_2 emissions in 2020 (unit: million tons)

Provinces	Survival emissions	Developmental emissions	Total emissions	Provinces	Survival emissions	Developmental emissions	Total emissions
Beijing	163.49	6.73	170.21	Henan	309.17	266.86	576.03
Tianjin	106.84	73.38	180.21	Hubei	174.63	274.86	449.49
Hebei	274.58	561.72	836.30	Hunan	180.22	182.78	363.00
Shanxi	117.81	392.85	510.66	Guangdong	538.68	130.97	669.65
Inner Mongolia	126.99	499.70	626.69	Guangxi	112.72	113.70	226.43
Liaoning	223.59	397.23	620.82	Hainan	24.13	16.29	40.42
Jilin	109.75	177.86	287.61	Chongqing	86.91	102.06	188.98
Heilongjiang	147.95	160.69	308.64	Sichuan	200.92	193.27	394.19
Shanghai	201.30	67.46	268.76	Guizhou	55.34	186.94	242.27
Jiangsu	454.00	238.52	692.52	Yunnan	92.82	154.39	247.21
Zhejiang	312.91	127.60	440.51	Shaanxi	118.36	173.84	292.20
Anhui	144.57	208.58	353.16	Gansu	59.05	106.63	165.68
Fujian	168.61	77.58	246.18	Qinghai	16.88	23.44	40.32
Jiangxi	110.19	93.78	203.97	Ningxia	18.87	98.98	117.85
Shandong	495.69	408.11	903.80	Xinjiang	72.22	153.26	225.47

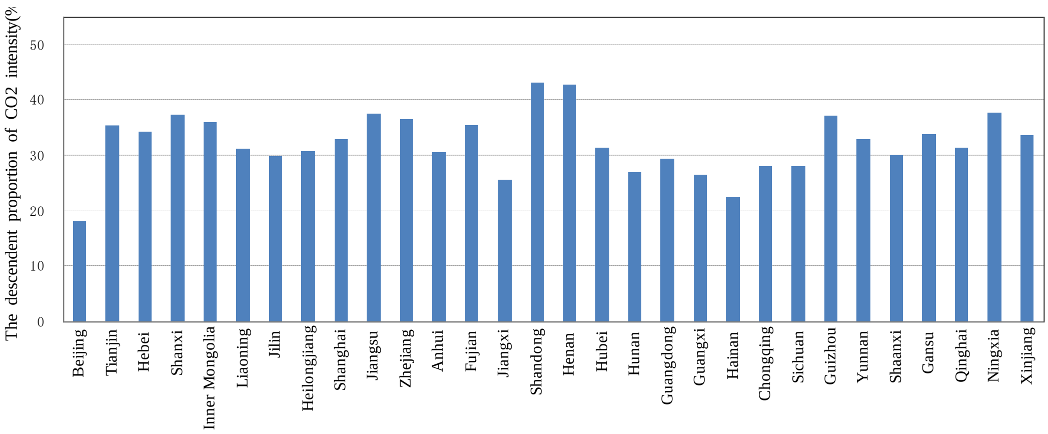

Fig. 8. CO_2 intensity reduction burdens for the 30 provinces of China.

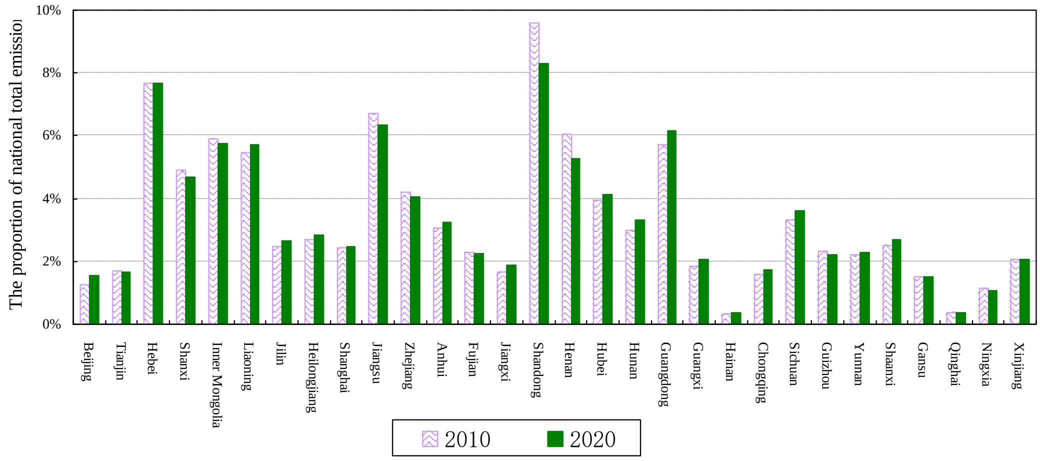

Fig. 9. Proportional comparison of emissions of the 30 provinces in 2010 and 2020.

The following conclusions can be drawn from the results in Table 6 and Figs. 8 and 9:

(1) To ensure that the goal to reduce carbon intensity in 2020 by 30.8% compared with that in 2010 is achieved, 15 provinces should exceed their average reduction rates.

(2) The provinces with the largest CO_2 emissions, and thus, with the highest reduction requirements are Shandong and Henan. These provinces should lower their emissions by 43.2% and 42.7%, respectively. The results indicate that the provinces with the highest carbon emission intensities in 2010 do not exhibit the largest decline among the 30 provinces because the layout of the national energy strategy base is considered. However, the reduction rates of these provinces remain higher than 36%.the layout of the national energy strategy base.

(3) The decline in developed provinces, such as Jiangsu, Zhejiang, and Fujian, are between 35% and 37%, thus indicating that these provinces should adjust their economic structures, strictly restrict the energy consumption of their secondary industry, and further improve their energy efficiency to realize the national intensity targets.

(4) Beijing represents the provinces with the lowest intensity reduction of only 18.2% because a number of enterprises with high emissions have moved out of Beijing in recent years[5]. In 2010, Beijing had the lowest carbon intensity in China (32.8%) compared with its emissions in 2005. Therefore, the potential for reduction in the next 10 years is limited.

[5]For example, the Capital Iron and Steel Company has moved to Caofeidian, Tangshan City, Hebei Province in 2006.

(5) The proportion of the total national emissions in 2020 will exhibit some changes compared with that in 2010. Compared with 2010, the contribution of each province to the total national emissions will change in 2020. The proportions of the provinces with large GDPs and high carbon emissions, such as Shandong, Henan, Jiangsu, and Zhejiang, as well as the provinces with high carbon intensities, such as Ningxia, Shanxi, and Guizhou, have declined. Of these provinces, the emission contribution of Shandong has decreased from 9.6% to 8.3%, but remains the highest in China. The emission proportions of the rest of the provinces have remained unchanged or have slightly increased.

Furthermore, Wang et al. (2013) report a huge gap in the reduction burdens between the highest (more than 61%) and lowest (less than 30%) allocations. By contrast, the gap in the reduction burdens among provinces in the present study is nonsignificant (i.e., between 19% and 43%). Thus, the energy structure, industrial structure, and social development of different regions should be considered.

4. Conclusions and Implications

This paper proposed a decomposition approach based on PSO-FCM-Shapley to set provincial emission reduction targets. This method divides total emissions into three parts: survival, developmental, and reserved emissions. Based on the PSO-FCM clustering of the carbon emissions in each province to macro factors, we selected a representative province for each category, decomposed its emission growth using the Shapley value method, and identified the key factors of emission growth in each category of provinces. With full consideration of the provincial economic developmental level, industrial structure, and total emissions, the present proposes the key points and the extent of the mitigation policy to accomplish the national emission reduction target. The following conclusions and implications are drawn from the results:

(1) The 30 provinces of China can be clustered into four classes, each with distinct characteristics, according to the 13 macro factors influencing carbon emissions. The categories are (i) the tertiary industry-developed municipalities of Beijing, Tianjin, and Shanghai; (ii) the resources-based and high emission intensity provinces such as Shanxi, Ningxia, and Inner

Mongolia; (iii) the more developed coastal provinces; and (iv) the rest of the provinces in the central and western areas, which are less developed;

(2) The energy consumption per unit of value added of the secondary industry is the primary factor for the increasing carbon emissions in the different representative provinces. Therefore, to achieve emission reduction targets, all provinces of China should limit the growth rate of their secondary industries, particularly those with high energy consumption, to lessen their contribution to emission growth. However, the limitations set for the various types of provinces should be of different degrees depending on the ratio of their contributions to the total CO_2 emission intensity.

(3) Different provinces should shoulder different mitigation burdens in terms of the 13 macro-influencing factors. High degrees of emission reduction are required for provinces with large total emissions. The allocation results of intensity reduction show that the largest reduction burdens should be shouldered by provinces with high cardinality of emissions, such as Shandong and Henan, and by resource-based provinces with high emission intensities (average reduction of 37.1%). The minimum requirements for emission reduction are met by first-category provinces, such as Beijing, Tianjin, and Shanghai, which have low emission intensities.

(4) Fifteen provinces are expected to exceed the national average decrease rate (30.8%) from 2010 to 2020. Several developed provinces, such as Jiangsu, Zhejiang, and Fujian, should adjust their economic structures, strictly restrict the energy consumption of their second industry, and further improve their energy efficiency.

Appendix

Table A1.

13 macro influencing factors of carbon emission data (2010)

	Populatioin	Per capita added value of the primary industry	Primary industry energy consumption of per-unit added value	Primary industry carbon emission of the per-unit energy consumption	Per capita added value of the secondary industry	Secondary industry energy consumption of the per-unit added value	Secondary industry carbon emission of the per-unit energy consumption	Per capita added value of the tertiary industry	Tertiary industry energy consumption of the per-unit added value	Tertiary industry carbon emission of the per-unit energy consumption	Per capita resident income	Energy consumption of the per-unit resident income	Carbon emission of the per-unit resident energy consumption
Unit	10 thousand	10,000 RMB /person	tce/10,000 RMB	t CO_2/tce	10,000 RMB / person	tce/10,000 RMB	T CO_2/ tce	10,000 RMB /person	tce/10,000 RMB	t CO_2 / tce	10,000 RMB /person	tce/10,000 RMB	t CO_2/ tce
Beijing	1536	0.0638	0.5113	2.4423	1.3193	1.2178	2.3300	3.1001	0.2314	2.0989	1.4809	0.2018	2.1599
Tianjin	1043	0.1078	0.3732	2.2398	1.9675	1.5182	2.5576	1.4715	0.3846	2.1628	0.9651	0.1611	2.1383
Hebei	6844	0.2196	0.0657	2.2532	0.7645	3.0296	2.6084	0.4910	0.2715	2.2594	0.4905	0.3191	2.5220
Shanxi	3352	0.0783	0.6549	2.5089	0.7020	4.1790	2.5058	0.4666	0.3284	2.2515	0.4621	0.4154	2.4968
I. Mongolia	2386	0.2471	0.3146	2.3709	0.7431	4.3416	2.5831	0.6424	0.6523	2.2960	0.5308	0.5149	2.5602
Liaoning	4220	0.2091	0.2344	2.3198	0.9368	2.5410	2.4056	0.7520	0.3982	2.1323	0.6207	0.1851	2.4183
Jilin	2715	0.2304	0.2745	2.2730	0.5823	3.0522	2.5443	0.5207	0.4828	2.3939	0.5629	0.2319	2.2540
Heilongjiang	3818	0.1793	0.3721	2.1362	0.7783	1.8825	2.5045	0.4859	0.3885	2.1284	0.5597	0.1651	2.1132
Shanghai	1778	0.0452	0.9731	2.1434	2.5045	1.0980	2.4201	2.5989	0.3606	2.1412	1.6861	0.0983	1.9811
Jiangsu	7468	0.1957	0.1517	2.2417	1.3866	1.4079	2.5604	0.8689	0.1445	2.1169	0.8153	0.0648	2.0096
Zhejiang	4894	0.1824	0.3224	2.1324	1.4643	1.1700	2.5625	1.0991	0.1670	2.0868	0.9189	0.0990	1.9920
Anhui	6114	0.1581	0.1112	2.2379	0.3633	2.3325	2.6026	0.3578	0.1616	2.1962	0.3808	0.1806	2.4278
Fujian	3532	0.2382	0.2964	2.2471	0.9061	1.2019	2.5295	0.7156	0.2269	2.1124	0.6764	0.1288	2.3432
Jiangxi	4307	0.1689	0.2043	2.1364	0.4452	1.5300	2.5266	0.3278	0.2583	2.0988	0.4489	0.1208	2.3694
Shandong	9239	0.2125	0.2900	2.2942	1.1504	1.7879	2.6047	0.6413	0.3568	2.1297	0.6158	0.1520	2.2396

Table A1. continued

Henan	9371	0.2019	0.1126	2.3018	0.5884	1.8964	2.5893	0.3395	0.1866	2.0841	0.4017	0.2587	2.5429
Hubei	5707	0.1896	0.2198	2.2820	0.4924	2.1566	2.5622	0.4605	0.3804	2.1467	0.5214	0.1471	2.4556
Hunan	6320	0.2016	0.2307	2.6228	0.4109	2.0787	2.5996	0.4178	0.3505	2.2201	0.4508	0.1615	2.5369
Guangdong	9185	0.1555	0.1678	2.2322	1.2346	0.9669	2.4566	1.0450	0.2226	2.0771	0.9689	0.1106	1.8991
Guangxi	4655	0.1960	0.0488	2.1816	0.3245	2.0027	2.4464	0.3550	0.3383	2.1243	0.3674	0.1101	1.9269
Hainan	826	0.3640	0.1227	2.1536	0.2663	2.5113	2.0994	0.4523	0.4264	2.0886	0.4894	0.0360	1.8684
Chongqing	2797	0.1657	0.4272	2.6126	0.4502	2.0007	2.5188	0.4819	0.2576	2.1187	0.4689	0.1726	2.1536
Sichuan	8208	0.1805	0.0966	2.2142	0.3737	1.6260	2.6308	0.3456	0.2706	2.0703	0.4037	0.2160	2.2331
Guizhou	3725	0.0990	0.5890	2.6531	0.2219	5.0689	2.6393	0.2103	0.7077	2.3716	0.2826	0.7226	2.6316
Yunnan	4442	0.1508	0.2543	2.5659	0.3225	2.8315	2.6216	0.3085	0.4306	2.1533	0.3187	0.2274	2.5124
Shaanxi	3718	0.1172	0.1095	2.1827	0.4974	1.6902	2.6112	0.3740	0.5349	2.2014	0.3583	0.3440	2.3490
Gansu	2592	0.1189	0.2015	2.3349	0.3236	3.2481	2.5871	0.3038	0.3571	2.1668	0.3340	0.3402	2.5976
Qinghai	543	0.1204	0.1086	2.3061	0.4878	2.1342	2.4905	0.3933	0.7220	1.8352	0.3862	0.8586	1.9227
Ningxia	595	0.1211	0.1371	2.2751	0.4727	6.2189	2.6395	0.4249	0.5594	2.2095	0.4451	0.3677	2.5651
Xinjiang	2008	0.2540	0.3457	2.3443	0.5800	3.2142	2.3051	0.4628	0.6173	2.1272	0.4799	0.3877	2.5178

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