

Article



# Decomposition Analysis and Trend Prediction of CO<sub>2</sub> Emissions in China's Transportation Industry

# Ming Meng<sup>D</sup> and Manyu Li \*

Department of Economics and Management, North China Electric Power University, Baoding 071003, Hebei, China; 51851341@ncepu.edu.cn

\* Correspondence: 2182218043@ncepu.edu.cn

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Abstract: China's transportation industry has become one of the major industries with rapid growth in CO<sub>2</sub> emissions, which has a significant impact in controlling the increase of CO<sub>2</sub> emissions. Therefore, it is extremely necessary to use a hybrid trend extrapolation model to project the future carbon dioxide emissions of China. On account of the Intergovernmental Panel on Climate Change (IPCC) inventory method of carbon accounting, this paper applied the Logarithmic Mean Divisia Index (LMDI) model to study the factors affected by CO<sub>2</sub> emissions. The affected factors are further subdivided into the scale of employees, per capita carrying capacity, transport intensity, average transportation distance, energy input and output structure, energy intensity and industrial structure. The results are as follows: (1) Per capita carrying capacity is the most important factor to promote the growth of  $CO_2$ emissions, while industrial structure is the main reason to inhibit the growth of  $CO_2$  emissions; (2) the expansion of the number of employees has played a positive role in the growth of  $CO_2$  emissions and the organization and technology management of the transportation industry should be strengthened; (3) comprehensive transportation development strategy can make the transportation intensity effect effectively reduce  $CO_2$  emissions; (4) the  $CO_2$  emissions of the transportation industry will continue to increase during 2018–2025, with a cumulative value of about 336.11 million tons. The purpose of this study is to provide scientific guidance for the government's emission reduction measures in the transportation industry. In addition, there are still some deficiencies in the study of its influencing factors in this paper and further improvements are necessary for the subsequent research expansion.

Keywords: CO<sub>2</sub> emissions; LMDI model; decomposition analysis; hybrid trend extrapolation model

## 1. Introduction

At present, the intensification of the greenhouse effect and its derivative effects is an important issue of common concern to governments of all countries [1,2]. Studies show that the CO<sub>2</sub> emissions from fossil fuels are the most significant reason for the exacerbated greenhouse effect [3–5]. As a country with high production efficiency, China consumes a large amount of fossil energy and emits a lot of CO<sub>2</sub> emissions. For the sake of restraining the growth of CO<sub>2</sub> emissions from fossil energy, the Paris Agreement was convened at the end of 2015. In the Intended Nationally Determined Contributions (INDCs) submitted to the Paris Agreement, it was pointed out that China's CO<sub>2</sub> emissions shall get to the crest value around 2030 and strive to reach the peak with the fastest speed and shortest time [6]. The Chinese government promised that by 2030, the CO<sub>2</sub> emission per unit of GDP shall be 60% to 65% less than in 2005 [7].

The industrial sector is the traditional subject of  $CO_2$  emissions in China. However, since China's economy entered the 'new normal' [8], the impact of the tertiary industry sector, especially the transportation industry, on China's  $CO_2$  emissions has become increasingly important. China's transportation industry is characterized by high energy consumption [9]. Through calculation of

the data in the *Energy Statistical Yearbook* [10], energy consumption increased at an average annual ascending rate of 8.17% from 2001 to 2017 and reached 357.10 million tons in 2017 [10]. With the rapid increase of the transportation scale, its effect on China's  $CO_2$  emissions is expected to continue to expand. Therefore, for the sake of cutting down  $CO_2$  emissions effectively, it is significant to determine the factors that cause the increase of  $CO_2$  emissions. Based on this, this article proposed policy recommendations for reducing  $CO_2$  emissions of the transportation industry. Achieving the goal of energy conservation and emission reduction is significant to China [11].

Generally, decomposition analysis is extensively applied for studying the affected elements of CO<sub>2</sub> emission [12]. It quantitatively measures the contribution value of each factor in a given process by decomposing the comprehensive or relative index into several driving elements. There are mainly two decomposition methods: Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA) [13]. In contrast to SDA, IDA has the strong points of simple structure, low data demand and fewer restricted conditions [14]. LMDI is the best developed model in the IDA method [15], which is not subject to zero value or residual value, and directly calculates the logarithmic weighting factor [16]. Ang proposed eight LMDI models, summarizing their origins, decomposition formulas, strengths and weaknesses to help users choose which model to use to provide a selection guide [17].

Compared with other decomposition methods, the LMDI model is considered to be the most effective tool to study the decomposition analysis of influencing factors, and its results are more applicable and explanatory [18,19]. The LMDI method has experienced a period of rapid growth and has made a great dedication to the analysis of CO<sub>2</sub> emissions in the states, regions and provinces [20]. Meanwhile, it is also increasingly used to research the affected factors of CO<sub>2</sub> emissions in various industries [21–23]. With the ongoing improvement of academics, the LMDI method has become a mainstream application in the factor analysis of the transportation industry. The following are examples of many scholars applying LMDI to decompose CO<sub>2</sub> emissions from the transportation industry. Zhang et al. established a regional elastic decoupling model and LMDI model for the transportation industry to analyze the factors affecting CO<sub>2</sub> emissions [24]. Zhang and Yao established the LMDI to analyze the contribution of earnings, energy strength and transport structure factors to  $CO_2$  emissions of China's transportation industry [7]. Liang et al. made use of the LMDI to study the restraining effect of energy structure, energy efficiency and population scale on CO<sub>2</sub> emissions in the transportation industry [11]. A study by Timilsina and Shrestha studied the contribution of per capita GDP, population increase and energy intensity to the growth of CO<sub>2</sub> emissions in the transport sector [25]. Fan and Lei measured the impact of energy structure, energy intensity, unit traffic turnover rate and traffic intensity on  $CO_2$  emissions of Beijing's transportation industry [26]. This article mainly used the LMDI to decompose the elements that affected the CO<sub>2</sub> emissions of China's transportation industry in order to find the driving factors for reducing CO<sub>2</sub> emissions.

Meanwhile, this study also predicted future  $CO_2$  emissions. Some scholars have made many explorations in predicting  $CO_2$  emissions. Feng's study used system dynamics to predict the trend of  $CO_2$  emissions in Beijing from 2005 to 2030 [27]. Decai et al. established a GM (1, 1) grey model and multinomial regression hybrid model to forecast  $CO_2$  emissions based on Jiangsu's gross national product and energy consumption statistics [28]. Because the curve of the sample data to be predicted in this study is between linear and exponential trends, the above methods are not suitable. The Meng scholar added a linear equation based on the gray prediction to the hybrid trend model, which could use a small number of specimens for fitting and predict the above two tendencies simultaneously. These tests' results had proved that the hybrid trend extrapolation model had better adaptability and prediction results than the single trend extrapolation method [29,30]. It can be seen that this article is suitable for applying the hybrid trend extrapolation method to predict  $CO_2$  emissions in the next few years.

Therefore, this article applied the LMDI and hybrid trend extrapolation model in the transportation industry to decompose the elements that affect  $CO_2$  emissions in 2001–2017 and forecast  $CO_2$  emissions in 2018–2025. The factors influencing  $CO_2$  emission studied in this paper are: Energy input–output

structure, energy intensity, industrial structure, average distance, transportation intensity, per capita carrying capacity and the size of employees of the industry. The decomposition results can also supply a benchmark for government policies on how to cut down carbon dioxide emissions. This article consists of the following parts: Section 2 contains methods and data processing. Section 3 gives the contribution value of factors,  $CO_2$  emissions results and predicted values. Section 4 gives the analysis of these factors; Section 5 gives the conclusion and political opinions. Finally, Section 6 gives the limitation and prospect of the article.

#### 2. Methodology and Data

#### 2.1. Extended LMDI

The transportation industry refers to the business activities that transport goods or passengers to their destinations by means of transportation so as to transfer their spatial positions. This article divided the elements affecting  $CO_2$  emissions into seven: Energy input–output structure, energy intensity, industrial structure, average transportation distance, transportation intensity, per capita carrying capacity and the scale of employees in the industry. There are eight typical types of fuel consumed by China's transportation industry: Coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas.

In this article, the Intergovernmental Panel on Climate Change's (IPCC) checklist [31] method was applied to calculate  $CO_2$  emissions.  $CO_2$  emissions are derived from energy consumption multiplied by its corresponding emission coefficient. Specifically,  $SCC_i$  and  $M_i$  data are derived from the general principle of total calculation, the production energy consumption [32]. The key to the calculation is the  $CO_2$  emission factor. IPCC default values for international standards are usually used as emission factors to compute  $CO_2$  emissions. On the basis of the assumption of a carbon emission factor, the IPCC calculates that  $CO_2$  emissions remain unchanged as shown in Equation (1):

$$C = \sum_{i=1}^{8} K_i \times SCC_i \times M_i \times N_i \tag{1}$$

where *C* is the overall CO<sub>2</sub> emissions of China's transportation industry;  $K_i$  is the *i*-th energy use of the transportation industry (suit: kgce/m<sup>3</sup>; kgce/kg); *SCC<sub>i</sub>* is the standard coal coefficient of the *i*-th fuel (suit: kgce/m<sup>3</sup>; kgce/kg);  $M_i$  is the average low calorific value of different fuels;  $N_i$  is the CO<sub>2</sub> emissions factor of various fuels; *i* is the *i*-th energy source.

For the sake of studying the potential impact elements on  $CO_2$  emissions, according to the classic Kaya identity [33], the LMDI is applied to establish the decomposition model of impact elements on  $CO_2$  emissions, as shown in Equation (2):

$$C = \sum_{i=1}^{8} C_{it}$$

$$= \sum_{i=1}^{8} \frac{C_{it}}{E_t} \times \frac{E_t}{V_t} \times \frac{V_t}{G_t} \times \frac{Q_t}{W_t} \times \frac{1}{\frac{Q_t}{G_t}} \times \frac{W_t}{P_t} \times P_t$$
(2)

where  $C_{it}$  is the consumption of CO<sub>2</sub> in the *t*-year of the *i*-th fuel;  $E_t$  is the energy use of the *t*-year;  $G_t$  is the GDP of the *t*-year;  $V_t$  represents the added value of the transportation industry in the *t*-year;  $Q_t$  is the turnover volume of the *t*-year (passenger traffic plus freight volume);  $W_t$  is the *t*-year shipment (passenger traffic plus freight volume);  $P_t$  is the employees of transportation industry in the *t*-year. Among them, the selection of GDP, P, energy use and turnover indicators came from [7,34], and the rest of the indicators were selected according to the relevant indicators in the *China Statistical Yearbook* [10]. Furthermore, Equation (2) is expressed as follows:

$$C = \sum_{i=1}^{8} C_{it}$$

$$= \sum_{i=1}^{8} KS_{it} \times EI_t \times IS_t \times L_t \times QI_t \times Y_t \times P_t$$
(3)

where  $KS_{it} = C_{it}/E_t$  represents the energy input and output structure of the *i*-th energy;  $EI_t = E_t/V_t$ means the energy intensity of the *t*-year;  $IS_t = V_t/G_t$  means the industrial structure of the *t*-year;  $L_t = Q_t/W_t$  means the average transportation distance of the *t*-year;  $QI_t = 1/Q_t/G_t$  represents the reciprocal of transport intensity in the *t*-year;  $Y_t = W_t/P_t$  represents the per capita carrying capacity of the transportation industry in the *t*-year;  $P_t$  is the scale of employees of the transportation industry in the *t*-year.

LMDI is able to partition into two classifications: Multiplication decomposition and addition decomposition. Some absolute indicators (such as total energy consumption, indirect  $CO_2$  emissions of residents, etc.) are usually decomposed by addition. At present, due to the problem of the development of method model, the application of addition decomposition is more common than multiplication decomposition, and the following are examples of using addition decomposition analysis to solve the problem of  $CO_2$  emissions. Lin and Xie used the method of addition structure decomposition to sum up the changes of  $CO_2$  emissions in China's food industry from 1992 to 2010 into four aspects [35]. Wang and Yang's indirect  $CO_2$  emissions to urban and rural residents in Beijing from 2000 to 2010 were decomposed into eight influencing factors by adding an LMDI structure [36]. Therefore, this article used addition decomposition to study  $CO_2$  emissions from the transportation industry. The sum of the contribution of the seven impacts is the total growth of  $CO_2$  emissions from year *t1* to year *t*. The Kaya identity is improved as follows:

$$\Delta C = C^T - C^{T-1} = \Delta C_{KS} + \Delta C_{EI} + \Delta C_{IS} + \Delta C_L + \Delta C_{OI} + \Delta C_Y + \Delta C_P \tag{4}$$

where  $\Delta C$  represents the increase in total CO<sub>2</sub> emissions from the *t*-1 year to the target year *t*; where  $\Delta C_{KS}$ ,  $\Delta C_{EI}$ ,  $\Delta C_{IS}$ ,  $\Delta C_L$ ,  $\Delta C_{QI}$ ,  $\Delta C_Y$  and  $\Delta C_P$  reflect the degree of the elements' impact. The contribution of the seven variables to CO<sub>2</sub> emissions can be based on the LMDI method decomposition equation. The specific decomposition formula is as follows, in Table 1, where  $KS \neq 0$ ,  $EI \neq 0$ ,  $IS \neq 0$ ,  $L \neq 0$ ,  $QI \neq 0$ ,  $Y \neq 0$ ,  $P \neq 0$ .

Change Scheme	LMDI Equation
	$\Delta C_{KS} = \sum_{i=1}^{8} \frac{C_i^{t} - C_i^{t-1}}{\ln C_i^{t} - \ln C_i^{t-1}} \times \ln \frac{KS^{t}}{KS^{t-1}}$
	$\Delta C_{IS} = \sum_{i=1}^{8} rac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}}  imes \ln rac{IS^t}{IS^{t-1}}$
	$\Delta C_L = \sum_{i=1}^{8} rac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}}  imes \ln rac{L^t}{L^{t-1}}$
$\Delta C = C^{t} - C^{t-1} = \Delta C_{KS} + \Delta C_{EI} + \Delta C_{IS} + \Delta C_{L} + \Delta C_{QI} + \Delta C_{Y} + \Delta C_{P}$	$\Delta C_{KI} = \sum_{i=1}^{8} \frac{C_i^{t} - C_i^{t-1}}{\ln C_i^{t} - \ln C_i^{t-1}} \times \ln \frac{KI^{t}}{KI^{t-1}}$
	$\Delta C_Y = \sum_{i=1}^{8} \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \times \ln \frac{Y^t}{Y^{t-1}}$
	$\Delta C_{QI} = \sum_{i=1}^{8} \frac{C_i^{t} - C_i^{t-1}}{\ln C_i^{t} - \ln C_i^{t-1}} \times \ln \frac{QI^{t}}{QI^{t-1}}$
	$\Delta C_P = \sum_{i=1}^{8} \frac{C_i^t - C_i^{t-1}}{\ln C_i^t - \ln C_i^{t-1}} \times \ln \frac{P^t}{P^{t-1}}$

Table 1. The Logarithmic Mean Divisia Index (LMDI) formula.

#### 2.2. Hybrid Trend Extrapolation Model

Combining the GM (1, 1) prediction equation with the linear model, a mixed equation is established. When it is used for prediction, iteration is carried out on the premise of determining the starting point of iteration and a given time series  $x^{(0)}(k)$ . From this, the hybrid trend extrapolation equation is written by Meng et al. [29]:

$$\begin{cases} \hat{x}^{(0)}(k+1) = \lambda_1 \hat{x}^{(0)}(k) + \lambda_2 k + \lambda_3 \\ \hat{x}^{(0)}(1) = \hat{x}^{(0)}(1) + \lambda 4 \end{cases}$$
(5)

where  $\lambda_1 - \lambda_4$  are the equation parameters of the mixed trend extrapolation equation.

Equation (5) is a combination of an unconstrained optimization equation and a linear equation that can effectively enhance the usability of the hybrid model in simulating the above two trends and any trends between them. By changing the parameters of the equation, the corresponding tracking fit/prediction result is obtained.

When determining the parameters of the equation, *n* observations can be utilized to first estimate the values of three parameters in two steps. Estimation of  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$  are calculated by Liu et al. [37]:

$$\hat{\boldsymbol{\lambda}} = (\mathbf{B}'\mathbf{B})^{-1}\mathbf{B}'\mathbf{Y},$$
where :

$$\hat{\boldsymbol{\lambda}} = \begin{bmatrix} \hat{\lambda}_1 \\ \hat{\lambda}_2 \\ \hat{\lambda}_3 \end{bmatrix}, \ \boldsymbol{B} = \begin{bmatrix} x^{(0)}(1) & 1 & 1 \\ x^{(0)}(2) & 2 & 1 \\ \dots & \dots & \dots \\ x^{(0)}(n-1) & n-1 & 1 \end{bmatrix} \text{ and } \boldsymbol{Y} = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots \\ x^{(0)}(n) \end{bmatrix}.$$
(6)

The estimation of  $\lambda_4$  is calculated based on the aforementioned results by minimizing the fitting errors. That is,

$$\min_{\hat{\beta}_4} \sum_{k=1}^{n} \left[ \hat{x}^{(1)}(k) - x^{(1)}(k) \right]^2 \tag{7}$$

The results of the above unconstrained optimization equation is given by Zeng and Meng [38]:

$$\hat{\lambda}_{4} = \frac{\sum_{k=1}^{n-1} \left[ x^{(1)}(k+1) - \hat{\lambda}_{1}^{k} x^{(1)}(1) - \hat{\lambda}_{2} \sum_{j=1}^{k} j \hat{\lambda}_{1}^{k-1} - \frac{1 - \hat{\lambda}_{1}^{k}}{1 - \hat{\lambda}_{1}} \hat{\lambda}_{3} \right] \hat{\lambda}_{1}^{k}}{1 + \sum_{k=1}^{n-1} \hat{\lambda}_{1}^{2k}}$$
(8)

where  $x^{(1)}$  is the cumulative generation time series of  $x^{(0)}$ , which is achieved by

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)bt = \frac{2}{n-1} \Big( M_t^{(1)} - M_t^{(2)} \Big)$$
(9)

After obtaining the estimations of  $\lambda_1 - \lambda_4$ , let k = 1, 2, 3, ..., in Equation (9), the suiting and prediction results to  $x^{(0)}(k)$  are then achieved.

#### 2.3. Data Source

In this article, data are obtained from the use of coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas in "transportation, storage and postal industries" of the *China Energy Statistics Yearbook* [10]. Energy use data need to be changed into standard quantity according to the standard coal coefficient. Specifically,  $SCC_i$ ,  $M_i$  and  $CO_2$  emissions coefficient data are derived from the general principle of total calculation, production energy consumption of 2008 [32], as shown in Table 2 below.

Factors (kgCO <sub>2</sub> /TJ)	Average Low Calorific Value (KJ/kg)	Standard Coal Coefficient (kgce/m <sup>3</sup> ; kgce/kg)		
94,600	20,908	0.7143		
107,000	28,435	0.9714		
73,300	41,816	1.4286		
70,000	43,070	1.4714		
71,900	43,070	1.4714		
74,100	42,652	1.4571		
77,400	41,816	1.4286		
56,100	35,544	1.2143		
	Factors           (kgCO2/TJ)           94,600           107,000           73,300           70,000           71,900           74,100           77,400           56,100	Factors (kgCO2/TJ)Average Low Calorific Value (KJ/kg)94,60020,908107,00028,43573,30041,81670,00043,07071,90043,07074,10042,65277,40041,81656,10035,544		

Table 2. The correlation coefficient of fuel.

In order to eliminate the impact of inflation, on the premise of knowing the GDP index and the transportation industry index in 2001–2017, the constant price GDP and the transportation industry added value in 2017 are, respectively, multiplied by the respective ratio between the index in 2001–2016 and the index in 2017 to obtain the constant price GDP and the transportation industry added value for 2001–2016. The calculation results are shown in Table 3.

Year	GDP (10 <sup>6</sup> Yuan)	Industry Added Value (10 <sup>6</sup> Yuan)	GDP Index	Transportation Industry Index
2001	197,334.21	10,662.93	851.90	823.60
2002	215,352.10	11,422.69	912.60	898.80
2003	236,963.98	12,122.37	968.50	989.00
2004	260,923.94	13,878.46	1108.80	1089.00
2005	290,658.25	15,433.03	1233.00	1213.10
2006	327,628.46	16,971.32	1355.90	1367.40
2007	374,254.54	18,975.24	1516.00	1562.00
2008	410,386.16	20,364.59	1627.00	1712.80
2009	448,961.69	21,051.75	1681.90	1873.80
2010	496,713.88	23,044.40	1841.10	2073.10
2011	544,082.72	25,271.11	2019.00	2270.80
2012	586,827.28	26,809.41	2141.90	2449.20
2013	632,351.20	28,578.01	2283.20	2639.20
2014	678,498.08	30,434.23	2431.50	2831.80
2015	725,315.84	31,668.37	2530.10	3027.20
2016	774,050.39	33,722.35	2694.20	3230.60
2017	827,121.70	36,802.70	2940.30	3452.10

Table 3. The data of GDP and industry added value.

Note: The GDP index and transportation industry index in 2001–2017 as well as the GDP and transportation industry added value in 2017 are derived from the China Statistical Yearbook [10].

Conversion turnover is a comprehensive indicator reflecting the total turnover of passenger and cargo transportation in the transportation sector. It is calculated by converting the passenger turnover into a ton-kilometer (ton of nautical miles) using the conversion factor, and then adding it to the cargo turnover. It is expressed as "converted ton-kilometer" (for shipping companies as "converted ton of nautical miles"). On the basis of the transfer coefficient of the mode of transportation, the conversion between passenger and cargo is completed. Of course, turnover should be converted into flow that can be compared or added according to specific conditions. In Houda and Mounir's research, the turnover is measured by ton-km. Therefore, the passenger turnover calculated by people per kilometer must be converted into tons per kilometer by the conversion factor. Among them, 1 passenger-km for railway transportation is converted into 1 ton-km, and 13.8 passenger-km for air transportation is converted into 1 ton-km [39].

#### 3. Results

#### 3.1. CO<sub>2</sub> Emission Results

As shown in Figure 1 below, the current situation and trend of  $CO_2$  emissions in the transportation industry can be analyzed clearly and intuitively to understand the progress of emission reduction. CO<sub>2</sub> emissions generated by eight energy sources consumed by the transportation industry gradually increased from 2001 to 2017, with an average ascending rate of 7.97%, from 314.35 million tons in 2001 to 1.07 billion tons in 2017. During 2001–2004, the CO<sub>2</sub> emissions were in a fast growth period. China's opening to the outside world had been further strengthened, which required the support of the transportation industry, leading to the fast increase of  $CO_2$  emissions. In 2005–2008, it was in a period of slow growth, and the growth rate gradually decreased due to the implementation of the Kyoto Protocol [40]. The Olympic Games in Beijing organized in 2008 had also played a greater role in driving transportation, post and telecommunications, communications and other industries. First, the scale of infrastructure expansion was shown by a large increase in public transport vehicles, a large increase in passenger and freight traffic by air and the expansion of expressways. Secondly, in terms of freight transportation, there was a lot of equipment transportation before and after the competition and people's travel and transportation needs [41]. In 2009, the U.S. sub-prime crisis broke out, and China's transportation industry was also greatly affected. Later, in response to the crisis, China introduced a national policy to expand domestic demand and strengthened the construction of an integrated transportation system, which had promoted the development of the transportation industry. In 2012, the State Department released the 12th Five-Year project [42], which set stricter emission reduction targets for the transportation industry. Until 2017, the ascending rate of  $CO_2$ emissions fluctuated slightly.



Figure 1. CO<sub>2</sub> emissions and growth rate of China's transportation industry.

#### 3.2. Forecasting Results

In view of the above, this article substituted the relevant data into the hybrid trend extrapolation model to predict the  $CO_2$  contribution of the seven influencing factors in 2018–2025. Table 4 shows that during this forecast period, the total contribution of influencing factors to  $CO_2$  emissions will increase year by year. Among the influencing elements, except for the scale of employees and the per capita carrying capacity, the contribution of other factors to carbon dioxide emissions is negative growth.

Year	ΔQI	$\Delta L$	ΔΡ	ΔΕΙ	ΔΙS	ΔΥ	ΔKS	Total
2018	3786.25	-1369.13	1958.62	-2255.84	-455.99	3003.01	-266.67	4400.26
2019	4174.60	-1614.12	1997.63	-2490.97	-418.12	2982.95	-288.43	4343.54
2020	4562.96	-1859.11	2036.46	-2726.09	-380.26	2962.89	-310.19	4286.65
2021	4951.31	-2104.10	2075.39	-2961.22	-342.39	2942.82	-331.95	4229.85
2022	5339.66	-2349.09	2114.26	-3196.35	-304.53	2922.76	-353.72	4173.00
2023	5728.01	-2594.08	2153.16	-3431.47	-266.66	2902.70	-375.48	4116.17
2024	6116.36	-2839.07	2192.05	-3666.60	-228.80	2882.64	-397.24	4059.34
2025	6504.71	-3084.06	2230.94	-3901.73	-190.93	2862.58	-419.00	4002.51
Total	41,163.86	-17,812.77	16,758.51	-24,630.27	-2587.70	23,462.35	-2742.68	33,611.31

Table 4. Prediction results of CO<sub>2</sub> emissions decomposition (unit: ten thousand tons).

Note: QI—reciprocal of transportation intensity; L—average transportation distance; P—size of employees; EI—energy intensity; IS—industrial structure; Y—per capita carrying capacity; KS—energy input-output structure.

The predicted  $CO_2$  emissions of China's transportation industry from 2018 to 2025 can be obtained by adding the predicted contribution of the influencing factors in Table 4 to the total  $CO_2$  emissions of the previous year. The detailed forecast values can be seen in Table 5. It indicates that  $CO_2$  emissions from the transportation industry may still be on an upward trend during 2018–2025.

Table 5. Prediction results of CO<sub>2</sub> emissions from 2018 to 2025 (unit: ten thousand tons).

Year	Predicted Value
2018	111,602.2983
2019	115,945.8432
2020	120,232.4907
2021	124,462.3395
2022	128,635.3375
2023	132,751.5123
2024	136,810.8492
2025	140,813.3560

#### 3.3. Decomposition Results of the LMDI Model

According to Equations (1)–(4), the analysis is based on the data from 2001 to 2017. Based on the LMDI, we are able to determine the influence of these factors on the overall  $CO_2$  emissions. The  $CO_2$  emission decomposition results are shown in Table 6: uring 2001–2017, the combined impact of  $CO_2$  emissions was about 757.67 million tons. Among them, transportation intensity, average transportation distance, transportation industry employees, energy intensity, industrial structure, per capita carrying capacity and energy input–output structure contributed to -100.83 million tons, 90.96 million tons, 236.58 million tons, -53.49 million tons, -123.15 million tons, 518.93 million tons and -67.36 million tons of  $CO_2$  emissions. A negative value indicates a reduction in  $CO_2$  emissions compared to the previous year.

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Year	ΔQI	ΔL	ΔΡ	ΔΕΙ	ΔΙS	ΔΥ	ΔKS	Total
2002	925.87	213.58	-939.17	260.79	-610.52	2651.21	47.16	2548.92
2003	1613.29	415.04	4568.99	2708.67	-1282.67	-3116.14	-738.78	4168.39
2004	-6430.78	6647.07	-224.08	2255.95	1664.58	4121.92	-2936.68	5097.99
2005	-1462.36	2802.73	-527.96	-574.78	-83.56	4513.30	-755.41	3911.97
2006	1036.10	592.89	578.91	-220.23	-1342.64	4271.06	-194.36	4721.73
2007	221.56	1270.35	699.23	-2624.72	-1261.33	5634.70	-722.64	3217.14
2008	565.95	-3299.02	10.02	-308.81	-1347.50	8489.67	-872.06	3238.26
2009	-415.01	940.13	6513.45	-1394.90	-3668.96	-1216.71	-521.03	236.96
2010	-3119.33	1034.22	-156.93	721.85	-734.45	9174.77	-280.21	6639.92
2011	-1780.04	-797.99	5253.14	-678.55	96.85	4148.00	-793.56	5447.86
2012	-643.05	-1175.68	-12,697.03	2992.10	-1350.38	20,699.01	-211.92	7613.05
2013	9362.11	174.23	20,992.37	-97.92	-973.81	-23,909.88	2787.00	8334.11
2014	-562.80	5510.02	1655.23	-1986.22	-680.79	-69.75	-748.21	3117.49
2015	7760.77	-1716.96	-797.01	1255.75	-2633.21	1232.31	-253.75	4847.90
2016	1976.59	-365.28	-577.77	-3784.06	-208.07	5529.40	-335.96	2234.85
2017	1034.48	-3149.34	-693.72	-3873.47	2101.43	9739.94	-206.51	4952.81
Total	10,083.34	9096.00	23,657.69	-5348.54	-12,315.00	51,892.81	-6736.93	70,329.34

Table 6. Contribution value of CO<sub>2</sub> emissions from 2001 to 2017 (unit: ten thousand tons).

Note: QI—reciprocal of transportation intensity; L—average transportation distance; P—size of employees; EI—energy intensity; IS—industrial structure; Y—per capita carrying capacity; KS—energy input–output structure.

## 4. Discussion

#### 4.1. Transport Intensity Factor Analysis

Transport intensity is a common analysis index reflecting the relationship between traffic volume and economic aggregate. As can be seen from Table 6, the reciprocal curve of transport intensity effect from 2002 to 2017 increased CO<sub>2</sub> emissions by 100.83 million tons, taking up 14.34% of the overall contribution value of carbon dioxide emissions in the transportation industry. Figure 2 reveals that, except for the period 2002–2005, the reciprocal curve of transportation intensity is roughly the same as the tendency of CO<sub>2</sub> emissions. Overall, the cumulative transport intensity effectively reduced carbon dioxide emissions, which is identical with Wang et al. [43]. The improvement of transportation technology, organization and management of the transportation industry and the restriction of high energy consuming industries by the state [26] can achieve the purpose of reducing transportation intensity, so unit transportation volume can create more GDP value. The increase in the intensity of transportation in some years may be due to the increase in transportation activities and the implementation of the national demand expansion policy, which make the growth rate of traffic flow exceed GDP, thus increasing energy consumption and CO<sub>2</sub> emissions.



Figure 2. CO<sub>2</sub> emissions contribution effects of QI factor from 2002 to 2017.

#### 4.2. Average Transportation Distance Factor Analysis

The average transportation distance refers to the average transportation distance of goods or passengers transported by the transportation industry in a certain period of time. It is an index reflecting the working intensity of transportation. It can be seen from Table 6, the cumulative increase of CO<sub>2</sub> emissions from the average distance effect was 90.96 million tons in 2001–2017, taking up 12.93% of the overall contribution value of  $CO_2$  emissions in the transportation industry. Figure 3 reveals that the trend of average transportation distance effect and CO<sub>2</sub> emissions of the transportation industry in 2002–2009 is almost the same; the change trend of average transportation distance effect and  $CO_2$  emissions of the transportation industry in 2010–2017 is almost the opposite. The length of the average transportation distance is closely related to the industrial layout. From 2001 to 2007, China's production layout was unreasonable, among which the second and third industries in the middle and the east accounted for the highest proportion, and the west of the first industry accounted for the highest proportion [44]. The transportation distance of raw materials and finished products between industries increased, thus increasing the turnover of goods and  $CO_2$  emissions. Due to the launch of the medium and long-term railway network planning [45] in 2008, the number of short-distance passenger dedicated lines for intercity railway will be increased. The Ministry of Transport actively promotes the development of the integration of urban and rural highway passenger transport, adjusts the line structure, and increases the short-distance passenger transport of highways; in terms of freight transport, roadway transport accounts for the largest proportion of freight transport, mainly short-distance transport [46]. This resulted in a significant reduction in the average transportation distance in 2008 compared to 2007, resulting in a reduction in  $CO_2$  emissions. The year 2009–2013 is still under planning [45], with little change in average transportation distance and stable change in CO<sub>2</sub> emissions. By observing the data in China's Energy Statistical Yearbook [10], it can be seen that the demand for coal, metallurgy and other heavy industries is not strong in 2015–2017, resulting in the continuous decline of railway transportation. The positive development of E-commerce increased the road freight volume and shortened the average transportation distance.



Figure 3. CO<sub>2</sub> emissions contribution effects of the L factor from 2002–2017.

## 4.3. Scale of Employees Factor Analysis

As can be seen from Table 6, the scale effect of industry employees in 2001–2017 increased  $CO_2$  emissions by 236.58 million tons, taking up 33.64% of the overall contribution value of  $CO_2$  emissions change of the transportation industry. Except for 2012, the  $CO_2$  emissions of the whole line increased year by year. Figure 4 reveals that the tendency of personnel effect and  $CO_2$  emissions of the transportation industry in 2002–2009 is almost the same; the tendency of personnel effect and  $CO_2$  emissions of the transportation industry in 2010–2017 is almost the opposite. Li suggested that for every 2.5 people who moved to Beijing, the number of cars would increase by one. This brought great pressure to urban traffic and promoted the increase of traffic  $CO_2$  emissions [47]. With the development of the economy, the increase of transportation volume needed to expand the scale of employees and the number of transportation vehicles to complete the transportation. This increased energy consumption and  $CO_2$  emissions in the transportation industry. However, affected by the economic crisis in 2012, the domestic express delivery industry was facing a huge reshuffle. The transportation industry's population was significantly lower than that of the previous year, so the contribution to  $CO_2$  emissions was negative. Therefore, how to keep the scale of employees unchanged or even reduced while meeting the transportation activities is a problem to be considered.



Figure 4. CO<sub>2</sub> emissions contribution of the P factor from 2002 to 2017.

#### 4.4. Energy Intensity Factor Analysis

Energy intensity reflects the comprehensive utilization efficiency of fuel. As can be seen from Table 6, the energy intensity effect reduced CO<sub>2</sub> emissions by 53.49 million tons in 2001–2007, taking up -7.61% of the overall contribution value of CO<sub>2</sub> emissions. Figure 5 reveals that the energy intensity effect is almost in accord with the change tendency of CO<sub>2</sub> emissions in the transportation industry. It shows that a prominent progress in energy efficiency helps to decrease CO<sub>2</sub> emissions. In Lakshmanan's study, it was also pointed out that the reduction of energy intensity of passenger cars and light trucks was the main factor in reducing CO<sub>2</sub> emissions of transportation in the United States [48].



Figure 5. CO<sub>2</sub> emissions contribution effects of the EI factor from 2002 to 2017.

The rapid development of China's society and economy has promoted the development of the transportation industry. Energy intensity is related to factors such as the structure of energy use, energy efficiency and national policies. Similarly, Huang and Wang pointed out that energy intensity is closely related to energy structure, energy utilization technology and other factors [49]. At present, the cargo is still mainly transported by road, and the vehicles are mainly light and heavy trucks. According to the data in the *China Statistical Yearbook* [10], the volume of passenger transport by road has declined, but it still dominates, and air transport is gradually rising. Most of the transportation vehicles consume high energy-consumption fuels such as diesel and gasoline, which makes the energy intensity contribution increase. However, the contribution of energy intensity has been negative in some years, because the Ministry of Transport regards the construction of resource-saving and environmentally friendly transportation as a major strategy for transportation development in the new period [50], and promotes the overall upgrade of energy utilization technology and sustainable use of energy. With the promotion of emission decreased technology and the introduction of emission decreased policies, the energy intensity will decrease with the continuous increase of energy efficiency. As shown in the forecast data in Table 6, energy intensity is still the significant factor in restraining the growth of carbon dioxide emissions. In the future, efforts should be made to enhance energy intensity.

#### 4.5. Industrial Structure Factor Analysis

On the basis of the results in Table 6, industrial structure effect has reduced  $CO_2$  emissions by 123.15 million tons, taking up 17.51% of the overall contribution value of CO<sub>2</sub> emissions from the transportation industry in 2001–2017. Similarly, in the research of Tang et al., it was pointed out that the cumulative industrial structure effect is a negative contribution to the  $CO_2$  emission of Jiangsu Province [28]. Figure 6 reveals that the trend of the industrial structure effect is almost the same as the change tendency of CO<sub>2</sub> emission of the transportation industry. Except for 2004 and 2017, the whole curve shows a state of CO<sub>2</sub> emissions reduction year by year. After the outbreak of the economic crisis, in order to restore the economy, we should implement the policy of expanding domestic demand, which requires the rapid development of the transportation industry in order to provide support for the growth of the national economy. The increasing scale of the heavy chemical industry requires a large number of raw material transportation activities, which makes the added value of the transportation industry increase in proportion to the national GDP, and the industrial structure effect increases CO<sub>2</sub> emissions. In addition, the impact of accession to the World Trade Organization (WTO) has further expanded, which provides support for the stable growth of China's economy and makes the GDP grow rapidly, faster than the growth rate of the transportation industry. To a certain extent, the sustainable development strategy and price changes (including transport price and fuel price) also caused the growth rate of added value of the transport industry to be lower than the growth rate of GDP, thus reducing the proportion of the transport industry in GDP, and reducing CO<sub>2</sub> emissions due to the industrial structure effect.



Figure 6. CO<sub>2</sub> emissions contribution effects of the IS factor from 2002 to 2017.

## 4.6. Per Capita Carrying Capacity Factor Analysis

According to the results in Table 6, the per capita carrying capacity effect increased the total  $CO_2$  emissions by 518.93 million tons from 2001 to 2017, taking up 73.79% of the overall contribution value of  $CO_2$  emissions in the transportation industry. Economic development directly drives the increase of traffic volume. As shown in Figure 7 below, the per capita carrying capacity effect is roughly consistent with the change trend of  $CO_2$  emission of the transportation industry. Along with the popularization of network technique and the continuous progress of e-commerce business, the number of employees has been growing steadily. The growth of traffic volume is faster than that of employees, resulting in the growth of per capita traffic pressure and vehicle energy consumption. However, as the statistical caliber of road traffic volume changed in 2013 [10], the transport volume dropped sharply, making  $CO_2$  emissions lower than the previous year. From 2014 to 2017, the traffic volumes were in a stable growth stage, and there was only a little change in the employees. Therefore, the per capita traffic volume continues to increase, and the  $CO_2$  emissions continue to increase.



Figure 7. CO<sub>2</sub> emissions contribution effects of the Y factor from 2002 to 2017.

## 4.7. Energy Input and Output Factor Analysis

In sight of the results in Table 6, the structural effect of energy input–output reduced  $CO_2$  emissions by 67.37 million tons, making up 9.58% of the overall contribution value of  $CO_2$  emissions from the transportation industry in 2001–2017. The structural effect of energy input and output has little impact on  $CO_2$  emissions. It can reveal that the structural effect of energy input and output is basically unanimous with the change tendency of  $CO_2$  emissions of the transportation industry from Figure 8, mainly because of the adjustment of energy use structure. With the rapid growth of freight turnover light and heavy truck transportation activities increases, and the energy consumption is mainly diesel. Diesel consumption is related to vehicle control technology, road slope and load factor [51]. In the GB1589 new national standard, the upper limit of truck weight is large, so the increase of diesel input–output structure leads to the increase of  $CO_2$  emissions. Affected by the oil crisis, the price of fuel oil rose sharply afterwards, resulting in a significant decrease in fuel oil, but the total energy consumption increased, which caused the decrease in the input and output structure of fuel oil and reduced  $CO_2$  emissions. In addition, residents are more inclined to take high-speed rail for long-distance travel [52], thereby reducing  $CO_2$  emissions from the transportation industry.



Figure 8. CO<sub>2</sub> emissions contribution effects of the KS factor from 2002 to 2017.

#### 5. Conclusions and Policy Implications

From 2001 to 2017, LMDI factor decomposition of China's transport sector was carried out, and additive factorization analysis was given. The results of the study are as follows: The per capita carrying capacity is the core element to augment  $CO_2$  emissions and the scale of employees is the significant element. Average transportation distance is the indirect element to augment  $CO_2$  emissions; on the contrary, transportation intensity, energy intensity and industry structure are main elements in inhibiting the increase of  $CO_2$  emissions, while the energy input–output structure has a limited influence on curbing  $CO_2$  emissions. Among them, because the transportation volume is constantly increasing, the per capita carrying capacity will not decrease. As predicted in Table 4, future per capita carrying capacity will still be the main factor for increasing  $CO_2$  emissions, so the government needs to focus on optimizing the remaining factors to reduce  $CO_2$  emissions.

According to the above analysis, we aim to supply recommendations for the administration to formulate emission control policies to decrease CO<sub>2</sub> emissions in the transportation industry.

The government continues to increase energy efficiency to reduce more CO<sub>2</sub> emissions. In particular, the volume of road transport has increased for many years [10], and transportation vehicles are fueled by diesel and gasoline (carbon emission coefficient and standard coal coefficient are high). As a result, the price between gasoline and diesel has been reduced through government tax reforms [32] to reduce the number of diesel-fueled vehicles. A vehicle using a full hybrid drive system can more than double the fuel economy and reduce greenhouse gas emissions by more than half [53]. The government should also increase publicity for public transportation or purchase of clean fuel vehicles, and provide tax incentives for residents who purchase environmentally friendly vehicles. The Korean government is providing tax incentives and subsidies for environmentally friendly vehicles [21]. However, coal is still the main energy consumption in most industries in China. It shows that China's clean energy initiative has not been fully promoted, so we should also actively adjust and optimize the energy consumption structure [54].

The government should reduce the proportion of the primary industry and expand the proportion of the tertiary industry, especially the modern service industry and clean technology industry in the tertiary industry to drive the rapid growth of GDP. The Belt and Road Initiative (BRI) countries will use the high-tech industry as the driving force and develop towards the optimization and upgrading of the industrial structure of the modern service industry and modern manufacturing industry [55].

The government should also increase financial support for technology. Under the "Internet" situation, the government uses big data analysis and intelligent transportation technology to improve the level of traffic policy decision-making and build an energy-saving comprehensive transportation system.

According to the prediction results of this article, the transportation industry's employees and per capita capacity will continue to increase  $CO_2$  emissions, and energy intensity and transportation intensity will become the main factors to reduce  $CO_2$  emissions. The  $CO_2$  emissions of China's transportation industry will be about 1.41 billion tons by 2025. It can be seen that China is actively fulfilling its international responsibilities to attain the goal of saving fuel and reducing emissions. Since this article does not consider Chinese features and it is general, the methods are able to study the  $CO_2$  emissions of transport sectors in other states. This article takes China's transportation industry as the target of study to supply instructions and consultation for analyzing  $CO_2$  emissions in other states.

#### 6. Limitations and Prospects of Research

The research is mainly based on the LMDI decomposition model to analyze the influencing factors of transportation  $CO_2$  emissions. The model is almost modeled using traditional econometric theory. It may lack consideration of spatial factors, so there will be some errors in measuring its influencing factors. In recent years, although the application of space metrology in the research of transportation  $CO_2$  emissions has been gradually explored by domestic scholars, there are relatively few related studies.

Therefore, in the subsequent research and development, further improvements are needed: (1) This paper uses the fossil energy consumption data of China's transportation, storage and post industry in the research area to calculate the industry's  $CO_2$  emissions. The calculated results only consider the direct consumption of fossil energy in the transportation industry; (2) the indirect  $CO_2$  emission caused by the consumption of electricity and heat is relatively small, and the data of the thermal  $CO_2$  emission coefficient and grid carbon emission factor are relatively lacking. Therefore, the indirect energy consumption of electricity and heat is not taken into account in the calculation of traffic  $CO_2$  emissions; (3) there is still a lot of room for development research in the application of space factors in  $CO_2$  emissions, and the unremitting efforts of more researchers are needed.

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