Academic Journal of Engineering and Technology Science
ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

Examining the CO_2 Emission Efficiency and its Influencing Factors for the Transport Sector in Central China

Xinyi Li[1, *]

[1] *School of Management, Shanghai University, Shanghai 200444, China*
[*] *Corresponding author e-mail: 980971719@qq.com*

ABSTRACT. *The transportation industry is the main CO_2 emission industry in China. How to formulate and implement the policies of transportation energy saving and emission reduction policies while meeting the people's growing transportation needs has become an important issue to face Chinese society. The central region, as a transportation hub connecting north and south and connecting east and west, has developed rapidly with the support of policies in recent years, and the transportation sector has also developed accordingly. This paper firstly adopts the Super-SBM model that considers undesired output to calculate and evaluate the CO_2 emission efficiency of transportation sector in 6 provinces in central region of China from 2005 to 2016; then, it considers the impact of per capita GDP, urbanization level, number of buses per 10,000, energy intensity and transportation intensity on the CO_2 emission efficiency of transportation sector. Based on the analysis results, reasonable policy recommendations are provided for further improving the CO_2 emission efficiency of transportation department and developing low-carbon transportation.*

KEYWORDS: *CO_2 emission efficiency, transport sector, central region, influencing factors*

1. Introduction

Since the 1990s, global warming has attracted the attention of the international community. The CO_2 produced by the burning of fossil fuels is recognized as one of the main causes of global warming. China is a big country in the production and consumption of energy resources. Huge energy consumption produces a large amount of CO_2 during the process of rapid economic development. In 2017, my country's carbon dioxide emissions have reached 9.1 billion tons, accounting for 28.17% of global emissions. Therefore, as a major developing country, China is facing international pressure and having responsibility to reduce greenhouse gas emissions.

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

CO_2 emissions in the transport sector are an important source of CO_2 emissions in China. Residents' daily life and social development need the support of a certain number of transportation vehicles. The use of these vehicles will generate corresponding CO_2 emissions, which will have a certain impact on the environment. The transportation industry is the basic carrier for the operation of the entire social economic system, and the trend of its industrial scale continues to develop. How to coordinate the development of the transportation industry and transportation CO_2 emissions has become an urgent problem that needs to be solved.

The central region of China included 6 provinces included Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The population accounts for 26.59% of the total population of the country. In 2018, GDP grew by 7.8%, ranking first among the four major regions. Located in the Central Plains of China, the central region is Chinese transportation hub, connecting the east to the west, and south to the north, and is a bridge and link for the flow of China's production factors. Its geographical location is very important. Meanwhile, the central region is also an important transportation fortress, a distribution center and transit center for passenger and freight transportation. Transportation is an important foundation for the booming economy of the central region and the key to the rise of the central region and regional coordinated development. Therefore, this article will use the super-efficiency SBM model(super-SBM) to calculate the CO_2 emission efficiency of transportation department in the central region, and use panel data to explore its main influencing factors, and propose targeted transportation CO_2 emissions reduction recommendations based on the actual conditions of each province. CO_2 emission efficiency provides guarantee for promoting the coordinated development of regional transportation industry.

2. Literature review

In recent years, transportation CO_2 emissions have become a hot issue of concern to our country and even the international community. Scholars have conducted researches on transportation CO_2 emissions from different perspectives and using various methods. Previous studies focus on the measurement and prediction of transportation CO_2 emissions [1,2,3,4]、the analysis of the spatial characteristics of transportation carbon emissions [5,6,7] and indicators exploration[8,9]. In summary, there are few literatures on transportation CO_2 emissions from the perspective of CO_2 emission efficiency or environmental efficiency.

CO_2 emission efficiency generally refers to the economic benefits of CO_2 emissions released by various production factors in a certain period of time. It mainly includes two concepts: single-factor CO_2 emission efficiency and total-factorCO_2 emission efficiency. Kaya and Yokobori [10] first defined CO_2 emission efficiency from the perspective of a single element, and defined it as the ratio of GDP to CO_2 emissions. Ang [11] then measured the CO_2 emission efficiency by energy consumption per unit of GDP. In addition, some scholars have measured

CO_2 emission efficiency with single-element indicators such as CO_2 emissions per unit of energy and CO_2 emissions per unit of GDP [12, 13, 14].

The efficiency measured from the perspective of all factors is based on the frontier of production, and the efficiency is measured according to the deviation of the production unit from its production boundary, which is more comprehensive and accurate than the efficiency measured from the single factor. At present, the measurement methods of total factor carbon emission efficiency mainly include stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Since DEA can avoid strong assumptions of SFA method about the model setting and the normal distribution of random interference items, it can fit multi-output activities with expected and undesired outputs better, and it has a wider scope of application than SFA. Ramanathan [15] used the DEA method to integrate four indicators of CO_2 emissions and calculated the CO_2 emissions efficiency of 17 countries in the Middle East and North Africa. Yao et al. [16] used the DEA model to measure energy efficiency from a regional perspective according to the cross-sectional data of 30 provinces in China in 2011, after integrating the regional heterogeneity. Guo et al. [17] studied the energy-saving technologies and energy structure adjustments of 29 provinces in China based on the environmental DEA model, and evaluated Chinese potential for emission reduction and energy conservation. Meanwhile, with the continuous expansion of DEA application fields, the methods have also achieved innovation and development. Tone [18] proposed the SBM model (Slack Based Measure, SBM) in 2001, this model considers the slack improvement part. It is a non-radial and non-angle DEA model, which avoids the calculation deviation caused by the difference between the radial and angular choices. Choi et al. [19] used SBM model to estimate China's CO_2 emission efficiency and marginal abatement cost. Gómez-Calvet et al. [20] used the modified SBM-DEA method to analyze the undesired output and CO_2 efficiency of EU countries.

Regarding the influencing factors of CO_2 efficiency, the current research mainly focuses on single-element CO_2 emission efficiency relying on IPAT, STIRPAT and Kaya equations to explore the influencing factors through exponential decomposition [21]. Furthermore, econometric models can also be applied to explore influencing factors [22]. From the review of the literature, it can be seen that the previous literatures mostly started from the perspective of a single factor. There are few studies that have conducted calculations under the comprehensive consideration of the organic unity of economy, energy and environment, and most of the efficiency calculations are for the entire industry. The whole CO_2 emission efficiency cannot be a comprehensive and true reflection of the actual situation in various regions and specific industries. At the same time, it has not further explored influencing factors of transportation CO_2 emission efficiency, and most of the research is based on the entire China which did not consider from a regional perspective. Therefore, the purpose of this research is to grasp the transportation carbon emission efficiency in central region of China, clarify its differences, and put forward targeted recommendations on transportation CO_2 emission reduction based on the actual conditions of each province, which will help improve the transportation CO_2 emission efficiency of each province. The efficiency

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

improvement method can formulate effective strategies and methods for the industry management department.

3. Methodology and Data

3.1 Super-SBM model

The basic and typical DEA methods are CCR model proposed by Charnes et al. [23] in 1978 and BCC model proposed by Banker et al. [24] in 1984. Both of them measure efficiency from radial and angle (input or output angle), which are called radial DEA models. When this model is used to measure the efficiency, for the invalid decision-making units (DMUs), the relaxed and improved part is not taken into account, which makes the calculation results inaccurate. Based on this, Tone proposed the SBM model in 2001[18]. The model considered the improved part of relaxation and was a non-radial and non-angular DEA model. When the DEA model measures the efficiency, the efficiency values are all less than or equal to 1, and there will usually be situations where the efficiency values of multiple evaluated DMUs are all 1, that is, there are multiple effective DMUs. In this case, it cannot further judge which effective DMU has a higher efficiency level and which effective DMU has a relatively low efficiency level, that is, it is impossible to judge its effectiveness. Super Efficiency Model is a good solution to this problem.

This paper supposes that there are n DMUs, $DMU_j(j = 1,2,3,\cdots,n)$. There are m inputs and r_1 desired outputs and r_2 undesired outputs which showed as follows: $X_i = (x_{1k}, x_{2k}, \cdots, x_{mk})$, $Y_p^d = (y_{1k}^d, y_{2k}^d, \cdots, y_{r_1 k}^d)$ and $Y_q^u = (y_{1k}^u, y_{2k}^u, \cdots, y_{r_2 k}^u)$. Then the super-SBM model is constructed as follows:

$$min\beta = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1 - \frac{1}{r_1 + r_2}\left(\sum_{p=1}^{r_1} s_p^+ / y_{r_1 k}^d + \sum_{q=1}^{r_2} s_p^{u-} / y_{r_2 k}^u\right)}$$

s.t.

$$\sum_{j=1;j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik}$$

$$\sum_{j=1;j\neq k}^{n} y_{pj}\lambda_j + s_p^+ \geq y_{pk}$$

$$\sum_{j=1;j\neq k}^{n} y_{qj}\lambda_j - s_p^{u-} \leq y_{qk}$$

$$\lambda_j, s_i^-, s_p^+, s_p^{u-} \geq 0$$

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

$$i = 1,2,\cdots,m; p = 1,2,\cdots,r_1; q = 1,2,\cdots,r_2; j = 1,2,\cdots,n(j \neq k)$$

3.2 Input and Output Indicators

Based on the model described above, this paper will apply the Super-SBM model to calculate the CO_2 emission efficiency change of transport sector of 6 provinces in central China from 2004 to 2016. The input and output indicators are described below.

Input indicators: Based on economic growth theory, labor and capital are the basic and core input factors. Therefore, we chose labor input which is characterized by the number of transportation employees. Considering the availability of data, this paper selects amount of fixed capital investment in the transportation sector as capital input as some scholars did [25, 26]. This study also selects road density as one part of capital input. Meanwhile, we choose energy consumption in the transportation industry as an energy input. Utilizing the consumption of various types of energy by the transportation industry, unified conversion into "10000 tons of standard coal."

Output indicators: We chose gross domestic product by transportation, freight turnover and passenger turnover as the desirable outputs, while the amount of CO_2 emissions of the transport sector from energy consumption are chosen as the undesirable output. Among them, the CO_2 emissions of the transport sector will be calculated according to the following formula:

$$CO_2 = \sum_{1=1}^{5} E_i \cdot F_i$$

Where E_i represents the total consumption of the ith fuel in the transportation sector, and F_i means carbon emission factor for the ith fuel. The main five energy carbon emission coefficients of the transportation sector are as follows:

Table 1 Carbon emission coefficients of different fossil fuels

Fuel	Gasoline	Diesel	Natural Gas	Fuel Oil	Kerosene
Emissions coefficient	0.5538	0.5921	0.4483	0.6185	0.5714

3.3 Driving factors

Based on the data availability and the relevant literature, per-capita GDP, urbanization, transportation intensity, transportation energy intensity, the number of private vehicles per 10,000 people, the number of public vehicles per 10,000 people were chosen to be the dominant driving factor of transport sector CO_2 emission efficiency.

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

Per-capita GDP (pGDP) refers to the gross domestic product divided by the total population, which was selected as the variable for the socio-economic development level.

Urbanization (UR) refers to the proportion of the permanent residents of an urban area in a region to the total resident population in that region. The level of urbanization can well describe the process and degree of population gathering in a certain area to the city.

The number of public vehicles per 10,000 people (PUV). The development of public transportation is low-carbon and environmentally friendly to a certain extent.

Energy intensity (EI) refers to the total energy consumption per unit of the industry’s unit GDP which characterizes the industry’s energy efficiency. A decrease in transportation energy intensity indicates an improvement in the efficiency of energy utilization and the technological progress level in the transport sector [27].

Transportation intensity (TI) refers to the ratio of comprehensive transportation service and the added value in transport sector, which reflects the economic efficiency of the transport sector. The converted transportation turnover is calculated by railway, highway, waterway and civil aviation passenger turnover and the corresponding conversion coefficient, which takes 1, 0.1, 1 and 0.075 respectively [28].

Therefore, the econometric model of CO_2 emission efficiency in the transportation sector can be expressed as:

$$\ln CEE_{it} = \alpha + \beta_1 \ln pGDP_{it} + \beta_2 \ln UR_{it} + \beta_3 \ln PUV_{it} + \beta_4 \ln EI_{it} + \beta_5 \ln TI_{it} + \varepsilon_{it}$$

4. Results and Discussion

4.1 Analysis of CO_2 Emission Efficiency

Table 2 clearly shows the CO_2 emissions efficiency of transport sector in central China.

Table 2 CO_2 emission efficiency in the central region from 2005-2016

Province	Shanxi	Henan	Hubei	Hunan	Jiangxi	Anhui	Average
2005	1.17	1.16	1.11	0.74	0.56	1.27	1.00
2006	1.26	1.14	1.01	0.79	0.52	1.20	0.99
2007	1.23	1.11	1.02	0.84	0.53	1.18	0.99
2008	1.12	1.07	1.02	1.01	0.46	1.29	0.99
2009	1.08	1.07	1.07	1.00	0.50	1.30	1.01
2010	1.09	1.05	1.01	0.68	0.56	1.32	0.95
2011	1.08	1.05	1.01	0.71	0.59	1.34	0.96
2012	1.08	1.05	1.03	1.07	0.60	1.27	1.02
2013	1.11	1.12	1.02	1.12	0.53	1.24	1.02

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

2014	1.12	1.11	1.04	1.04	0.57	1.26	1.02
2015	1.15	1.12	1.05	1.07	0.68	1.20	1.05
2016	1.16	1.12	1.04	1.05	0.64	1.18	1.03
Average	1.14	1.10	1.04	0.93	0.56	1.25	1.00

It can be seen from the Table2 that in the central region, Anhui Province has the highest carbon emission efficiency. During the 12 years from 2005 to 2016, the average CO_2 emission efficiency of the transport sector in Anhui Province was 1.25, which is greater than 1, indicating that they are at the forefront of production. The province's transportation CO_2 emission efficiency is at the advanced level in the country, and the resource allocation is relatively reasonable. Shanxi Province is closely followed. Shanxi Province is rich in coal resources and has a particularly large demand for cargo transportation. However, since 2009, Shanxi Province's CO_2 emissions of transport sector have hardly increased. In recent years, Shanxi Province has adopted management skills and new technologies. For example, traditional buses have been gradually replaced by hybrid or pure electric buses. Jiangxi Province has the lowest CO_2 emission efficiency, and the annual efficiency value has been lower than 1 for 12 years, indicating that the province has insufficient investment in the treatment of environmental pollution problems, the level of transportation energy-saving technology is not high, and the effectiveness of CO_2 emission reduction work is not obvious.

4.2 Analysis of Influencing Factors of CO_2 Emission Efficiency

Using equation (3) to regress the influencing factors of carbon emission efficiency, and the results are shown in Table3.

Table 3 Influencing factors of CO_2 emission efficiency in the central region

	Coef.	Std. err.	t	p
lnpGDP	0.866***	0.143	6.06	0.000
lnUR	-2.543***	0.475	-5.35	0.000
lnPUV	0.141	0.240318	0.59	0.599
lnEI	0.334***	0.12	2.78	0.007
LnTI	-0.053*	0.0555	-0.96	0.034
R-squared		0.7067		

* for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$.

The coefficient of per capita GDP is 0.866, and it has passed the significance test with a significance level of 1%. It shows that per capita GDP has a positive impact on the CO_2 emission efficiency of the transport sector in the central region. Although economic development will increase transportation activities, it has brought huge economic benefits, thus promoting the growth of CO_2 emission efficiency. The level of urbanization has a negative impact on CO_2 emission efficiency. With the continuous advancement of urbanization, people's daily life and the construction of large-scale housing and infrastructure have led to an increase in the demand for transportation, which drives the development of transportation at the same time. This has led to an increase in energy consumption and CO_2 emissions, and reduced transportation CO_2 emissions efficiency. Energy intensity has a positive effect on the CO_2 emission efficiency of transportation, while the transportation intensity has an inhibitory effect on the CO_2 emission efficiency of transportation. Energy intensity can characterize the energy-saving technology level of the transportation sector, which also fully demonstrates that my country's the reduction policies current transportation CO_2 emissions to improve energy efficiency are reasonable and necessary. Although the coefficient of the PUV is 0.141, it has not passed the significance test, so it has not had a significant impact on the CO_2 emission efficiency of transportation.

5. Conclusion

This paper constructs a scientific and reasonable input-output evaluation index system, introduces transportation CO_2 emissions as undesired output, and calculates the transportation CO_2 emission efficiency in central China from 2005 to 2016 based on the super-SBM model. Then, selecting per capita GDP, urbanization level, the number of buses per 10,000 people, energy intensity, and transportation intensity as the influencing factors of transportation CO_2 emission efficiency, build a suitable panel data model, and quantify the influence factors of transportation CO_2 emission efficiency. It can be seen that the overall CO_2 emission efficiency of transport sector in central China is not high, and the transportation industry has great potential for energy conservation and emission reduction. Among these six provinces, there are certain differences in transportation CO_2 emission efficiency. Therefore, when formulating transportation energy-saving and emission-reduction measures, it is necessary to formulate differentiated emission-reduction measures based on the actual conditions of each province's own economic development stage, the development scale of the transportation industry, and the transportation structure and level. At the same time, the central region should improve the level of energy-saving technologies, increase investment in energy-saving technologies in transportation, rely on technological progress to improve transportation energy efficiency, as well as popularizing the use of new energy vehicles.

References

[1] L. Chapman (2007). Transport and climate change: a review. Journal of Transport Geography, vol.15, no.5, p354-367.

[2] F. Creutzig and D. He (2009). Climate change mitigation and co-benefits of feasible transport demandpolicies in Beijing. Transportation Research Part D, vol.14, p.120-131.

[3] T.V. Ramachandra and Shwetmala (2009). Emissions from India's transport sector: Statewise synthesis. Atmospheric Environment, vol.43, no.34, p.5510-5517.

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

[4] I. Meyer, M. Leimbach and C.C. Jaeger (2007). International passenger transport and climate change: a sector analysis in car demand and associated CO_2 emissions from 2000 to 2050. Energy Policy.
[5] M.O.D. Eicker, R. Zah and R. Triviño (2008). Spatial accuracy of a simplified disaggregation method for traffic emissions applied in seven mid-sized Chilean cities. Atmospheric Environment, vol.42, no.7, p.1491-1502.
[6] M. Lesiv and R. Lesiv (2010), Geoinformation Technologies and Spatial Analysis of Carbon Dioxide Transport through Border Line. vol.4, p.322-329.
[7] Z. Peng, Q. Wu, D. Wang and M. Li (2019). Temporal-spatial pattern and influencing factors of china's province-level transport sector CO_2 emissions efficiency. Polish Journal of Environmental Studies, 29(1),233-247.
[8] A. Das, and S.K. Paul (2014). CO_2 emissions from household consumption in india between 1993–94 and 2006–07: a decomposition analysis. Energy Economics, vol.41, no.1, p.90-105.
[9] C. Zhang and J. Nian (2013). Panel estimation for transport sector CO_2 emissions and its affecting factors: a regional analysis in china. Energy Policy, vol.63, no.12, p.918-926.
[10] Y. Kaya and K. Yokobori (1993). Global environment, energy, and economic development. Tokyo: United Nations University.
[11] B.W. Ang (1999). Is the energy intensity a less useful indicator than the carbon factor in the study of climate change?. Energy Policy, vol.27.
[12] J.E. Aldy (2005). Per capita carbon dioxide emissions: convergence or divergence?. Ssrn Electronic Journal.
[13] Y. Fan, L.C. Liu, G. Wu, H.T. Tsai and Y.M. Wei (2007). Changes in carbon intensity in china: empirical findings from 1980-2003. Ecological Economics, vol.62, no.3-4, p.683-691.
[14] T. Jobert, F. Karanfil and A. Tykhonenko (2010). Convergence of per capita carbon dioxide emissions in the eu: legend or reality?. Energy Economics, vol.32, no.6, p.1364-1373.
[15] R. Ramanathan, (2005). An analysis of energy consumption and carbon dioxide emissions in countries of the Middle East and North Africa. Energy, vol.30, no.15, p.2831-2842.
[16] X. Yao, H. Zhou, A. Zhang and A. Li (2015). Regional energy efficiency, carbon emission performance and technology gaps in china: a meta-frontier non-radial directional distance function analysis. Energy Policy, vol.84, no.9, p.142-154.
[17] X.D. Guo, L. Zhu and Y. Fan (2011). Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. Energy Policy, vol.39, no.5, p.2352-2360.
[18] K. Tone (2001). A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, vol.130, no.3, p.498-509.
[19] Y. Choi, N. Zhang and P. Zhou (2012). Efficiency and abatement costs of energy-related CO_2 emissions in china: a slacks-based efficiency measure. Applied Energy, vol.98, p.198-208.
[20] R. Gomez-Calvet, D. Conesa, A. R. Gomez-Calvet and E. Tortosa-Ausina (2014). Energy efficiency in the european union: what can be learned from the

ISSN 2616-5767 Vol.3, Issue 7: 169-178, DOI: 10.25236/AJETS.2020.030717

joint application of directional distance functions and slacks-based measures?. Applied Energy, vol.132, no.11, p,137-154.
[21] C. Wang, J. Chen and J. Zou (2005). Decomposition of energy-related CO_2 emission in china: 1957–2000. Energy,vol.30, no.1, p.73-83.
[22] A. Jalil and S.F. Mahmud (2009). Environment kuznets curve for CO_2 emissions: a cointegration analysis for china. Energy Policy, vol.37, no.12, p.5167-5172.
[23] A. Charnes, W.W. Cooper and E. Rhodes (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, vol.2, no.6, p.429-444.
[24] R.D. Banker, A. Charnes and W.W. Cooper (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, vol.30, no.9, p.1078-1092.
[25] Y. Bian and F. Yang (2010). Resource and environment efficiency analysis of provinces in China: A DEA approach based on Shannon's entropy. Energy Policy, vol.38, no.4, p.1909.
[26] G.M. Shi, J. Bi and J.N. Wang (2010). Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy, vol.38, no. 10, p.6172.
[27] W. Zhang, K. Li, D. Zhou, W. Zhang and H. Gao (2016). Decomposition of intensity of energy-related CO_2 emission in Chinese provinces using the LMDI method. Energy Policy, vol.92, no.3, p.369-381.
[28] S. Lu, H. Jiang, Y. Liu and S. Huang (2017). Regional disparities and influencing factors of average CO_2 emissions from transportation industry in yangtze river economic belt. Transportation Research Part D Transport and Environment, vol.57, no.12, p.112-123.