##### Optimizing regional allocation of CO2 emission considering output under overall efficiency

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## Conflicts of Interest

### The authors declare no conflict of interest for the order and cooperation.

### Highlight：

**Optimizing regional allocation of CO2 emissions considering output under overall efficiency**

* 1. The study develops a three-stage empirical system to identify the CO2 emissions allocation scheme at the provincial level.
	2. Chinese construction industry panel data during 2005-2017 is used in the empirical study.
	3. CO2 emissions need to be reduced by *ca.* 10% on the base of 2017.
	4. 86.7% of the provinces have a relatively large capacity for CO2 emissions reduction.
	5. The East region of China is a key area, accounting for 44.0% of the total amount of CO2 emissions reduction for the country.
	6. About 1/3 of the provinces face major pressure to reduce CO2 emissions by more than 10% on the basis of 2017.
	7. The study demonstrates empirically how emission reduction effectiveness can be improved.

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1. **efficiency**
2. **Abstract**
3. Reduction of CO2 emissions is a strategic priority for the construction industry, however
4. current schemes do not provide the level of performance that is required. There is also a lack
5. of understanding of how to allocate CO2 emissions targets within regions. Therefore, this
6. research study develops a three-stage empirical system to identify the CO2 emissions
7. allocation scheme for the Chinese construction industry at the provincial level. The results
8. indicate that (a) the construction industry’s CO2 emissions need to be reduced by *ca.* 10%
9. from the base level in 2017; (b) 86.7% of the provinces have a relatively large capacity for CO2
10. emissions reduction; (c) China’s East region accounts for 44.0% of the total amount for CO2
11. emissions reduction; and (d) about one-third of the provinces face enormous pressure to
12. reduce CO2 emissions by more than 10% on the base of 2017. This research study provides
13. unique insights and guidance to support assessment of the regional allocation of CO2
14. emissions for the construction industry, which is a valuable reference for other countries and
15. industries.
16. **Keywords**: CO2 emissions allocation; overall efficiency; construction industry; data
17. envelopment analysis; Inverse DEA

##### 1 Introduction

1. In recent years, global greenhouse gas (GHG) emissions have unfortunately continued to
2. rise. During the period 1990-2014, global greenhouse gas emissions increased from 33.8 to
3. 48.9 billion tons. This represents an increase of 45%, which includes a 52% increase in CO2
4. emissions that accounts for 85% of total GHG emissions [1]. The built environment and
5. building construction sectors are the main source of CO2 emissions, accounting for around 40%
6. of global CO2 emissions. In 2018, CO2 emissions from the construction industry have reached
7. the highest level since 2013 and are still increasing [2]. Therefore, the construction industry is
8. the key sector where CO2 emissions need to be reduced.
9. China is currently the largest construction sector in the world. The construction industry
10. has been and will continue to be one of the pillar industries of the national economy. In 2018,
11. the value of the construction industry in China amounted to USD $893.6 billion [3].
12. Consequently, it is now essential that China is able to balance the relationship between CO2
13. emissions reduction and the continued development of the construction industry. In this
14. context, the Stern Review [4] highlighted that the reasonable allocation of CO2 emissions is a
15. valuable political tool for tackling climate change and achieving a low carbon transition, which
16. can provide a feasible solution for CO2 emissions reduction of construction industry. In 2015,
17. China announced that its CO2 emissions per unit of GDP would be reduced to a range of 35-40%
18. of the 2005 level by 2030. It is useful to note that this implementation target is on a national
19. level and needs to be refined to a higher level of geographical granularity. In order to improve
20. the effectiveness of CO2 emissions reduction, there is therefore a need to refine the national
21. target and develop a regional-based CO2 emissions allocation scheme for the construction
22. industry for both China and elsewhere.
23. However, there are certain defects in the existing allocation methods that are available,
24. which may not strike the required balance between CO2 emissions reduction and industrial
25. development. Latterly, most of the research studies allocate CO2 emissions based on the
26. fairness principle, while the efficiency principle has more recently received increasing attention.
27. Based on these two principles, previous studies have developed various methods to allocate
28. CO2 emissions at different levels. Data Envelopment Analysis (DEA) is a typical method to
29. allocate CO2 emissions from the efficiency perspective. In this regard, Gomes and Lins [5]
30. proposed the Sum Gains DEA (ZSG-DEA) model to identify the CO2 emissions allocation
31. scheme among the non-Annex I and Annex I countries. Similarly, Chiu et al. [6] explored a fair
32. and more efficient CO2 emissions allocation scheme among 24 European Union countries. In
33. recent work, Fang et al [7] integrated multi-criteria allocation principles and indicators into the
34. ZSG-DEA model and applied it to develop an optimal CO2 emissions allocation scheme for
35. application in China at the provincial level. These research studies converted all inefficient
36. Decision-Making Units (DMUs) into efficient DMUs by decreasing the CO2 emissions but
37. without any limit. This enabled optimal system efficiency but did not take into account the risk
38. of excessive reductions in output, which may cause irrationality for the CO2 emissions
39. allocation scheme.
40. In order to overcome the aforementioned defect identified for current strategies, this
41. research study develops a three-stage approach to develop the CO2 emissions allocation
42. scheme for the Chinese construction industry at the provincial level. As a consequence of
43. allowing decision makers to set output reduction thresholds independently, this approach
44. achieves an effective control over output reduction, thereby improving rationality of the CO2
45. emissions allocation scheme. This research aims to enrich the existing theoretical system of
46. CO2 emission reduction target allocation through improving on existing methods. The study
47. has policy implications for China's construction industry as well as other countries and different
48. industries to achieve greenhouse gas emission targets.
49. The structure of this article is as follows: Section 2 reviews the literature on CO2 emissions
50. of construction, CO2 emissions allocation and the application of InvDEA. Section 3 describes
51. the three-stage method to calculate provincial CO2 emission quota. Section 4 and Section 5
52. present the results and discussions respectively. Section 6 provides the conclusion of this
53. study.

##### 2 Literature review

###### 2.1 CO2 emissions of construction

1. Currently, research on CO2 emissions of the construction industry is mainly focused on
2. CO2 emissions measurement and analysis of the influencing factors. In this regard various
3. methods have been employed to measure CO2 emissions by scholars. Acquaye and Duffy [8]
4. employed the input-output analysis technique to evaluate the greenhouse gas emissions
5. intensity of the construction industry in Ireland. Using the same method, Nassen et al. [9]
6. assessed CO2 emissions of the construction industry in Sweden. Whereas Zhang and Wang
7. [10] used a life-cycle-based method to measure CO2 emissions of the Chinese construction
8. industry during the period 2005-2012. Also, from the perspective of building life cycle,
9. Gustavsson et al. [11] measured primary CO2 emissions for a timber-framed apartment
10. building.
11. In regard to analysis of the influencing factors, scholars have mainly examined the effect
12. of building materials, energy consumption, restrictions, and economic levels on CO2 emissions
13. of the construction industry. Lu et al. [12] analyzed the impact of seven key drivers, including
14. building material consumption and energy intensity on the Chinese construction industry CO2
15. emissions during the period 1994-2012. Wu et al. [13] provided an analysis on the effect of
16. economic output on CO2 emissions of the Chinese construction industry using a decoupling
17. method. Whereas Xu et al. [14] employed the log mean Divisia index (LMDI) to study the
18. drivers of CO2 emissions in China during the period 1990-2009. Finally, Xu and Lin [15] applied
19. the Vector Autoregressive model to provide an analysis on main driving factors affecting CO2
20. emissions change and the researchers concluded that optimizing the energy structure can
21. effectively promote CO2 emissions reduction.
22. It can be observed that previous research has established a reliable method for
23. measuring CO2 emissions and analyzing the influencing factors in the construction industry.
24. However, there appears to be a gap in the knowledge base regarding CO2 emissions
25. allocation and CO2 emissions prediction.

###### 2.2 CO2 emissions allocation method

1. Existing CO2 emissions allocation methods include indicator, optimization, game theoretic
2. and hybrid methods [16, 17]. The indicator method allocates CO2 emissions based on a
3. specific indicator. Due to its simplicity and practicality, the indicator method has been widely
4. used for CO2 emissions allocation. Zetterberg et al. [18] used economic analysis to evaluate
5. three CO2 emissions allocation methods for the grandfather, auction, and benchmark levels.
6. Zhou et al. [19] identified the Chinese provincial CO2 emissions reduction goal based on five
7. categories of indicators, such as population, CO2 emissions and others. Moreover, Luzzati and
8. Gucciardi [20] cited European countries as a case to explain the trustworthiness of the
9. comprehensive indicator method. However, the allocation results rely too much on selection of
10. the indicator, leading to the concern of reliability. Meanwhile, the CO2 emissions allocation
11. scheme based on the indicator method is usually more favorable to one group of entities
12. unfairly.
13. The optimization method allocates CO2 emissions from an efficiency perspective.
14. Nordhaus and Yang [21] developed the Regional Integrated model of Climate and the
15. Economy (RICE model) to explore the optimal emission paths of GHGs in different regions.
16. Filar and Gaertner [22] also proposed a mathematical programming technology to assign CO2
17. emissions worldwide on the basis of maximizing economic utility. The above methods have the
18. advantage of integrating climate and economy, but they are very complicated to operate. Later,
19. with the broad use of the DEA method in the efficiency evaluation considering undesirable
20. output, researchers began to pay attention to using this method for CO2 emissions allocation.
21. In this regard, Gomes and Lins [5] proposed a ZSG-DEA model to allocate CO2 emissions by
22. setting a cap on emissions. Thereafter, this model has been employed for CO2 emissions
23. allocation in different regions or industries [23-26]. It is worth noting that the DEA method was
24. initially developed for efficiency evaluation rather than resource allocation. Therefore, when
25. allocating CO2 emissions with the DEA method, changes in input and output cannot be
26. effectively identified, which may harm the rationality of the allocation scheme.
27. The game theoretic method ascertains the optimal CO2 emissions allocation plan through
28. considering the negotiation between different emissions reduction units. Filar and Gaertner [22]
29. used the Shapley value based on the game theoretic method to study the global CO2
30. allocation scheme. Furthermore, Zhang et al. [27] conducted a study on the CO2 emissions
31. allocation with a game theoretic method. Liao et al. [28] also employed the Shapley value to
32. evaluate CO2 emissions allocation quotas of three power stations located in Shanghai, China.
33. The game theoretic method has the advantage of incorporating the negotiations among
34. different entities in CO2 emissions allocation, but it is also complicated and lacks transparency.
35. The hybrid method refers to the use of multiple methods to allocate CO2 emissions, which
36. has the advantage of considering different criteria simultaneously. For example, Zhou et al. [29]
37. applied a DEA method with multiple abatement factors to study the CO2 emissions allocation
38. of Chinese cities. However, compared with the other three methods, the hybrid method is more
39. complex in the calculation process, lower performance for operability and more
40. time-consuming in data collection, which may compromise the accuracy of the allocation
41. scheme.
42. Recently, with the increasing attention on the efficiency principle [16], the optimization
43. method has attracted the attention of scholars. Due to its simplicity and practicality, the DEA
44. method has been extensively used to study CO2 emissions allocation. It is worth highlighting
45. that CO2 emission allocation in the DEA model actually involves changes of input and output,
46. which is not only the positive efficiency measurement, but also the solution to the inverse DEA
47. problem. Indeed, applying the InvDEA model to allocate CO2 emissions can improve the
48. accuracy of allocation under the perspective of efficiency and consequently this method has
49. received extensive attention in the literature [30].

###### 2.3 The application of InvDEA

1. DEA is an efficiency analysis method based on the relative comparison between the
2. evaluated objects. It has unique features for dealing with multi-input and multi-output problems
3. and has been extensively applied in different regions, industries and departments [31, 32]. The
4. purpose of efficiency evaluation is not only to reveal the level of efficiency but more importantly
5. to find a way to improve efficiency. Previous studies have found that the improvement of
6. resource allocation may potentially improve efficiency levels [33-35]. Although the DEA
7. method can be used to calculate the efficiency of DMUs effectively by finding the optimal
8. solution, it could not observe the impact of resource allocation changes on efficiency. In recent
9. years and with the deepening of DEA focused research, the problem of inverse DEA has
10. attracted the attention of scholars. The inverse DEA problem is basically the inverse of the
11. DEA problem and therefore its principle is inverse optimization. The reverse DEA method aims
12. to solve the following problems: For a group of DMUs, assuming that the current level of
13. efficiency remains the same, how much can the output increase if the inputs increase by a
14. certain amount? Or, if outputs are increased by a certain amount, how much should inputs
15. increase [36]? Consequently, use of the InvDEA method provides a new perspective for
16. dealing with resource allocation problems at current efficiency levels.
17. The current application of inverse DEA mainly includes efficiency prediction and resource
18. allocation. In the prediction of efficiency and through adopting 22 chain stores in a home
19. decoration company in Taiwan as the study objects, Lin [37] studied the efficiency
20. measurement and income problem with the fuzzy DEA model and the InvDEA model, thereby
21. providing a reference for decision-makers to clarify the efficiency and income of the new store.
22. Frija et al. [38] estimated the demand for agriculture irrigation water for individual farmers in
23. Tunisia with the InvDEA model. Furthermore, Gattoufi et al. [39] employed the InvDEA model
24. to the case of bank consolidation decisions and proposed recommendations for the combined
25. banks' input-output levels to achieve the expected efficiency targets. Lim [40] combined the
26. inverse optimization problem with the DEA time series application and applied the InvDEA
27. model to the case of expected production frontier changes. Whereas other researchers [41-43]
28. used the banking industry as a case to study the impact of corporate restructuring or mergers
29. on operational efficiency with the InvDEA model. Chen et al. [44] developed an InvDEA model
30. considering undesirable outputs on the basis of the sustainable perspective and applied the
31. model to predict the level of sustainable development investment in China. In regard to
32. investigating resource allocation, Lertworasirikul et al. [45] proposed a linear programming
33. InvDEA model, and applied this model in the resource allocation of motorcycle parts
34. companies. Later, Ghiyasi [46] developed the InvDEA model for the case of Variable Returns
35. to Scale (VRS). As a result of combining the InvDEA model with artificial neural networks,
36. Modhej et al. [47] improved the ability of the model to process large data sets and successfully
37. applied the model to 600 banks in Iran.
38. It can be observed that application of the InvDEA model provides significant advantages
39. for processing efficiency prediction and resource allocation problems, especially for dealing
40. with resource allocation problems at current efficiency levels. Therefore, the InvDEA model is
41. an ideal tool for enabling CO2 emissions allocation as part of supporting the overall scheme
42. efficiency since the negative impact of CO2 emissions reduction on outputs can be limited.

###### 2.4 Gap in the knowledge base

1. As elucidated from the comprehensive literature review, the gap in the knowledge base
2. can be summarized as follows: (1) Previous methods for CO2 emissions allocation have not
3. considered the risk of the excessive reduction in output, which may have a negative impact on
4. the rationality of the allocation scheme. (2) There is still a limited focus on the CO2 emissions
5. allocation scheme for the construction industry.
6. In order to narrow the gap, this research study has conducted the following empirical
7. investigation: (1) The output reduction threshold was introduced into the model to limit the
8. excessive reduction in output, thereby improving the rationality of the CO2 emissions allocation.
9. (2) Based on the perspective of system efficiency, an optimized CO2 emissions allocation
10. scheme for the Chinese construction industry was identified leading to overall efficiency.

##### 3 Methodology

1. The overall methodology follows a three-stage approach, as shown in Fig. 1, and the main
2. characteristics of each stage are as follows. Stage 1: According to the *Guidelines for National*
3. *Greenhouse Gas Inventories* released in 2006 [48], the research study calculated CO2
4. emissions for the Chinese construction industry during the period 2005-2017, and identified
5. the total amount of the construction industry’s CO2 emissions reduction based on Chinese
6. government's emissions reduction goals. Stage 2: From the perspective of efficiency, this
7. study used the DEA-BCC model to evaluate the construction industry’s CO2 emissions
8. reduction capacity for 30 provinces in China in order to identify the priority of CO2 emissions
9. reduction, and inefficient DMUs were selected as reduction objects. Stage 3: The InvDEA
10. model was employed to allocate the total amount of CO2 emission reduction to each inefficient
11. DMU, thereby identifying the CO2 emissions allocation scheme.

##### < Insert Fig. 1 here >

1. **Fig. 1.** Framework of the research methodology
2. The data used in this research study were derived from the *China Statistical Year Book*
3. (2006-2018) [49], *China Energy Statistical Year Book* (2006-2018) [50], *China Statistical*
4. *Yearbook on Construction* (2006-2018) [51] and other relevant statistical year-books for
5. various provinces of China. Considering the availability and completeness of the data, the
6. research study selected 30 provinces in China as study objects.

###### 3.1 Carbon emission coefficient method

1. This research study used the carbon emission coefficient method to calculate the CO2
2. emissions of the Chinese construction industry from 2005 to 2017. This method is
3. recommended by the United Nations Intergovernmental Panel on Climate Change (IPCC) [48],
4. since it has high computational accuracy and has been widely used for CO2 emissions
5. measurement [33-35, 52].

𝑖=1

CO2 = ∑𝑛

𝐸𝑖 × 𝑁𝐶𝑉𝑖 × 𝐶𝐸𝐹𝑖 × 𝐶𝑂𝐹𝑖 × (44)

12

(1)

|  |  |
| --- | --- |
| 230 | Where *i* represents the i-th energy source, *Ei* represents the terminal consumption of the |
| 231 | i-th energy source, *NCVi* represents the average low calorific value of the i-th energy source, |
| 232 | *CEFi* represents the carbon emission factor, *COFi* represents the carbon oxidation rate, and |
| 233 | *44/12* is the carbon conversion coefficient. According to China's relevant statistical information, |
| 234 | Zhang et al. [53] obtained the carbon emission coefficient of each energy by formula (1), as |
| 235 | shown in Table A-1 in the Appendix. |
| 236 | ***3.2 DEA-BCC model and super efficiency DEA model*** |
| 237 | It is assumed that there are *n DMU*s. For any *DMUj (*𝑗 = 1, … 𝑛*)*, the input is defined as |
| 238 | 𝑥𝑖𝑗(𝑖 = 1, … 𝑀), the desirable output as 𝑜𝑟𝑗(𝑟 = 1, … , 𝑅) and undesirable output as 𝑢𝑜𝑝𝑗(𝑝 = |
| 239 | 1,2, … , 𝑃). In this research study, the DEA-BCC model is employed as the basic model of the |
| 240 | InvDEA model, and the directional distance function (DDF) is used to deal with the undesirable |
| 241 | output. |
| 242 | → (𝑋𝑘, 𝑂𝑘, 𝑈𝑂𝑘, 𝑔𝑜, −𝑔𝑢𝑜) = max →𝐷 𝐷𝐷𝐹 𝛽𝑘 |
| 243 | 𝑠. 𝑡. |

𝑛

244 ∑ 𝜆𝑗𝑥𝑖𝑗 ≤ 𝑥𝑖𝑘, i = 1,2, … M

𝑗=1

### 245

𝑛

∑ 𝜆𝑗𝑜𝑟𝑗 ≥ (1 +→ ) 𝑜𝑟𝑘, r = 1,2, … , R

𝛽𝑘

𝑗=1

### 246

𝑛

∑ 𝜆𝑗𝑢𝑜𝑝𝑗 = (1 −→ ) 𝑢𝑜𝑝𝑘, p = 1,2, … , P

𝛽𝑘

### 247

248

𝑗=1

n

∑ λj = 1 , j = 1,2, … n

j=1

λj ≥ 0 (2)

### 249

When →

𝐷 𝐷𝐷𝐹

(𝑋𝑘, 𝑂𝑘, 𝑈𝑂𝑘, 𝑔𝑜, −𝑔𝑢𝑜) = 0, it represents that the DMU is efficient, otherwise

1. the DMU is inefficient. As for the inefficient DMU, its DDF could be improved by reducing CO2
2. emissions, while the DDF of the efficient DMU cannot be improved further. Considering this, in
3. the study of Emrouznejad et al. [30], only inefficient DMUs are selected as CO2 emissions
4. reduction objects. It is worth noting that, when the above DEA-BCC model is used for
5. efficiency evaluation, multi DMUs may be efficient. Ignoring the CO2 emissions reduction
6. capacity of multi efficient DMUs may have a negative impact on the rationality of the CO2
7. emissions allocation. Therefore, it is essential to further evaluate the CO2 emissions reduction
8. capacity of efficient DMUs.
9. Based on the study of Emrouznejad et al. [30], we proposed the following process to
10. evaluate the CO2 emissions reduction capacity of efficient DMUs. Firstly, the super efficiency
11. DEA model was used to calculate the super efficiency value of efficient DMUs. Secondly, the
12. inputs of each efficient DMU were augmented with the corresponding super efficiency value.
13. Finally, the efficiency frontier of the DEA-BCC model was kept unchanged and the following
14. was calculated for efficient DMUs whose inputs has been adjusted

→

𝐷 𝐷𝐷𝐹

(𝑋𝑘, 𝑂𝑘, 𝑈𝑂𝑘, 𝑔𝑜, −𝑔𝑢𝑜) . Therefore, the super efficiency DEA model is as follows.

→

𝐷 𝐷𝐷𝐹

(𝑋𝑘, 𝑂𝑘, 𝑈𝑂𝑘, 𝑔𝑜, −𝑔𝑢𝑜) = max →

𝛽𝑘

𝑠. 𝑡.

𝑛

267 ∑ 𝜆𝑗𝑥𝑖𝑗 ≤ 𝑥𝑖𝑘, i = 1,2, … M

𝑗=1

𝑗≠𝑘

𝑛

### 268

∑ 𝜆𝑗𝑜𝑟𝑗 ≥ (1 +→ ) 𝑜𝑟𝑘, r = 1,2, … , R

𝛽𝑘

𝑗=1

𝑗≠𝑘

𝑛

### 269

∑ 𝜆𝑗𝑢𝑜𝑝𝑗 = (1 −→ ) 𝑢𝑜𝑝𝑘, p = 1,2, … , P

𝛽𝑘

### 270

271

𝑗=1

𝑗≠𝑘

n j=1

∑

λj = 1 , j = 1,2, … n, j ≠ k

λj ≥ 0 (3)

1. When evaluating the efficiency of a certain DMU, the super efficiency DEA would firstly
2. exclude the DMU. This is the main difference between the super efficiency DEA model and the
3. DEA-BCC model. Therefore, as for the inefficient DMU, the efficiency value will remain
4. unchanged while the efficiency value of the efficient DMU would become larger. As shown in
5. Fig. 2, when evaluating the efficiency of B1, B1 is excluded from the DMU set. At that time,
6. A1-C1-D1 turns to be the new efficiency frontier. The distance between B1 and B2 represents
7. the extent value of augment in B1’s inputs, and B1’s super efficiency value is OB2/OB1, which is
8. more than 1. When the efficiency frontier of the DEA-BCC model remains unchanged, there is
9. a need to adjust the inputs with the super efficiency value, which will enable the efficient DMUs
10. to move away from the efficiency frontier (as shown in Fig. 3). This change provides the
11. condition for improving the DDF of efficient DMUs in order to identify their CO2 emissions
12. reduction amount.

|  |  |
| --- | --- |
| 284 | **< Insert Fig. 2 here >** |
| 285 | **Fig. 2.** Super efficiency DEA model |
| 286 | **< Insert Fig. 3 here >** |

1. **Fig. 3.** Efficient DMUs in DEA-BCC model after adjustment

###### 3.3 InvDEA model

1. The InvDEA model proposed by Emrouznejad et al. [30] was introduced in stage 3. In
2. addition and in order to achieve the overall scheme efficiency, CO2 emissions reduction should
3. not deteriorate the efficiency of DMUs. Considering this situation, this research study makes
4. the following assumptions:
5. *Assumption 1: The reduction of CO2 emissions does not change the efficiency frontier.*
6. In the DEA model, the efficiency of the DMU is determined by its distance from the
7. efficiency frontier. The change of efficiency frontier would cause a change of the efficiency
8. evaluation criteria, thus the efficiency values of DMUs before and after the reduction of CO2
9. emissions cannot be compared. In this situation, the overall efficiency of the CO2 emissions
10. allocation scheme may not be achieved. Meanwhile, the change of efficiency frontier also
11. increases the difficulty of calculation in the model. Therefore, the assumption is introduced in
12. the InvDEA model.
13. *Assumption 2: The reduction of CO2 emissions does not deteriorate the efficiency of*
14. *DMUs.*
15. Since the concept of the low-carbon economy was proposed in 2003 [54], many countries
16. have been actively exploring a feasible path for economic low-carbon transformation. It is
17. worth noting that a low-carbon economy refers to not only reducing greenhouse gas emissions
18. but also providing a win-win situation for both economic and social development and
19. ecological protection. Therefore, we introduce Assumption 2 in the model.
20. *Assumption 3: Desirable outputs have a specific threshold.*
21. In theory, there are countless paths for an inefficient DMU to approach the efficiency
22. frontier. However, some of these paths may lead to an excessive reduction of desirable
23. outputs in the DMU. For example, there may be situations to reduce CO2 emissions, in which
24. the production scale is reduced, thereby resulting in an excessive reduction in desirable
25. outputs. To avoid these situations, a threshold needs to be introduced. Meanwhile, in reality, as
26. one of the main industries in China [55], the construction sector has made major contributions
27. to the development of the national economy. In order to ensure that environmental pollution is
28. being reduced while the economy maintains steady growth, the Chinese government may
29. potentially set a threshold for outputs reduction of the construction industry when formulating
30. relevant policies. This is consistent with the view of Emrouznejad et al. [30] and to allow the
31. model to be more reasonable, this research study has adopted assumption 3.
32. On the basis of the above assumption, the InvDEA model is constructed as follows:

𝑚 𝑅

321 𝑚𝑖𝑛 ∑ ∑ 𝛼𝑖𝑘 − ∑ ∑ 𝛽𝑟𝑘

### 322

𝑘∈𝐿 𝑖=1

𝑘∈𝐿 𝑟=1

*s.t.*

323 ∑ 𝜆𝑘 𝑥𝑖𝑗 − 𝛼𝑖𝑘 ≤ 0, ∀𝑘 ∈ 𝐿, 𝑖 = 1, … , 𝑚

𝑗

𝑗∈𝐹

324 ∑ 𝜆𝑘𝑜𝑟𝑗 − (1 + 𝛽̂𝑘)𝛽𝑟𝑘 ≥ 0, ∀𝑘 ∈ 𝐿, 𝑟 = 1, … , 𝑅

𝑗

𝑗∈𝐹

325 ∑ 𝜆𝑘𝑢𝑜𝑝𝑗 − (1 − 𝛽̂𝑘)γ𝑝𝑘 = 0, ∀𝑘 ∈ 𝐿, 𝑝 = 1, … , 𝑃

𝑗

### 326

𝑗∈𝐹

∑ 𝜆𝑘 = 1, ∀𝑘 ∈ 𝐿

𝑗

𝑗∈𝐹

|  |  |
| --- | --- |
| 327 | ∑ 𝛾𝑝𝑗 = 𝑎𝑝, 𝑝 = 1, … , 𝑃 |
| 328 | 𝑗∈𝐿0 ≤ 𝛼𝑖𝑘 ≤ 𝑥𝑖𝑘, ∀𝑘 ∈ 𝐿, 𝑖 = 1, … , 𝑀 |
| 329 | (1 − 𝑐𝑟𝑘)𝑜𝑟𝑘 ≤ 𝛽𝑟𝑘, ∀𝑘 ∈ 𝐿, 𝑟 = 1, … , 𝑅 |

330 0 ≤ 𝛾𝑝𝑘 ≤ 𝑢𝑜𝑝𝑘, ∀𝑘 ∈ 𝐿, 𝑝 = 1, … , 𝑃

331 𝜆𝑘 ≥ 0, ∀𝑗 ∈ 𝐹𝑘, 𝑘 ∈ 𝐿 (3)

𝑗

1. Where 𝛼𝑖𝑘, 𝛽𝑟𝑘 and 𝛾𝑝𝑘 represent the level of the *i-th* input, the *r-th* desirable output
2. and the *p-th* undesirable output respectively, after the DMUk reduces its undesirable output.
3. 𝑐𝑟𝑘 is a policy threshold to limit the reduction of undesirable outputs. 𝑎𝑝 is the sum of 𝛾𝑝𝑗 *(*𝑗 ∈
4. 𝐿), representing the pth undesirable output level of all inefficient DMUs in *L*. In addition, 𝛽̂𝑘 is
5. a parameter that ensures that the efficiency value of the DMUs in *L* does not decrease after

the reduction of CO2 emissions [30], meeting this condition of 0 ≤ 𝛽̂𝑘 ≤→∗, where

𝛽𝑘

→∗

𝛽𝑘

is the

1. optimal solution for model (2).
2. In this research study, we selected the DEA-BCC model as the basic model of the InvDEA
3. model. It indicates that the InvDEA model is also formulated under the variable return to scale
4. (VRS) assumption, rather than the constant return to scale (CRS) assumption. If the
5. assumption changes from VRS to CRS, the efficiency frontier of InvDEA model would change
6. from multi-segment linear to linear and move forward. Due to this change, except when DMUs
7. are efficient under the CRS assumption, the distance between other DMUs’ and efficiency
8. frontier would increase, indicating that the CO2 emissions reduction space of these DMUs
9. would expand. Therefore, compared with the VRS assumption, DMUs in the InvDEA model
10. under CRS assumption may have a larger space for CO2 emissions reduction overall. Actually,
11. in the production process, not all DMUs’ return to scale keeps constant. Considering this,
12. allocating CO2 emissions under the VRS assumption would be more reasonable. Therefore,
13. this study proposed the InvDEA model under VRS assumption to allocate CO2 emissions.

###### 3.4 Dataset and indicators

1. This research study used a comprehensive indicator system with multiple inputs and
2. multiple outputs to evaluate the efficiency of the Chinese construction industry. The indicator
3. system consists of three parts, namely the inputs, desirable outputs and undesirable outputs.
4. Reasonable indicators are critical to the accurate measurement of efficiency. In order to
5. ensure the rationality of the indicator selection, we conducted a systematic review on the
6. previous studies relating to the construction industry efficiency, as shown in Table 1.
7. **Table 1**
8. Evaluation indicators system of construction industry in previous studies

Equipment, (4) Energy space of buildings completed

|  |  |  |  |
| --- | --- | --- | --- |
| Authors | Year | Input indicators | Output indicators |
| Li and Liu [56] | 2010 | (1) Labor, (2) Capital | (1) Gross value added |
| Wang et al. [57] | 2011 | (1) Labor, (2) Capital | (1) Gross value added |
| Liu et al. [58] | 2013 | (1) Labor, (2) Capital | (1) Value added |
|  |  | (1) Labor, (2) Capital, (3) | (1) Total income of enterprises, (2) |
| Li et al. [59] | 2014 | Number of enterprises, (4) | Floor space of buildings |
|  |  | Value of machine per laborer | completed |
|  |  | (1) Capital, (2) Operational | (1) Total amount of profits and |
| Shi et al. [60] | 2016 taxes, (2) Profits of settlement ofinputprojects |
| Hu and Liu [61] | (1) Labor, (2) Construction2016 (1) Gross value addedwork done, (3) Energy |
| Hu and Liu [62] | (1) Labor, (2) Construction (1) Gross value added, (2) CO22017work done emissions |
| Hu et al. [63] | (1) Labor, (2) Construction (1) Gross value added, (2) CO22017work done emissions |
| Chen et al. [64] | (1) Labor, (2) Equipment (1) Value added, (2) Gross output2018value, (3) Total pre-tax profits |
| Hu and Liu [65] | (1) Labor, (2) Capital, (3)2018 (1) Gross value addedEquipment |
| Zhang et al. [53] | (1) Labor, (2) Capital, (3) (1) Gross output value, (2) Total2018Equipment, (4) Energy profits, (3) CO2 emissions |
| Huo et al. [55] | (1) Labor, (2) Capital, (3) (1) Gross output value, (2) Floor2018 |

1. Analysis of the related literature identifies that the efficiency evaluation indicator system
2. for the construction industry, with labor, capital and equipment as input indicators, as well as
3. total output value as the output indicator, has been widely used. Along with the increasingly
4. prominent environmental problems and corresponding energy crisis, the efficiency of the
5. construction industry in regard to environmental factors and energy consumption has received
6. significant attention. Referring to previous studies, this research has established an evaluation
7. indicator system for Chinese construction industry efficiency on the basis of the research
8. question, as illustrated in Table A-2 in the Appendix.
9. Input indicators consist of the number of employees, the total power of machinery and
10. equipment owned, total assets and energy consumption, representing the input level of labor,
11. equipment, capital and energy of the construction industry respectively. The desirable output
12. indicator is gross output value, reflecting the total income of the construction industry. The
13. undesirable output indicator is CO2 emissions, representing the environmental costs of the
14. construction industry. The descriptive statistics of the Chinese construction industry in 2017
15. are shown in Table 2.

##### Table 2

1. Descriptive statistics of the Chinese construction industry in 2017

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Indicators Units | Mean | SD | Min. | Max. |
| Number of engaged persons CNY 10,000 | 184.1980 | 195.2284 | 7.42 | 792.89 |
| Total assets of construction104 kw | 6812.9154 | 5442.0272 | 271.02 | 23158.96 |
| Total power of machinery andCNY 10,000 | 849.3400 | 777.8883 | 29.40 | 3415.40 |
| Energy consumption of10,000 tons | 248.5147 | 160.7572 | 50.12 | 750.03 |
| Gross output value ofCNY 10,000 | 7126.5210 | 6704.5240 | 322.76 | 27956.71 |
| CO2 emissions Tons | 228.3467 | 163.5353 | 23.68 | 672.36 |

enterprises equipment owned construction construction

##### 4 Empirical results

###### 4.1 CO2 emissions reduction total amount calculation

1. The CO2 emissions reduction goal of the Chinese government is to reduce its CO2
2. emissions per unit of GDP to a range of 35-40% of the 2005 level by 2030 [66]. Considering
3. that this is a target range, this research study used the upper bound of 40% as the emissions
4. reduction goal. The gross output value of construction (GVOC) is an indicator representing the
5. total output of the construction industry over a certain period of time, similar to the GDP
6. reflecting the sum output of the nation or region. Therefore, the CO2 emissions reduction goal
7. of the Chinese construction industry can be described as the following: by 2030, the CO2
8. emissions per unit of GVOC will be reduced to 40% of the level in 2005.
9. This study uses the carbon emission coefficient method to calculate the CO2 emissions
10. during the period 2005-2017. In addition, to avoid the impact of price level changes, this study
11. used the Consumer Price Index (CPI) of China to transform the GVOC into the constant price
12. in 2010. As shown in Table 3, from 2005 to 2017, the CO2 emissions increased year by year,
13. but CO2 emissions / GVOC was generally in a state of decline, only a slight rebound in 2015
14. when compared to 2014, indicating that the CO2 emissions per unit of GVOC were in effective
15. control. Among them, the CO2 emissions / GVOC in 2017 reached 0.0378. If the CO2
16. emissions reduction goal were achieved in 2017, the CO2 emissions/GVOC in 2017 should be
17. 0.0341, which means that the CO2 emissions in 2017 should be controlled below 6124.32
18. (10,000 tons). However, the actual total CO2 emissions are 6789.84 (10,000 tons). Therefore,
19. the total amount of CO2 emissions reduction is 665.52 (10,000 tons), accounting for about 10%
20. of total CO2 emissions in 2017.

##### Table 3

CO2 emission/GVOC in China from 2005 to 2017

Gross output value of

Consumer Price

Year

CO2 emission (10,000 tons)

construction (current prices-2010)

CO2 emissions/ GVOC

index (CPI) of China

1. Based on the geographical location and economic development level of each province

|  |  |  |
| --- | --- | --- |
|  | (100 million yuan) |  |
| 2005 | 3404.63 | 39913.57 | 0.0853 | 86.5673 |
| 2006 | 3677.94 | 47311.73 | 0.0777 | 87.8369 |
| 2007 | 3771.21 | 55467.94 | 0.0680 | 92.0238 |
| 2008 | 4262.29 | 63658.05 | 0.0670 | 97.4532 |
| 2009 | 4755.22 | 79360.45 | 0.0599 | 96.7834 |
| 2010 | 5556.43 | 96031.13 | 0.0579 | 100.0000 |
| 2011 | 6126.33 | 110987.90 | 0.0552 | 105.4706 |
| 2012 | 5992.73 | 126792.80 | 0.0473 | 108.2221 |
| 2013 | 6392.86 | 143434.30 | 0.0446 | 111.0703 |
| 2014 | 6500.15 | 155993.60 | 0.0417 | 113.2825 |
| 2015 | 6641.23 | 157360.30 | 0.0422 | 114.8685 |
| 2016 | 6425.31 | 165112.44 | 0.0389 | 117.1659 |
| 2017 | 6789.84 | 179598.89 | 0.0378 | 119.0406 |

1. and city, this research study divided 30 provinces into three regions of East, Middle and West
2. China through adopting the approach by Zhu et al. [67], thereby enabling analysis of the
3. regional differences of CO2 emissions of China’s construction industry during the period
4. 2005-2017. The result of the division is shown in Fig. 4. Additionally, Fig. 5 highlights the trend
5. of CO2 emissions in the Chinese regional construction industry from 2005 to 2017. It can be
6. observed that CO2 emissions in the Middle and West regions are close, and except for the
7. year 2015, the CO2 emissions in these two regions are significantly lower than that in the East
8. region. As for the trend, the CO2 emissions in the East region showed a downward trend after
9. reaching a peak of 2703.3 (10,000 tons) in 2011, and the growth trend of CO2 emissions in the
10. West region slowed down after 2011, while the Middle region remained growing in this period.
11. The CO2 emissions data of China's provinces from 2005 to 2017 are shown in Appendix Table

|  |  |  |
| --- | --- | --- |
| 413 | B-2. |  |
| 414 |  | **< Insert Fig. 4 here >** |
| 415 |  | **Fig. 4.** Geography of the three regions in China (East, Middle and West). |
| 416 |  | **< Insert Fig. 5 here >** |
| 417 |  | **Fig. 5.** Regional construction industry CO2 emissions during 2005-2017 |

###### 4.2 CO2 emissions reduction capacity evaluation

1. At this stage, the DEA-BCC model and super efficiency DEA model were employed in
2. combination to evaluate the CO2 emissions reduction capacity of the construction industry in
3. 30 provinces in 2017. The measurement results are shown in Table 4. Original efficiency and
4. super efficiency were respectively measured by the DEA-BCC model and super efficiency
5. DEA, while adjusted efficiency was measured by the DEA-BCC model after the efficient DMUs’
6. inputs have been adjusted with a super efficiency value.

##### Table 4

1. The results of efficiency measurement

|  |  |  |  |
| --- | --- | --- | --- |
| DMUs | Original efficiency | Super efficiency | Adjusted efficiency |
| Beijing | 1.0000 | 3.0207 | 0.8682 |
| Tianjin | 1.0000 | 1.0376 | 0.9679 |
| Hebei | 0.8692 | 0.8692 | 0.8692 |
| Shanxi | 0.8025 | 0.8025 | 0.8025 |
| Inner Mongolia | 1.0000 | 1.0012 | 0.6879 |
| Liaoning | 1.0000 | 1.6451 | 1.0000 |
| Jilin | 1.0000 | 1.0023 | 0.9967 |
| Heilongjiang | 1.0000 | 2.8221 | 0.9210 |
| Shanghai | 1.0000 | 1.0708 | 1.0000 |
| Jiangsu | 1.0000 | 2.2634 | 1.0000 |
| Zhejiang | 1.0000 | 1.4126 | 0.9101 |
| Anhui | 0.9101 | 0.9101 | 0.9101 |
| Fujian | 0.8852 | 0.8852 | 0.8852 |
| Jiangxi | 1.0000 | 1.0346 | 0.9743 |
| Shandong | 0.8076 | 0.8076 | 0.8076 |
| Henan | 0.8974 | 0.8974 | 0.8974 |

|  |  |  |  |
| --- | --- | --- | --- |
| Hubei | 1.0000 | 1.0718 | 0.9482 |
| Hunan | 1.0000 | 1.0025 | 0.9966 |
| Guangdong | 0.8895 | 0.8895 | 0.8895 |
| Guangxi | 1.0000 | 1.7643 | 0.8588 |
| Hainan | 1.0000 | 3.5784 | 0.9005 |
| Chongqing | 1.0000 | 1.1126 | 0.9478 |
| Sichuan | 0.8249 | 0.8285 | 0.8285 |
| Guizhou | 0.7353 | 0.7353 | 0.7353 |
| Yunnan | 0.7276 | 0.7276 | 0.7286 |
| Shaanxi | 0.9978 | 0.9978 | 0.9978 |
| Gansu | 0.7314 | 0.7314 | 0.7314 |
| Qinghai | 1.0000 | 2.2543 | 0.7213 |
| Ningxia | 0.8126 | 0.8126 | 0.8126 |
| Xinjiang | 1.0000 | 1.0226 | 1.0000 |

1. Based on the results of adjusted efficiency, 30 DMUs were divided into two groups as L
2. and F1. The adjusted efficiency value of the DMU in the *L* is less than 1, which means that their
3. DDFs can be improved, thereby indicating there is capacity for CO2 emissions reduction. The
4. value of the DMU in the *F* is 1, suggesting that it is on the production frontier, and there is no
5. reduction capacity for the DMUs in *F*.

###### 4.3 An optimized CO2 emissions allocation scheme identification

1. In this stage, the research study applied the InvDEA model to allocate the total amount of
2. CO2 emissions reduction for the Chinese construction industry in the 27 provinces with a
3. relatively large CO2 emissions reduction capacity. In order to achieve the overall scheme
4. efficiency, the parameter β̂k was introduced in the InvDEA model to ensure that the CO2
5. emissions reduction would not cause an efficiency decrease in the DMU. The construction
6. industry’s efficiency in this study is the productivity that considers CO2 emissions. In the real
7. production process, the reduction of undesirable outputs usually increases the efficiency level

1 L set: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia

F set: Liaoning, Shanghai, Jiangsu, Xinjiang

of the industry considering environmental factors. Considering this reality, we defined that

β̂k = 0.9 →∗ , representing the reduction of CO2 emissions that makes the direction distance

βk

function of the DMU improve by 10%. This results in an increase in the efficiency of the construction industry when considering CO2 emissions. In addition, in order to make the model more reasonable, Section 3.4 assumes that there is a specific policy threshold for the expected output. As for the setting of the policy threshold, referring to the policy threshold setting of the desirable outputs of the Chinese manufacturing industry by Emrouznejad et al. [30], the crk was selected as 0.05, which means that the loss of the desirable outputs of the construction industry caused by CO2 emissions reduction is 5% at most. The specific result of CO2 emissions allocation is shown in Table 5.

As shown in Table 5, the reduction ratio for roughly one third of the provinces accounted for more than 10%. Among them, the reduction ratio for Fujian accounts for more than 35%, indicating that this province is facing severe pressure of CO2 emissions reduction and therefore it is urgent to explore the green transformation of the construction industry in this province. In addition, there are also four provinces, where despite their β̂k is more than 0.3,

but the reduction ratio is less than 10%, which are Inner Mongolia, Qinghai, Yunnan and

Guizhou. The six provinces of Heilongjiang, Jiangxi, Anhui, Shaanxi, Chongqing and Zhejiang

are the opposite. The β̂k of these provinces is less than 0.1, but the reduction ratio is greater than 10% (β̂k is a parameter denoting the distance between the DMU and the production frontier, thereby reflecting the scope for technology improvement). Fig. 6 shows the total

emission reduction capacity in Eastern, Middle and Western China. According to the diagram

results, the CO2 emissions reduction amount in the East region is 292.987 (10,000 tons),

1. accounting for 44.0% of the total CO2 emissions reduction, and indicating that the East region
2. is a crucial area for reduction. CO2 emissions reduction amount in the Middle and West
3. regions accounted for 30.3% and 25.7% of CO2 emissions reduction, respectively. With the
4. use of the InvDEA model to allocate the CO2 emissions to the inefficient DMUs in the L set, the
5. overall optimal CO2 emissions allocation scheme of the Chinese construction industry can be
6. obtained, as shown in Fig. 7.

##### Table 5

1. The provincial quota of CO2 emission

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Fujian | L | 0.1187 | 0.1069 | 100.97 | 266.12 | 37.94% |
| Heilongjiang | L | 0.0482 | 0.0433 | 6.98 | 30.50 | 22.87% |
| Jiangxi | L | 0.0264 | 0.0237 | 19.06 | 85.02 | 22.42% |
| Guangxi | L | 0.1644 | 0.1480 | 14.48 | 64.75 | 22.37% |
| Beijing | L | 0.1519 | 0.1367 | 23.88 | 108.17 | 22.08% |
| Sichuan | L | 0.2070 | 0.1863 | 59.60 | 279.80 | 21.30% |
| Anhui | L | 0.0988 | 0.0889 | 65.55 | 329.12 | 19.92% |
| Shaanxi | L | 0.0022 | 0.0019 | 14.34 | 94.76 | 15.13% |
| Chongqing | L | 0.0551 | 0.0496 | 25.03 | 187.78 | 13.33% |
| Gansu | L | 0.3673 | 0.3306 | 13.72 | 114.84 | 11.94% |
| Hebei | L | 0.1505 | 0.1354 | 22.58 | 198.59 | 11.37% |
| Zhejiang | L | 0.0988 | 0.0889 | 65.55 | 627.59 | 10.44% |
| Hainan | L | 0.1105 | 0.0995 | 5.09 | 49.56 | 10.28% |
| Ningxia | L | 0.2305 | 0.2075 | 7.38 | 74.40 | 9.92% |
| Yunnan | L | 0.3724 | 0.3352 | 26.29 | 268.11 | 9.80% |
| Guangdong | L | 0.1242 | 0.1118 | 23.16 | 236.89 | 9.78% |
| Qinghai | L | 0.3864 | 0.3478 | 5.89 | 61.74 | 9.55% |
| Shandong | L | 0.2382 | 0.2144 | 26.00 | 292.94 | 8.88% |
| Guizhou | L | 0.3599 | 0.3239 | 18.45 | 213.29 | 8.65% |
| Shanxi | L | 0.2461 | 0.2215 | 14.19 | 209.69 | 6.77% |
| Henan | L | 0.1143 | 0.1029 | 25.34 | 385.49 | 6.57% |
| Hubei | L | 0.0546 | 0.0492 | 25.52 | 392.45 | 6.50% |
| Inner Mongolia | L | 0.4537 | 0.4084 | 19.01 | 357.48 | 5.32% |
| Jilin | L | 0.0033 | 0.0030 | 10.07 | 327.48 | 3.07% |

DMUs Sets

→∗

𝛽𝑘

β̂k

The amount of CO2 emission reduction allocation

The amount of CO2

emission in 2017

Reductio n ratio

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Tianjin | L | 0.0331 | 0.0298 | 11.26 | 435.80 | 2.58% |
| Hunan | L | 0.0034 | 0.0030 | 16.11 | 672.36 | 2.40% |
| Liaoning | F | 0 | 0 | 0 | 23.68 | 0.00% |
| Shanghai | F | 0 | 0 | 0 | 166.47 | 0.00% |
| Jiangsu | F | 0 | 0 | 0 | 125.92 | 0.00% |
| Xinjiang | F | 0 | 0 | 0 | 169.61 | 0.00% |

|  |  |
| --- | --- |
| 470 | **< Insert Fig. 6 here >** |
| 471 | **Fig. 6.** CO2 emissions reduction amount in three regions (unit: 10,000 tons) |
| 472 | **< Insert Fig. 7 here >** |
| 473 | **Fig. 7.** CO2 emissions provincial quota in Chinese construction industry (unit: 10,000 tons) |
| 474 | **5 Discussion** |
| 475 | In order to achieve the overall scheme efficiency, a three-stage empirical approach has |
| 476 | been applied in this research study to identify an optimized CO2 emissions allocation scheme |
| 477 | for the Chinese construction industry. |
| 478 | The results of the first stage show that the total CO2 emissions of the Chinese |
| 479 | construction industry increased year by year during the period 2005-2017. Indeed, Wang and |
| 480 | Feng [68] used the carbon emission coefficient method to calculate the energy-related CO2 |
| 481 | emissions from 2000 to 2014 and obtained the same conclusion. In addition, trends in the |
| 482 | construction industry’s CO2 emissions for the three regions are different. The amount of CO2 |
| 483 | emissions in the East region peaked in the year 2011 and then began to decline. Compared |
| 484 | with the Middle and West regions, the East region has more sound environmental |
| 485 | protection-related laws and regulations, and has achieved effective control of CO2 emissions, |
| 486 | thereby allowing a rapid decrease after the CO2 emissions peak has been initially reached. |
| 487 | Since 2012, with the release of the report "Opinions on Accelerating the Development of |
| 488 | Green Building", China's construction industry has changed its development mode and paid |

1. more attention to the quality and efficiency of development [2]. In addition, through
2. implementation of preferential policies, the utilization rate of green production capacity of the
3. construction industry in the West region is gradually improved [69]. Therefore, the growth trend
4. of CO2 emissions in the West region is gradually flattening, which indicates that this region has
5. further controlled the level of CO2 emissions. However, the West region has not been able to
6. significantly reduce CO2 emissions to the same level achieved in the East region and
7. consequently the West region still faces challenges in this area. How to break through this
8. challenge is the main problem that the West region needs to solve in regard to the future
9. low-carbon transformation of the construction industry. Unlike the East and West regions, the
10. CO2 emissions in the Middle region were still growing. Consequently, the Middle region should
11. consider how to reach the peak of CO2 emissions as soon as possible.
12. In the second stage, it has been found that the Chinese construction industry is still
13. following the trajectory of the extensive industrial development model and consequently there
14. is significant scope for improvement in the level of CO2 emissions. The primary source of CO2
15. emissions of the construction industry is energy consumption [70]. Indeed, the 13th Five-Year
16. Development Plan of the Chinese Construction Industry identified the need to promote building
17. energy conservation and green building development [71], thereby providing a feasible
18. implementation path for the control of CO2 emissions. It has also been found that the DMU
19. value of four provinces (namely Liaoning, Jiangsu, Shanghai and Xinjiang) is 1, and there is
20. therefore no capacity for CO2 emission reduction. Jiangsu and Shanghai have small land
21. areas and high levels of economic development, and the construction industry has high CO2
22. emissions, but the industry has low carbon intensity and high carbon emission efficiency [35,
23. 72, 73]. The "Low Carbon Development Report" issued by Jiangsu and Shanghai Ministry of
24. Ecological Environment identifies that through orderly promoting the construction and
25. management of low-carbon buildings, energy-saving transformation of existing buildings can
26. be achieved. It can be observed that both provinces have fulfilled the CO2 emission reduction
27. targets set by the state ahead of time. Therefore, there is no capacity for CO2 emission
28. reduction.
29. In the third stage, it has been found that the Chinese construction industry has ample
30. scope for CO2 emissions reduction, and the East region is a crucial area for the reduction. The
31. economic development level of the East region is high, and the laws and regulations of the
32. East region are sound. Also, the technical level is high in this area, so it is more likely to
33. achieve the CO2 emission reduction targets set by the state and the province. Therefore, the
34. relatively developed areas in the East have significant capacity for emission reduction. This is
35. consistent with previous studies [74]. At the same time, it was found that the relation between
36. β̂k and the CO2 emissions reduction capacity is not very strong. The results highlight that the
37. scope for technological progress in Inner Mongolia is obviously larger than that in other
38. provinces, but the capacity for CO2 emission reduction is only about 5% of its total amount.
39. This study suggests that this may be affected by the output threshold set in the research
40. process, and the introduction of threshold reduces β̂k and CO2 emission reduction capacity.
41. The reason for this phenomenon may be the impact of the scale effect. Therefore, we propose
42. that optimizing the scale of the construction industry is also a feasible path for CO2 emissions
43. reduction. In addition, the study found that Fujian leads the way among all provinces, with the
44. reduction ratio of 37.94%. In this regard, Su et al. [75] found that due to the change of energy
45. consumption and the negative attitude of industrial enterprises towards energy conservation
46. and CO2 emission reduction, it is a difficult task for Fujian to achieve CO2 emission reduction
47. targets as scheduled. After the reform in China and the opening up process, Fujian's economy
48. grew rapidly, and it was close to the level of medium-sized developed countries in 2008.
49. However, Fujian now needs to reduce CO2 emission intensity while maintaining a high GDP
50. growth rate, which is a huge challenge [76].
51. In addition, in order to illustrate the advance of Method II proposed in this study, the DEA
52. Method (Method I) was adopted to allocate the carbon dioxide emissions of China's
53. construction industry without considering the policy threshold and super efficiency, and the
54. distribution results of the two methods are compared and analyzed. As can be seen from Table
55. 6, 86.7% of the provinces and cities in the allocation results of Method II were selected as CO2
56. emission reduction targets, while in the allocation results of Method I, the value was only 40%.
57. This indicates that Method II can identify the DMU emission reduction capacity more effectively
58. than Method I. In addition, in the allocation results of Method I, the CO2 emission reduction
59. ratio of Shaanxi exceeds 60%. In contrast, in the distribution results of Method II, the CO2
60. emission reduction ratio of various provinces and cities is more concentrated. Among them, 60%
61. of the provinces and cities are in the range of 0 to 20%, and no provinces and cities cut
62. emissions by more than 40%. In conclusion, Method II can more effectively identify the CO2
63. emission reduction capacity of the decision unit and reduce the occurrence of extreme values
64. in the allocation results.

##### Table 6

1. The comparative analysis of two methods

Method I Method II

DMUs

Reduction ratio Set Reduction ratio Set

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| Beijing | 0.00% | F | 22.08% | L |
| Tianjin | 0.00% | F | 2.58% | L |
| Hebei | 19.28% | L | 11.37% | L |
| Shanxi | 18.65% | L | 6.77% | L |
| Inner Mongolia | 0.00% | F | 5.32% | L |
| Liaoning | 0.00% | F | 0.00% | F |
| Jilin | 0.00% | F | 3.07% | L |
| Heilongjiang | 0.00% | F | 22.87% | L |
| Shanghai | 0.00% | F | 0.00% | F |
| Jiangsu | 0.00% | F | 0.00% | F |
| Zhejiang | 0.00% | F | 10.44% | L |
| Anhui | 17.35% | L | 19.92% | L |
| Fujian | 32.58% | L | 37.94% | L |
| Jiangxi | 0.00% | F | 22.42% | L |
| Shandong | 25.20% | L | 8.88% | L |
| Henan | 18.29% | L | 6.57% | L |
| Hubei | 0.00% | F | 6.50% | L |
| Hunan | 0.00% | F | 2.40% | L |
| Guangdong | 39.16% | L | 9.78% | L |
| Guangxi | 0.00% | F | 22.37% | L |
| Hainan | 0.00% | F | 10.28% | L |
| Chongqing | 0.00% | F | 13.33% | L |
| Sichuan | 22.04% | L | 21.30% | L |
| Guizhou | 20.40% | L | 8.65% | L |
| Yunnan | 15.65% | L | 9.80% | L |
| Shaanxi | 63.44% | L | 15.13% | L |
| Gansu | 0.00% | L | 11.94% | L |
| Qinghai | 0.00% | F | 9.55% | L |
| Ningxia | 0.00% | F | 9.92% | L |
| Xinjiang | 0.00% | F | 0.00% | F |

##### 6 Conclusions

1. This research study has developed an optimized CO2 emissions allocation scheme for the
2. construction industry. A three-stage approach was adopted to empirically study the CO2
3. emissions allocation for the Chinese construction industry drawing on panel data for the period
4. 2005-2017. In order to achieve an optimum overall scheme efficiency, parameters were
5. introduced in the proposed model to limit the negative impact of CO2 emission reduction on the
6. production efficiency and output of the construction industry. Firstly, according to China's 2030
7. emissions reduction national goal, this research study identified the total amount of CO2
8. emissions reduction for the construction industry with the data of CO2 emissions from 2005 to
9. 2017. Secondly, the DEA-BCC model and super efficiency DEA model was applied to evaluate
10. the CO2 emissions reduction capacity of 30 provinces in China and divide the provinces into
11. the L and F groups. Group L represents the collection of provinces with CO2 emission
12. reduction capacity, including 27 provinces, and were selected as priority objects for CO2
13. emissions reduction. The InvDEA model was employed to allocate the total amount of CO2
14. emissions reduction to priority objects of the L group, and identified an optimized CO2
15. emissions allocation scheme, thereby achieving the overall scheme efficiency. This study uses
16. the DEA-BCC model to identify CO2 emission reduction target allocation objects, and on this
17. basis, introduces a super-efficiency DEA model to further evaluate high-efficiency DMUs,
18. thereby improving the accuracy of identification of CO2 emission reduction objects in the
19. construction industry, and further enriching and improving the theoretical system of CO2
20. emission reduction target allocation. In addition, this study adopts China's construction
21. industry as an example to allocate CO2 emission reduction capacity, which provides a scientific
22. basis for the formulation of CO2 emission reduction policies in China's construction industry. At
23. the same time, this study provides a reference for the formulation of CO2 emissions reduction
24. policies and has a further reference value for CO2 emissions allocation research in other
25. regions and industries. This study will also help China and other countries and regions to
26. achieve the objectives of the Paris Agreement and the wider United Nations Sustainable
27. Development Goals (SDGs). The main findings of this study are as follows:
28. (1) From 2005 to 2017, the CO2 emissions of the Chinese construction industry increased
29. from 3404.63 (10,000 tons) to 6789.84 (10,000 tons), but the CO2 emissions / GVOC overall
30. declined, from 0.0853 to 0.0378. In order to achieve China's 2020 CO2 emissions reduction
31. targets, the CO2 emissions of the Chinese construction industry needs to be reduced by
32. 665.52 (10,000 tons), accounting for about 10% of total CO2 emissions in 2017.
33. (2) During the inspection period, CO2 emissions from the construction industry in the East
34. region were on a downward trend after peaking at 27.033 million tons in 2011. The West
35. region leveled off in 2010, while CO2 emissions in the Middle region were volatile and still
36. growing. Therefore, the East region has improved control over carbon dioxide emissions.
37. (3) The results show that in 2017, about one-third of China's provinces are facing
38. significant pressure to reduce CO2 emissions, of which Fujian is are more than 35%. In
39. addition, the East region is the key area of CO2 emission reduction, and its CO2 emission
40. reduction capacity accounts for 44.0% of the total CO2 emission reduction.
41. (4) This study concludes through comparing with the calculated results of DEA without
42. considering the policy threshold and super efficiency that the CO2 emission allocation method
43. in the construction industry proposed is more effective than other approaches. Furthermore,
44. the proposed method can better reflect the actual situation of CO2 emission reduction capacity
45. in the construction industry in different provinces.
46. It has been found that the environmental issue arising from CO2 emissions has negative 602 externalities, and its resolution should be achieved through governmental intervention. This 603 will ensure the realization of the CO2 emissions reduction targets, and thereby balance 604 economic development and CO2 reduction. This research has provided four policy 605 recommendations with a view to facilitating the formulation of relevant CO2 emissions

606 reduction policies:

607 (1) *Implement CO2 emissions quota trading in the construction industry.* The trading of 608 CO2 emissions is an effective economic incentive to control emissions and wider pollution 609 (Zhang et al., 2019a). The optimized CO2 emissions allocation scheme for the construction 610 industry in this study provides a reference for developing CO2 emissions trading policies for 611 the construction industry.

612 (2) *Develop a systematic CO2 emissions reduction action plan for the construction* 613 *industry.* The adoption of the national-level CO2 emissions reduction action plan may face the 614 problem of being less targeted when it is implemented for a specific industry. Therefore, 615 governments should formulate a systematic CO2 emissions reduction action plan with 616 administrative measures based on the construction industry’s development characteristics. 617 For example: (a) Establishment of a CO2 emissions database for the construction industry to 618 accurately monitor, record and verify regional CO2 emissions. (b) The establishment of a think 619 tank, the threshold for CO2 emission reduction can be scientifically and reasonably set by 620 experts to ensure that the CO2 emission reduction action plan is practical and effective.

621 (3) *Establish a carbon tax system.* The carbon tax system restricts high-energy, 622 high-emission production behavior through the action of taxation, and encourages enterprises 623 to actively carry out energy conservation and emissions reduction. The revenue from the 624 carbon tax can be used to subsidize and develop new technologies to promote the green and 625 low-carbon transformation of the industry. At the same time, a system of carbon tax 626 assessment rewards and penalties should also be established. The government makes 627 statistics on the carbon tax payment value of each region and publishes the variation range of

628 carbon tax in each region every quarter. If the carbon tax is improved, it will be rewarded; if it

629 rises, it will be punished.

630 (4) *Develop and promote energy-saving and emission reduction technologies in the* 631 *construction industry.* The government should encourage the use of domestic and foreign 632 advanced energy conservation and emission reduction technologies. In addition, the 633 government should invest more funds to support the organization of scientific research 634 institutions and enterprises to jointly research and develop building energy-saving 635 technologies. At the same time, building energy conservation and emission reduction 636 technologies will be popularized and integrated application demonstration zones will be 637 established. Furthermore, there is a need to reduce carbon emissions from the construction 638 industry at source through technological innovation and progress.

639 There are also some limitations in this study. Firstly, in this study, we only selected 0.05 as 640 the policy threshold. Actually, due to the different risk attitude of the decision makers, the policy 641 threshold is usually not a specific value. Secondly, this study proposed an optimized CO2 642 emissions allocation scheme for the construction industry, but detailed policy 643 recommendations on how to reduce CO2 were not given. As for future research, we believe 644 that the InvDEA model could potentially be improved by introducing a parameter to reflect the 645 risk attitude of the decision-makers. Furthermore, regression analysis could be conducted to 646 identify the impact of environmental variables on the CO2 emissions reduction of the 647 construction industry so that policy recommendations would be more detailed.

##### 648 Conflict of interest

649 No potential conflict of interest is reported by the authors.

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655 **Reference**

656 [1] WRI. Climate Data Explorer, [http://cait.wri.org/;](http://cait.wri.org/) 2017.

657 [2] Li W, Wang W, Gao H, Zhu B, Gong W, Liu Y, Qin Y. Evaluation of regional 658 metafrontier total factor carbon emission performance in China’s construction industry: 659 Analysis based on modified non-radial directional distance function. Journal of 660 Cleaner Production 2020;256:120425. [http://doi.org/10.1016/j.jclepro.2020.120425.](http://doi.org/10.1016/j.jclepro.2020.120425)

661 [3] Thomala LL. Market value of the construction industry in China from 2018 to 2021(in 662 billion U.S. dollars), 663 [https://www.statista.com/statistics/1068161/china-construction-industry-value/;](https://www.statista.com/statistics/1068161/china-construction-industry-value/) 2019. 664 [4] Stern NH, Peters S, Bakhshi V, Bowen A, Cameron C, Catovsky S, Crane D, 665 Cruickshank S, Dietz S, Edmonson N. Stern Review: The economics of climate 666 change. London: Cambridge University Press; 2006.

667 [5] Gomes EG, Lins MPE. Modelling undesirable outputs with zero sum gains data 668 envelopment analysis models. Journal of the Operational Research Society 669 2008;59(5):616-623. [http://doi.org/10.1057/palgrave.jors.2602384.](http://doi.org/10.1057/palgrave.jors.2602384)

670 [6] Chiu YH, Lin JC, Su WN, Liu JK. An Efficiency Evaluation of the EU's Allocation of 671 Carbon Emission Allowances. Energy Sources Part B-Economics Planning and Policy 672 2015;10(2):192-200. [http://doi.org/10.1080/15567249.2010.527900.](http://doi.org/10.1080/15567249.2010.527900)

673 [7] Fang K, Zhang QF, Long Y, Yoshida Y, Sun L, Zhang HR, Dou Y, Li S. How can China 674 achieve its Intended Nationally Determined Contributions by 2030? A multi-criteria 675 allocation of China's carbon emission allowance. Applied Energy 2019;241:380-389. 676 [http://doi.org/10.1016/j.apenergy.2019.03.055.](http://doi.org/10.1016/j.apenergy.2019.03.055)

677 [8] Acquaye AA, Duffy AP. Input-output analysis of Irish construction sector greenhouse 678 gas emissions. Building and Environment 2010;45(3):784-791. 679 [http://doi.org/10.1016/j.buildenv.2009.08.022.](http://doi.org/10.1016/j.buildenv.2009.08.022)

680 [9] Nassen J, Holmberg J, Wadeskog A, Nyman M. Direct and indirect energy use and 681 carbon emissions in the production phase of buildings: An input-output analysis. 682 Energy 2007;32(9):1593-1602. [http://doi.org/10.1016/j.energy.2007.01.002.](http://doi.org/10.1016/j.energy.2007.01.002)

683 [10] Zhang Z, Wang B. Research on the life-cycle CO2 emission of China's construction

684 sector. Energy & Buildings 2016;112. <http://doi.org/10.1016/j.enbuild.2015.12.026>. 685 [11] Gustavsson L, Joelsson A, Sathre R. Life cycle primary energy use and carbon 686 emission of an eight-storey wood-framed apartment building. Energy and Buildings 687 2010;42(2):230-242. [http://doi.org/10.1016/j.enbuild.2009.08.018.](http://doi.org/10.1016/j.enbuild.2009.08.018)

Lu Y, Cui P, Li D. Carbon emissions and policies in China's building and construction industry: Evidence from 1994 to 2012. Building and Environment 2016;95. [http://doi.org/10.1016/j.buildenv.2015.09.011.](http://doi.org/10.1016/j.buildenv.2015.09.011)

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Wu Y, Chau KW, Lu WS, Shen LY, Shuai CY, Chen JD. Decoupling relationship between economic output and carbon emission in the Chinese construction industry. Environmental Impact Assessment Review 2018;71:60-69. [http://doi.org/10.1016/j.eiar.2018.04.001.](http://doi.org/10.1016/j.eiar.2018.04.001)

Xu JH, Fleiter T, Eichhammer W, Fan Y. Energy consumption and CO2 emissions in China's cement industry: A perspective from LMDI decomposition analysis. Energy Policy 2012;50:821-832. [http://doi.org/10.1016/j.enpol.2012.08.038.](http://doi.org/10.1016/j.enpol.2012.08.038)

Xu B, Lin BQ. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. Journal of Cleaner Production 2016;131:594-606. [http://doi.org/10.1016/j.jclepro.2016.04.129.](http://doi.org/10.1016/j.jclepro.2016.04.129)

Zhou P, Wang M. Carbon dioxide emissions allocation: A review. Ecological Economics 2016;125:47-59. [http://doi.org/10.1016/j.ecolecon.2016.03.001.](http://doi.org/10.1016/j.ecolecon.2016.03.001)

Zhang W, Zhang N, Yu Y. Carbon mitigation effects and potential cost savings from

carbon emissions trading in China's regional industry. Technological Forecasting and Social Change 2019;141:1-11. http://doi.org/https://doi.org/10.1016/j.techfore.2018.12.014.

Zetterberg L, Wrake M, Sterner T, Fischer C, Burtraw D. Short-Run Allocation of Emissions Allowances and Long-Term Goals for Climate Policy. Ambio 2012;41:23-32. [http://doi.org/10.1007/s13280-011-0238-1.](http://doi.org/10.1007/s13280-011-0238-1)

Zhou P, Zhang L, Zhou DQ, Xia WJ. Modeling economic performance of interprovincial CO2 emission reduction quota trading in China. Applied Energy 2013;112:1518-1528. [http://doi.org/10.1016/j.apenergy.2013.04.013.](http://doi.org/10.1016/j.apenergy.2013.04.013)

Luzzati T, Gucciardi G. A non-simplistic approach to composite indicators and rankings: an illustration by comparing the sustainability of the EU Countries. Ecological Economics 2015;113:25-38. [http://doi.org/10.1016/j.ecolecon.2015.02.018.](http://doi.org/10.1016/j.ecolecon.2015.02.018)

Nordhaus W, Yang Z. A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies. American Economic Review 1996;86:741-65. [http://doi.org/10.2307/2118303.](http://doi.org/10.2307/2118303)

Filar JA, Gaertner PS. A regional allocation of world CO2 emission reductions. Mathematics and Computers In Simulation 1997;43(3):269-275. [http://doi.org/10.1016/s0378-4754(97)00009-8.](http://doi.org/10.1016/s0378-4754%2897%2900009-8)

Ma CQ, Ren YS, Zhang YJ, Sharp B. The allocation of carbon emission quotas to five major power generation corporations in China. Journal of Cleaner Production 2018;189:1-12. [http://doi.org/10.1016/j.jclepro.2018.04.006.](http://doi.org/10.1016/j.jclepro.2018.04.006)

Cucchiella F, D'Adamo I, Gastaldi M, Miliacca M. Efficiency and allocation of emission allowances and energy consumption over more sustainable European economies.

Journal of Cleaner Production 2018;182:805-817. [http://doi.org/10.1016/j.jclepro.2018.02.079.](http://doi.org/10.1016/j.jclepro.2018.02.079)

Chen LL, He F, Wang JJ. Allocative Efficiency of Carbon Emission Allowances among Sectors in China. Polish Journal of Environmental Studies 2018;27(2):557-563. [http://doi.org/10.15244/pjoes/75821.](http://doi.org/10.15244/pjoes/75821)

732 [26] Zhang YJ, Hao JF. Carbon emission quota allocation among China's industrial sectors 733 based on the equity and efficiency principles. Annals of Operations Research 734 2017;255(1-2):117-140. [http://doi.org/10.1007/s10479-016-2232-2.](http://doi.org/10.1007/s10479-016-2232-2)

735 [27] Zhang YJ, Wang AD, Da YB. Regional allocation of carbon emission quotas in China: 736 Evidence from the Shapley value method. Energy Policy 2014;74:454-464. 737 [http://doi.org/10.1016/j.enpol.2014.08.006.](http://doi.org/10.1016/j.enpol.2014.08.006)

738 [28] Liao ZL, Zhu XL, Shi JR. Case study on initial allocation of Shanghai carbon emission 739 trading based on Shapley value. Journal of Cleaner Production 2015;103:338-344. 740 [http://doi.org/10.1016/j.jclepro.2014.06.045.](http://doi.org/10.1016/j.jclepro.2014.06.045)

741 [29] Zhou ZB, Liu CJ, Zeng XM, Jiang Y, Liu WB. Carbon emission performance evaluation 742 and allocation in Chinese cities. Journal of Cleaner Production 2018;172:1254-1272. 743 [http://doi.org/10.1016/j.jclepro.2017.10.208.](http://doi.org/10.1016/j.jclepro.2017.10.208)

744 [30] Emrouznejad A, Yang G-l, Amin GR. A novel inverse DEA model with application to 745 allocate the CO2 emissions quota to different regions in Chinese manufacturing 746 industries. Journal of the Operational Research Society 2018:1-12. 747 [http://doi.org/10.1080/01605682.2018.1489344.](http://doi.org/10.1080/01605682.2018.1489344)

748 [31] Chang S-C. Returns to scale in DEA models for performance evaluations. 749 Technological Forecasting and Social Change 2011;78(8):1389-1396. 750 http://doi.org/https://doi.org/10.1016/j.techfore.2011.03.015.

751 [32] Kiani Mavi R, Saen RF, Goh M. Joint analysis of eco-efficiency and eco-innovation 752 with common weights in two-stage network DEA: A big data approach. Technological 753 Forecasting and Social Change 2019;144:553-562.

754 http://doi.org/https://doi.org/10.1016/j.techfore.2018.01.035.

755 [33] Yang G-l, Fukuyama H. Measuring the Chinese regional production potential using a 756 generalized capacity utilization indicator. Omega-International Journal of Management 757 Science 2018;76:112-127. [http://doi.org/10.1016/j.omega.2017.05.003.](http://doi.org/10.1016/j.omega.2017.05.003)

758 [34] Emrouznejad A, Yang GL. CO2 emissions reduction of Chinese light manufacturing 759 industries: A novel RAM-based global Malmquist-Luenberger productivity index. 760 Energy Policy 2016;96:397-410. [http://doi.org/10.1016/j.enpol.2016.06.023.](http://doi.org/10.1016/j.enpol.2016.06.023)

761 [35] Du MX, Wang XG, Peng CH, Shan YL, Chen H, Wang M, Zhu QA. Quantification and 762 scenario analysis of CO2 emissions from the central heating supply system in China 763 from 2006 to 2025. Applied Energy 2018;225:869-875.

764 [http://doi.org/10.1016/j.apenergy.2018.05.064.](http://doi.org/10.1016/j.apenergy.2018.05.064)

765 [36] Wei Q, Zhang J, Zhang X. An inverse DEA model for inputs/outputs estimate. 766 European Journal of Operational Research 2000;121(1):151-163. 767 [http://doi.org/10.1016/s0377-2217(99)00007-7.](http://doi.org/10.1016/s0377-2217%2899%2900007-7)

768 [37] Lin HT. An efficiency-driven approach for setting revenue target. Decision Support

769 Systems 2010;49(3):311-317. [http://doi.org/10.1016/j.dss.2010.03.006.](http://doi.org/10.1016/j.dss.2010.03.006)

770 [38] Frija A, Wossink A, Buysse J, Speelman S, Van Huylenbroeck G. Irrigation pricing 771 policies and its impact on agricultural inputs demand in Tunisia: A DEA-based 772 methodology. Journal of Environmental Management 2011;92(9):2109-2118. 773 [http://doi.org/10.1016/j.jenvman.2011.03.013.](http://doi.org/10.1016/j.jenvman.2011.03.013)

774 [39] Gattoufi S, Amin GR, Emrouznejad A. A new inverse DEA method for merging banks.

775 Ima Journal of Management Mathematics 2014;25(1):73-87.

776 [http://doi.org/10.1093/imaman/dps027.](http://doi.org/10.1093/imaman/dps027)

777 [40] Lim DJ. Inverse DEA with frontier changes for new product target setting. European

778 Journal of Operational Research 2016;254(2):510-516.

779 [http://doi.org/10.1016/j.ejor.2016.03.059.](http://doi.org/10.1016/j.ejor.2016.03.059)

780 [41] Amin GR, Emrouznejad A, Gattoufi S. Modelling generalized firms' restructuring using 781 inverse DEA. Journal of Productivity Analysis 2017;48(1):51-61. 782 [http://doi.org/10.1007/s11123-017-0501-y.](http://doi.org/10.1007/s11123-017-0501-y)

783 [42] Amin GR, Emrouznejad A, Gattoufi S. Minor and major consolidations in inverse DEA: 784 Definition and determination. Computers & Industrial Engineering 2017;103:193-200. 785 [http://doi.org/10.1016/j.cie.2016.11.029.](http://doi.org/10.1016/j.cie.2016.11.029)

786 [43] Amin GR, Al-Muharrami S, Toloo M. A combined goal programming and inverse DEA 787 method for target setting in mergers. Expert Systems with Applications 788 2019;115:412-417. [http://doi.org/10.1016/j.eswa.2018.08.018.](http://doi.org/10.1016/j.eswa.2018.08.018)

789 [44] Chen L, Wang YM, Lai FJ, Feng F. An investment analysis for China's sustainable 790 development based on inverse data envelopment analysis. Journal of Cleaner 791 Production 2017;142:1638-1649. [http://doi.org/10.1016/j.jclepro.2016.11.129.](http://doi.org/10.1016/j.jclepro.2016.11.129)

792 [45] Lertworasirikul S, Charnsethikul P, Fang SC. Inverse data envelopment analysis 793 model to preserve relative efficiency values: The case of variable returns to scale. 794 Computers & Industrial Engineering 2011;61(4):1017-1023.

795 [http://doi.org/10.1016/j.cie.2011.06.014.](http://doi.org/10.1016/j.cie.2011.06.014)

796 [46] Ghiyasi M. On inverse DEA model: The case of variable returns to scale. Computers &

797 Industrial Engineering 2015;87:407-409. [http://doi.org/10.1016/j.cie.2015.05.018.](http://doi.org/10.1016/j.cie.2015.05.018) 798 [47] Modhej D, Sanei M, Shoja N, HosseinzadehLotfi F. Integrating inverse data 799 envelopment analysis and neural network to preserve relative efficiency values. 800 Journal of Intelligent & Fuzzy Systems 2017;32(6):4047-4058. 801 [http://doi.org/10.3233/jifs-152271.](http://doi.org/10.3233/jifs-152271)

1. [48] IPCC. Guidelines for national greenhouse gas inventories,
2. [http://www.ipccnggip.iges.or.jp/public/2006gl;](http://www.ipccnggip.iges.or.jp/public/2006gl) 2006.
3. [49] NBS NBoSotPRC China Statistical Yearbook (2006-2016). *In:* (ed.)^(eds.) ed. Beijing:
4. China Statistics Press.
5. [50] NBSMEP NBoSMoEPotPRC China Statistical Yearbook on Energy (2006-2016). *In:*
6. C.S. Press (ed.)^(eds.) ed. Beijing, P.R. China.
7. [51] NBS NBoSotPRC China Statistical Yearbook on Construction (2006-2016). *In:* C.S.
8. Press (ed.)^(eds.) ed. Beijing, P.R. China.
9. [52] Emrouznejad A, Yang GL. A framework for measuring global Malmquist-Luenberger 811 productivity index with CO2 emissions on Chinese manufacturing industries. Energy 812 2016;115:840-856. [http://doi.org/10.1016/j.energy.2016.09.032.](http://doi.org/10.1016/j.energy.2016.09.032)

813 [53] Zhang J, Li H, Xia B, Skitmore M. Impact of environment regulation on the efficiency of 814 regional construction industry: A 3-stage Data Envelopment Analysis (DEA). Journal of 815 Cleaner Production 2018(200):770-780. [http://doi.org/10.1016/j.jclepro.2018.07.189.](http://doi.org/10.1016/j.jclepro.2018.07.189) 816 [54] DTI. Our Energy Future - Creating a low carbon economy. Norwich: TSO; 2003.

817 [55] Huo T, Ren H, Cai W, Feng W, Tang M, Zhou N. The total-factor energy productivity 818 growth of China's construction industry: evidence from the regional level. Natural 819 Hazards 2018;92(3):1593-1616. [http://doi.org/10.1007/s11069-018-3269-0.](http://doi.org/10.1007/s11069-018-3269-0)

Li Y, Liu C. Malmquist indices of total factor productivity changes in the Australian construction industry. Construction Management & Economics 2010;28(9):933-945. [http://doi.org/10.1080/01446191003762231.](http://doi.org/10.1080/01446191003762231)

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Wang XQ, Zhou SG, Liu BS. The empirical research into efficiency of construction industry in regional China based on DEA model. Construction Economy 2011;12:8-12. China.

Liu B, Chen X, Wang X, Chen Y. Analysis on the changing trend and influencing factors of TFP about the regional construction industry in China. Systems Engineering-Theory & Practice 2013;33(4):1041-1049. China.

Li Y, Kang T, Wang K. Productivity differences of China's construction enterprises based on DEA. Journal of Liaoning Technical University (Social Science Edition) 2014;16(01):15-17. China.

Shi Q, Pang Y, Yang Z. Total Factor Productivity about the Regional Construction Industry in China. Journal of Civil Engineering and Management 2016;33(05):98-103+109, China.

Hu X, Liu C. Energy productivity and total-factor productivity in the Australian

construction industry. Architectural Science Review 2016;59(5):432-444. [http://doi.org/10.1080/00038628.2015.1038692.](http://doi.org/10.1080/00038628.2015.1038692)

Hu X, Liu C. Total factor productivity measurement with carbon reduction. Engineering Construction and Architectural Management 2017;24(4):575-592.

[http://doi.org/10.1108/ecam-06-2015-0097.](http://doi.org/10.1108/ecam-06-2015-0097)

Hu X, Si T, Liu C. Total factor carbon emission performance measurement and development. Journal of Cleaner Production 2017;142:2804-2815. [http://doi.org/10.1016/j.jclepro.2016.10.188.](http://doi.org/10.1016/j.jclepro.2016.10.188)

Chen Y, Liu BS, Shen YH, Wang XQ. Spatial analysis of change trend and influencing factors of total factor productivity in China's regional construction industry. Applied Economics 2018;50(25):2824-2843. [http://doi.org/10.1080/00036846.2017.1409421.](http://doi.org/10.1080/00036846.2017.1409421)

Hu X, Liu C. Measuring efficiency, effectiveness and overall performance in the Chinese construction industry. Engineering Construction and Architectural Management 2018;25(6):780-797. [http://doi.org/10.1108/ecam-06-2016-0131.](http://doi.org/10.1108/ecam-06-2016-0131)

Wang J, Hu M, Rodrigues JFD. The evolution and driving forces of industrial aggregate energy intensity in China: An extended decomposition analysis. Applied Energy 2018;228:2195-2206.

http://doi.org/https://doi.org/10.1016/j.apenergy.2018.07.039.

Zhu B, He J, Zhai ST. Does Financial Inclusion Create a Spatial Spillover Effect Between Regions? Evidence from China. Emerging Markets Finance and Trade 2019;55(5):980-997. [http://doi.org/10.1080/1540496x.2018.1518779.](http://doi.org/10.1080/1540496x.2018.1518779)

Wang M, Feng C. Exploring the driving forces of energy-related CO2 emissions in China's construction industry by utilizing production-theoretical decomposition

analysis. Journal of Cleaner Production 2018;202:710-719. [http://doi.org/10.1016/j.jclepro.2018.08.152.](http://doi.org/10.1016/j.jclepro.2018.08.152)

Wang Y, Pan J, Pei R, Yang G, Yi B. A Framework for Assessing Green Capacity Utilization Considering CO2 Emissions in China’s High-Tech Manufacturing Industry. Sustainability 2020;12(11):4424. [http://doi.org/10.3390/su12114424.](http://doi.org/10.3390/su12114424)

Chen JD, Shi Q, Shen LY, Huang Y, Wu Y. What makes the difference in construction carbon emissions between China and USA? Sustainable Cities and Society 2019;44:604-613. [http://doi.org/10.1016/j.scs.2018.10.017.](http://doi.org/10.1016/j.scs.2018.10.017)

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| 888 |  |

Wang Y, Ren H, Dong L, Park H-S, Zhang Y, Xu Y. Smart solutions shape for sustainable low-carbon future: A review on smart cities and industrial parks in China. Technological Forecasting and Social Change 2019;144:103-117. http://doi.org/https://doi.org/10.1016/j.techfore.2019.04.014.

Du Q, Zhou J, Pan T, Sun Q, Wu M. Relationship of carbon emissions and economic growth in China's construction industry. Journal of Cleaner Production 2019;220:99-109. [http://doi.org/10.1016/j.jclepro.2019.02.123.](http://doi.org/10.1016/j.jclepro.2019.02.123)

Zhang M, Wang W. Decouple indicators on the CO2 emission-economic growth linkage: The Jiangsu Province case. Ecological Indicators 2013;32:239-244. [http://doi.org/10.1016/j.ecolind.2013.03.033.](http://doi.org/10.1016/j.ecolind.2013.03.033)

Wang K, Yang K, Wei Y, Zhang C. Shadow prices of direct and overall carbon emissions in China’s construction industry: A parametric directional distance

function-based sensitive estimation. Structural Change and Economic Dynamics 2018;47:180-193. [http://doi.org/10.1016/j.strueco.2018.08.006.](http://doi.org/10.1016/j.strueco.2018.08.006)

Su K, Wei D, Lin W. Influencing factors and spatial patterns of energy-related carbon emissions at the city-scale in Fujian province, Southeastern China. Journal of Cleaner

Production 2020;244:118840. [http://doi.org/10.1016/j.jclepro.2019.118840.](http://doi.org/10.1016/j.jclepro.2019.118840)

Wang R, Liu W, Xiao L, Liu J, Kao W. Path towards achieving of China's 2020 carbon emission reduction target—a discussion of low-carbon energy policies at province level. Energy Policy 2011;39(5):2740-2747. [http://doi.org/10.1016/j.enpol.2011.02.043.](http://doi.org/10.1016/j.enpol.2011.02.043)

Figure

Stage 2

Stage 1

**Fig. 1.** Framework of the research methodology

CO2 emissions reduction goal

on the national level

Upper bound

of 45%

4 DMUs

Evaluate via 30 DMUs DEA-BCC model

26 DMUs

Priority DMUs

Optimized CO2 emissions

allocation scheme

CO2 emissions reduction space evaluation

CO2 emissions reduction total amount calculation

An optimized CO2 emissions allocation scheme

Total amount of CO2 emissions reduction

hold of 0.05 in

DEA model

A thres

Inv

Set L: 26 priority reduction DMUs

Set L: Inefficiency DMUs

CO2 emissions during 2005-2017

Calculate via carbon emission coefficient method

Set F: Efficiency DMUs

Total amount of CO2 emissions reduction

Stage 3

Input-1

A1

B2

B1

C1

D1

O Input-2

**Fig. 2.** Super efficiency DEA model

#### Input-1

A2

A1

B2

B1

C1

C2

D1

D2

O Input-2

**Fig. 3.** Efficient DMUs in DEA-BCC model after adjustment



**Fig. 4.** Geography of the three regions in China (East, Middle and West).

**Fig. 5.** Regional construction industry CO2 emissions during 2005-2017

**Year**

0

East area

Middle area West area

3000

2500

2000

1500

1000

500

**CO2 emissions/10000 tons**

Reduction amount of CO2 emissions

400.00

300.00

200.00

100.00

0.00

East region

201.84

Middle region

170.70

West region

292.99

**Fig. 6.** CO2 emissions reduction amount in three regions (unit: 10,000 tons)



**Fig. 7.** CO2 emissions provincial quota in Chinese construction industry (unit: 10,000 tons)