Using a network DEA model to assess the energy efficiency of regions in China

Geng Wu¹, Yichung Hu¹* and Peiyi Kong²

¹Department of Business Administration, Chung Yuan Christian University, Taoyuan, 320314, Taiwan
²Ph.D. Program in Business, Chung Yuan Christian University, Taoyuan, 320314, Taiwan
*wgobdye@163.vip.com

Abstract. This paper assesses 30 provinces’ data in China by using a network DEA model with undesirable output. The results denote that the proposed model could evaluate the internal energy consumption well. And the main cause of the energy inefficiency is environmental inefficiency. Therefore, China's provinces should tighten restriction on CO₂ emissions and reduce their dependence on fossil fuels by using more green energy.

1. Introduction
China has been the largest emitter of carbon dioxide since 2007 in the world, rapid economic development and ongoing industrialization of China has led to a large impact and harmful effect on the environment [1,2]. Hence, the serious problems concerning energy usage and carbon emissions has attracted great attentions from the Chinese government.

Energy efficiency can be considered as one of the easiest and most cost-effective ways to combat the global warming and climate change. In recent years, DEA method has become more popular for evaluating energy efficiency of industries, provinces or countries. Honma and Hu address the DEA method to measuring the total-factor energy efficiency of 47 regions in Japan during 1993 to 2003, with 3 production factors and 11 energy consumptions as inputs, GDP as the single output[3]. Moon and Min address a two-stage DEA model with pure energy efficiency and economy efficiency for assessing energy efficiency of energy-intensive firms in Korea. And the results show that pure energy efficiency is more important to improve overall energy efficiency.[4].

In recent decades, the study of China’s provincial energy efficiency has attracted more and more attention from many scholars[5]. Hu and Wang (2006) introduced a DEA method to assess the energy efficiency of 29 provinces in China, and found that energy efficiency eventually improves with economic growth and the central area of China has the worst energy efficiency[6]. Huang et al. (2017) use DEA-Malmquist model to investigates the driving forces of China's energy intensity. They also divide China into 3 regions including Eastern, Central, and Western regions, for exploring the factors influencing the regional differences[7].

We introduced a network DEA model based on Tone and Tsutsui’s method[8]. Therefore, the environmental efficiency and economic efficiency of 30 provinces are evaluated simultaneously. The rest of this paper is organized as follows: Section 2 denote the methodology. In the next section, variables and data information are proposed. Section 4 discusses the results of the analysis about energy efficiency. In the end, Sections 5 provides the conclusions.
2. Methodology

2.1. Framework of network DEA

Because almost all of China's energy consumption is fossil energy resources, thus the energy consumption will promote economic growth and produce harmful environmental gases at the same time. Therefore, this paper divide energy consumption into two stages: the environmental efficiency stage, and the economic efficiency stage. As shown in Figure 1, there are one input variables energy resources consumption, one intermediate-output variable CO2, two intermediate-input variables including capital stock and labor force, and one final output variable GDP.

![Figure 1. Framework for energy efficiency performance assessment.](image)

2.2. Network DEA model

The energy resources consumption process could be divided into two phases by the proposed model to assess economic and environmental efficiency, respectively. This model assumes that observations are formed from \( m \) \( DMU_0 \), \( p, n^1 \) and \( n^2 \) are the numbers of outputs, inputs, and intermediate inputs, respectively. We introduce the link from phase 1 to phase 2 by \((s_1, s_2)\), and the intermediates are regarded as phase 1 output and phase 2 input.

According to the above, the proposed network DEA model to evaluate the \( DMU_0 's \) efficiency is then represented as below:

\[
\theta_0^* = \min \frac{1}{2} \times \left( (1 - \sum_{i=1}^{n_1} \frac{s^-_i}{x^i_1}) + (1 - \sum_{i=1}^{n_2} \frac{s^+_i}{x^i_2}) \right)
\]

s.t.

\[
x^0_1 = X^1 \gamma + s^- \\
 e \gamma = 1 \\
x^0_2 = X^2 \omega + s^+ \\
y_o = Y \omega - s^+ \\
e \omega = 1 \\
Z(s_1, s_2) \omega = Z(s_1, s_2) \gamma \\
o = (1, \ldots, m) \\
\gamma \geq 0, \omega \geq 0, s^- \geq 0, s^+ \geq 0, s^+ \geq 0
\]

Where \( X^1 = (x^1_1, \cdots, x^1_1) \in R^{n_1 \times m} \), \( X^2 = (x^2_1, \cdots, x^2_n) \in R^{n_2 \times m} \), \( Y = (y_1, \cdots, y_n) \in R^{n \times m} \), and \( Z(s_1, s_2) = (z^1(s_1, s_2), \cdots, z^n(s_1, s_2)) \). \( s^- \), \( s^+ \), and \( s^+ \) are input slack vectors, intermediate input slack vectors, and final output slack vectors, respectively. \( \gamma \) and \( \omega \) is the intensity vector corresponding to environmental efficiency stage and economic efficiency stage, respectively. \( \theta_0^* \) is the energy efficiency score of \( DMU_0 \). If the \( \theta_0^* = 1 \), the \( DMU_0 \) is called energy-efficient. If the \( \theta_0^* < 1 \), the \( DMU_0 \) is called energy-inefficient. \( \theta_0^1 = (1 - \sum_{i=1}^{n_1} s^-_i / x^i_1) \) is the environmental efficiency score of \( DMU_0 \).
\( \theta_0^2 = (1 - \sum_{i}^{n_2} s_i^2 / x_{i0}^2) \) is the economic efficiency score of \( DMU_0 \).

3. Variables and data
This paper concentrates on evaluating both economic and environmental efficiency in different China’s provinces in 2017. The dataset only covers 30 provinces without Tibet’s data, because it was not available.

Based on the framework as shown in Figure 1, We use the approach in [9] and [10] to deal with the capital stock and CO₂ emissions, respectively. And the method in [11] is used to transform the CO₂ emissions, because it is appropriate to assess undesirable values for the energy and emission performance evaluation of provinces in China. The data of GDP, energy consumption and labor force are found in the National Bureau of Statistics. The variable data are described in Table 1.

| Variable | Unit | Count | Mean   | Std    | Min   | Max    |
|----------|------|-------|--------|--------|-------|--------|
| Capital  | ¥    | 30    | 55415.46 | 34698.78 | 9523.81 | 138711.82 |
| Labor    | persons | 30 | 2731.51 | 1839.89 | 265.36 | 6767.00 |
| Energy   | mTCE | 30 | 154.75 | 90.11 | 21.03 | 386.84 |
| GDP      | ¥    | 30    | 28194.31 | 22025.35 | 2624.83 | 89705.23 |
| CO₂      | tons | 30 | 116.00 | 80.47 | 16.06 | 375.15 |

The correlation matrixes for the variables in Table 2, shows that the variable selection is reasonable because all the correlation coefficients are significantly positive.

| Variable | Capital | Labor | Energy | GDP | CO₂ |
|----------|---------|-------|--------|-----|-----|
| Capital  | 1.000   |       |        |     |     |
| Labor    | 0.835*  | 1.000 |        |     |     |
| Energy   | 0.886*  | 0.753* | 1.000 |     |     |
| GDP      | 0.947*  | 0.794* | 0.820* | 1.000 |     |
| CO₂      | 0.663*  | 0.474* | 0.870* | 0.553* | 1.000 |

Notes: * represents the significance at 1% level.

4. Results
The efficiency scores are estimate by the proposed model as shown in Table 3. We could find that, for both environmental efficiency and energy efficiency, Ningxia (NX) and Hainan (HI) get the highest score equal to 1 with performing efficiently, and Hebei (HB) got the worst score, respectively.

| Provinces | Energy efficiency | Environmental efficiency | Economic efficiency | Provinces | Energy efficiency | Environmental efficiency | Economic efficiency |
|-----------|-------------------|--------------------------|---------------------|-----------|-------------------|--------------------------|---------------------|
| HA        | 0.332             | 0.170                    | 0.494               | BJ        | 0.675             | 0.350                    | 1.000               |
| HB        | 0.423             | 0.198                    | 0.648               | TJ        | 0.586             | 0.341                    | 0.831               |
| HN        | 0.433             | 0.198                    | 0.668               | HE        | 0.312             | 0.106                    | 0.519               |
| GD  | 0.674 | 0.347 | 1.000 | SX  | 0.357 | 0.114 | 0.600 |
|-----|-------|-------|-------|-----|-------|-------|-------|
| GX  | 0.353 | 0.224 | 0.481 | IM  | 0.338 | 0.115 | 0.561 |
| HI  | 1.000 | 1.000 | 1.000 | LN  | 0.327 | 0.112 | 0.541 |
| CQ  | 0.535 | 0.325 | 0.746 | JL  | 0.420 | 0.284 | 0.555 |
| SC  | 0.413 | 0.171 | 0.655 | HL  | 0.368 | 0.183 | 0.553 |
| GZ  | 0.418 | 0.215 | 0.621 | SH  | 0.671 | 0.342 | 1.000 |
| YN  | 0.325 | 0.208 | 0.443 | JS  | 0.787 | 0.573 | 1.000 |
| SN  | 0.744 | 0.489 | 1.000 | ZJ  | 0.535 | 0.255 | 0.815 |
| GS  | 0.429 | 0.286 | 0.572 | AH  | 0.388 | 0.190 | 0.586 |
| QH  | 0.557 | 0.500 | 0.613 | FJ  | 0.444 | 0.239 | 0.650 |
| NX  | 1.000 | 1.000 | 1.000 | JX  | 0.467 | 0.263 | 0.672 |
| XJ  | 0.587 | 0.365 | 0.810 | SD  | 0.464 | 0.168 | 0.761 |

However, there are 7 provinces including Beijing (BJ), Shanghai (SH), Ningxia (NX), Guangdong (GD), Shaanxi (SN), Hainan (HN) and Jiangsu, which are evaluated as performing efficiently. Compared with economic and environmental efficiency as shown in Figure 2, it shows that most of China's provinces focus on economic development, but pay less attention to environmental protection.

5. Conclusions
This paper evaluates the energy efficiency of 30 provinces in China by using a proposed network DEA model, which divide the energy efficiency into economic and environmental efficiency. It is found that most provinces in China have low energy efficiency, which is mainly caused by environmental inefficiency. Therefore, the provinces of China should pay more attention to the green efficiency of GDP rather than its scale. China's provinces should strengthen the restriction on CO2 emissions, and reduce the dependence on fossil energy by using more green energy.

Reference
[1] Chang, Y.-T., et al. (2013) Environmental efficiency analysis of transportation system in China: A non-radial DEA approach. 58: 277-283.
[2] Zhang, N., F. Kong, and Y.J.E.i. Yu. (2015) Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. 51: 165-172.
[3] Honma, S., & Hu, J.-L. J. E. P. (2008). Total-factor energy efficiency of regions in Japan. 36(2), 821-833.
[4] Moon, H., & Min, D. J. E. (2017). Assessing energy efficiency and the related policy implications for energy-intensive firms in Korea; DEA approach. 133, 23-34.
[5] Meng, F., et al. (2016) Measuring China's regional energy and carbon emission efficiency with DEA models: A survey. 183: 1-21.
[6] Hu, J.-L., & Wang, S. (2006). Total-factor energy efficiency of regions in China. 34(17), 3206-3217.
[7] Huang, J., Du, D., & Hao, Y. J. E. M. (2017). The driving forces of the change in China's energy
intensity: an empirical research using DEA-Malmquist and spatial panel estimations. 65, 41-50.

[8] Tone, K. and M.J.E.j.o.o.r. Tsutsui. (2009) Network DEA: A slacks-based measure approach. 197(1): 243-252.

[9] Zhang, J., G.Y. Wu, and J.Z. Peng. (2004) The Estimation of China's provincial capital stock: 1952~2000. Economic Research Journal, 10(35): 4.

[10] Wang, Q., et al. (2016) Exploring the relationship between urbanization, energy consumption, and CO2 emissions in different provinces of China. 54: 1563-1579.

[11] Seiford, L.M. and J.J. Zhu. (2002) Modeling undesirable factors in efficiency evaluation. 142(1): 16-20.