



Environmental Efficiency Evaluation by Data Envelopment Analysis and its Applications

Beibei Xiong

► To cite this version:

Beibei Xiong. Environmental Efficiency Evaluation by Data Envelopment Analysis and its Applications. Economics and Finance. Université de Technologie de Troyes; University of science and technology of China, 2019. English. NNT : 2019TROY0020 . tel-03620181

HAL Id: tel-03620181

<https://theses.hal.science/tel-03620181>

Submitted on 25 Mar 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Beibei XIONG

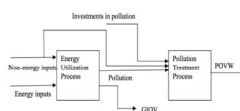
Environmental Efficiency Evaluation by Data Envelopment Analysis and its Applications



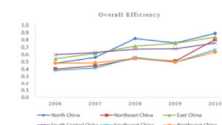
Pollution of thermal power firm



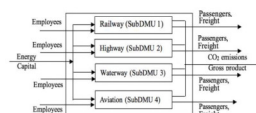
Map of Xiangjiang River basin



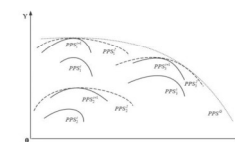
Two-stage structure of China's industry



Overall efficiency of industry



Structure of China's transportation sector



Productivity index for transportation

Champ disciplinaire :
Sciences pour l'Ingénieur

2019TROY0020

Année 2019

Thèse en cotutelle avec University of Science and Technology of China –
ANHUI – CHINE



THESE

pour l'obtention du grade de

DOCTEUR

de l'UNIVERSITE DE TECHNOLOGIE DE TROYES

EN SCIENCES POUR L'INGENIEUR

Spécialité : OPTIMISATION ET SURETE DES SYSTEMES

présentée et soutenue par

Beibei XIONG

le 12 juillet 2019

**Environmental Efficiency Evaluation by Data Envelopment Analysis
and its Applications**

JURY

M. J. SHU	PROFESSOR	Président
M. C. CHU	PROFESSEUR - HDR	Rapporteur
M. Y. WANG	PROFESSEUR DES UNIVERSITES - HDR	Rapporteur
Mme N. LABADIE	PROFESSEURE DES UNIVERSITES	Examinatrice
M. G. BI	PROFESSOR	Examineur
M. H. CHEN	PROFESSEUR DES UNIVERSITES	Directeur de thèse
M. J. WU	PROFESSOR	Directeur de thèse

Acknowledgements

I am very glad to have this chance to express my heartfelt gratitude to those who helped, supported, and accompanied me during my PhD study.

This work has been carried out between the Logistique et Optimisation des Systèmes Industriels (LOSI) at Université de technologie de Troyes (UTT) (France) and the School of Management at University of Science and Technology of China (USTC) (China). Thanks to UTT and USTC for having provided me with this excellent PhD program and wonderful working conditions. Besides, I would like to thank the China Scholarship Council for the financial support during my academic stay in France.

In both places of my doctoral studies, Troyes (France) and Hefei (China), I had valuable support without which this work would not have been possible. First of all, I would like to express my sincere gratitude to my supervisors, Prof. Haoxun Chen and Prof. Jie Wu, for their highly valuable guidance and constant encouragement. They have taught me a lot of professional knowledge, skills, and scientific research experiences which are very helpful to my research.

I thank Prof. Yingming Wang and Prof. Chengbin Chu for accepting to be my thesis reviewers. I really appreciate their constructive and insightful comments and suggestions which inspired me a lot and helped me to improve this thesis. Besides, I would like to thank Prof. Nacima Labadie, Prof. Jia Shu and Prof. Gongbing Bi for accepting to be my jury committee members. Their valuable remarks greatly helped me to improve the quality of this thesis.

I express my gratitude to Isabelle, Pascale, Thérèse, Veronique, Bernadette at the UTT, and Zhengsi Peng, Honglin Huang, Xiaowen Ye at the USTC. They have always been helpful and lovely. I appreciate my friends: Zhixiang, Dong, Junfei, Qingyuan, Yafei, Xiaohui, Yanli, Ke, Xue, Zhen, Zheng, Jinrui, Shijian, Feilipe, Junze, Yurui, and all others that ever helped me.

I am deeply indebted to my husband Dr. An for his love, his support, his patience, his company and for keeping me grounded whenever it was needed. Finally, I thank my parents Ximin, Yuping and my younger brother Guiyao for their support and love.

Abstract

With the development of economy, environmental pollution has become increasingly serious, especially in developing countries such as China and India. To realize the sustainable development of environment and economy, the scientific evaluation of environmental efficiency is very important.

This thesis investigates the environmental efficiency evaluation based on data envelopment analysis (DEA). Four environmental efficiency evaluation problems are studied. Firstly, an integrated Enhanced Russell measure model is proposed for evaluating the environmental efficiency with the presence of undesirable outputs in fuzzy circumstance. It is then applied to thermal power firms in China. Then, by considering undesirable outputs, a new closest target DEA model based on Range Adjusted Measure is established to measure the water environmental efficiency of Xiangjiang River Basin in China. In addition, a new two-stage DEA model with shared inputs is built to evaluate the total-factor energy efficiency and the overall environmental efficiency of China's industrial sector. Finally, the dynamic environmental efficiency evaluation of a parallel transportation network considering regional heterogeneity is considered. The Metafrontier Malmquist-Luenberger productivity index based on a network DEA model is built and then applied to analyze China's transportation sector.

All these DEA models are applied to real-life examples and used to measure their environmental efficiency and set the benchmark for their performance improvement.

Key words: Data envelopment analysis, Human beings--Effect of environment on, Linear programming, Industrial efficiency, Benchmarking

Résumé

Avec le développement de l'économie, la pollution de l'environnement est devenue de plus en plus grave, en particulier dans les pays en voie de développement tels que la Chine et l'Inde. Pour réaliser le développement durable de l'environnement et de l'économie, l'évaluation scientifique de l'efficacité environnementale est très importante.

Cette thèse examine l'évaluation de l'efficacité environnementale basée sur l'analyse d'enveloppement de données (DEA). Quatre problèmes d'évaluation de l'efficacité environnementale sont étudiés. Tout d'abord, un modèle de mesure Russell renforcé est proposé pour évaluer l'efficacité environnementale des entreprises de production d'énergie thermique en Chine. Ensuite, compte tenu de la production indésirable, un nouveau modèle DEA plus proche d'une cible basé sur un intervalle de mesure ajusté est établi pour mesurer l'efficacité environnementale du bassin de la rivière Xiangjiang en Chine. De plus, un nouveau modèle DEA en deux étapes avec entrées partagées est construit pour évaluer l'efficacité énergétique du facteur total et l'efficacité environnementale globale du secteur industriel de la Chine. Enfin, le modèle d'évaluation de l'efficacité environnementale d'un réseau parallèle de transport prenant en compte l'hétérogénéité régionale est proposé pour analyser le secteur de transport en Chine.

Tous ces DEA modèles sont appliqués à des exemples réels et utilisés pour mesurer leur efficacité environnementale et donner une référence pour l'amélioration de leur performance.

Mots clés: DEA, Méthode, Homme -- Effets de l'environnement, Programmation linéaire, Efficience (gestion), Référenciation

General introduction

Nowadays, the continuous exposure of environmental pollution has seriously restricted the social development of many countries, especially developing countries. With the acceleration of urbanization process, environmental pollution has become more and more serious. In the past 40 years, China's economy has achieved rapid development, but the high-speed economic growth mainly depended on huge investment and high resource consumption at the cost of high pollution and low efficiency. However, this model of development leads to a contradiction between economic development and environmental protection. As a result, the deterioration of the environment is becoming more and more serious. After the long-term practice, people have realized the importance of environmental protection in the sustainable development of the economy of a country. Sustainable development cannot be realized without effective management of the environment. To achieve effective environmental management, we require scientific and objective environmental performance evaluation methods.

In view of the above-mentioned context, this thesis investigates several environmental performance evaluation problems based on data envelopment analysis and develops relevant evaluation methods that can be used in practice. The problems to be addressed in this thesis include: how to evaluate the environmental performance of systems with fuzzy numbers, how to measure the environmental performance in order to set the closest target for the environmental inefficient system using least effort to achieve environmental efficiency, how to measure the overall environmental efficiency and total factor energy efficiency of a complex two-stage system, and how to evaluate the dynamic change of environmental performance of a parallel transportation network with regional heterogeneity. Based on the theoretical investigation of these problems, effective environmental performance evaluation methods are developed and applied to some practical problems in this thesis. This thesis is organized in seven chapters, and the main contents of the seven chapters are given as follows:

The first chapter is the introduction. We first present the background (context) of this thesis and provide a literature review on Data Envelopment Analysis (DEA), the basic method for our environmental performance evaluation. The problems studied in this thesis are then introduced. Finally, we present the structure and outline the main

contributions of this thesis.

The second chapter introduces the basic theory of DEA, including the basic concepts of data envelopment analysis (DEA), the basic DEA models and some basic concepts in environmental efficiency evaluation.

The third chapter is environmental efficiency evaluation for a single-stage system with fuzzy numbers and its application. In this chapter, an integrated Enhanced Russell measure model is proposed based on data envelopment analysis for evaluating the performance of decision making units in the presence of undesirable outputs in fuzzy circumstance. Then, the new model is applied to analyze the environmental efficiency and provide the benchmarks for the thermal power firms in China, which can guide the decision makers to make suitable future production plans for improving their performance.

The fourth chapter is environmental efficiency evaluation for a single-stage system considering the path for performance improvement and its application. By considering undesirable outputs, a new closest target DEA model based on Range Adjusted Measure (RAM) is established to measure the environmental performance of the system. The proposed model is used to measure the environmental efficiency of the regions in Xiangjiang River Basin in China, and the closest target is set for these inefficient regions so that they can make the least effort to achieve efficiency.

The fifth chapter is environmental efficiency evaluation of a two-stage system via total-factor energy efficiency and its application. With the rapid development of industry, the problems of growing energy consumption and environmental pollution in industry are drawing increasing attention of the government and scholars. In this chapter, we divide the industrial system into two stages, i.e., an energy utilization stage and a pollution treatment stage, for accurately evaluating the total-factor energy efficiency of the system as well as its overall environmental efficiency. We build a new two-stage data envelopment analysis model with shared inputs to analyze the China's industry that was commonly considered as a "black box" in traditional environmental efficiency methods. Based on the theoretical analysis of the model, some policy suggestions are given to this industry.

The sixth chapter is environmental efficiency evaluation of parallel transportation network considering regional heterogeneity and its application. In this chapter, we examine the China's transportation sector by dividing it into four main subsystems: railway, highway, waterway, and civil aviation, and further build a network data

envelopment analysis model for performance measurement of the sector with considering undesirable output-CO₂ emission. Moreover, considering the heterogeneity of transportation sectors in different areas of China, a new metafrontier Malmquist-Luenberger productivity index is proposed based on the network DEA model, which is used to investigate the productivity growth of 30 regions' transportation sectors during 2007-2013. Finally, some suggestions are given for guiding the development of China's transportation sector.

The seventh chapter concludes this thesis with prospective for future research. In this chapter, the main works of this thesis are first summarized, and the main contributions and possible improvements of this thesis are then outlined. Finally, some suggestions for future research directions are provided.

Contents

Acknowledgements	i
Abstract.....	iii
Résumé	v
General introduction	vii
Contents	xi
List of Figures.....	xv
List of Tables	xvii
CHAPTER 1	1
Introduction.....	1
1.1 Background for the evaluation of environmental efficiency.....	1
1.2 Literature review: DEA-based environmental efficiency evaluation.....	3
1.3 Research topics.....	7
1.4 Structure and Contributions of the thesis	8
1.4.1 Structure	8
1.4.2 Contributions.....	9
CHAPTER 2.....	11
Basic DEA theory	11
2.1 Data envelopment analysis.....	11
2.2 Basic concepts	12
2.3 Basic DEA models	15
2.4 Basic concepts of environmental efficiency evaluation	17
CHAPTER 3	21
Environmental efficiency evaluation of a single-stage system with fuzzy numbers	21
3.1 Introduction	22
3.2 Review of Russell Measure, Fuzzy DEA, and undesirable outputs.....	24
3.2.1 Russell measure.....	24
3.2.2 Fuzzy DEA models	25
3.2.3 Undesirable outputs and Environmental efficiency	25

3.3 Modelling of a single-stage system with undesirable outputs and fuzzy numbers	27
3.3.1 Russell DEA model and enhanced Russell DEA model.....	27
3.3.2 Fuzzy enhanced Russell DEA model considering undesirable outputs	29
3.4 Application to the environmental efficiency evaluation of thermal power firms in China	34
3.5 Conclusions	40
CHAPTER 4.....	43
Environmental efficiency evaluation of a single-stage system considering performance improvement path.....	43
4.1 Introduction	44
4.2 Traditional RAM model and the closest target	46
4.3 Closest target RAM model considering undesirable outputs	48
4.4 Application to the water environmental efficiency evaluation of Xiangjiang River Basin in China	52
4.4.1 Data and variables.....	53
4.4.2 Results analysis.....	55
4.5 Conclusions	60
CHAPTER 5.....	61
Environmental efficiency evaluation of a two-stage system via total-factor energy efficiency	61
5.1 Introduction	61
5.2 Modeling of environmental efficiency evaluation of the two-stage system of China's industry	66
5.3 Application to the environmental efficiency evaluation of China's industry	73
5.3.1 Data and variables.....	73
5.3.2 Results analysis.....	74
5.3.3 Benchmarking analysis.....	81
5.4 Conclusions	83
Chapter 6	85
Environmental efficiency evaluation of a parallel network system considering regional heterogeneity	85
6.1 Introduction	86
6.2 Environmental efficiency evaluation of a parallel transportation network system considering regional heterogeneity	90
6.2.1 Network DEA model	90
6.2.2 Metafrontier Malmquist-Luenberger productivity index	95

6.3 Application to the environmental efficiency evaluation of China's transportation sector considering regional heterogeneity	99
6.3.1 Data and variables	99
6.3.2 Results Analysis	101
6.4 Conclusions	108
CHAPTER 7	111
Conclusions and perspectives	111
7.1 Conclusions	111
7.2 Perspectives	113
ANNEXE A	115
Appendix of French Abstract	115
A.1 Introduction	115
A.2 Théorie DEA de base	118
A.3 Evaluation de l'efficacité environnementale d'un système à une seule étape avec paramètres flous	122
A.4 Évaluation de l'efficacité environnementale d'un système à une seule étape tenant compte de l'amélioration de performances	127
A.5 Evaluation de l'efficacité environnementale d'un système à deux étapes via l'efficacité énergétique de facteur total	131
A.6 Evaluation de l'efficacité environnementale d'un système de réseau parallèle prenant en compte l'hétérogénéité régionale	136
A.7 Conclusions et perspectives	140
References	143

List of Figures

Figure 1.1 The organization of this thesis.....	8
Figure 5.1 Two-stage structure system of China's industry.....	67
Figure 5.2 The industrial efficiencies of different areas in China.....	79
Figure 6.1 The network structure of China's transportation sector.....	92
Figure 6.2 Metafrontier in a Malmquist-Luenberger productivity index framework for Transportation sector.....	97
Figure 6.3 Metafrontier Malmquist-Luenberger index change of China and its three areas.....	104
Figure 6.4 Efficiency change of China and its three areas.....	106
Figure 6.5 Best-practice gap change of China and its three areas.....	107
Figure 6.6 Technology gap change of China and its three areas.....	107

List of Tables

Table 3.1 Statistical description.....	34
Table 3.2 The lower and upper bounds of the environmental efficiency.....	35
Table 3.3 Ranking of the firms.....	38
Table 3.4 Proportion for firms to be efficient in the fuzzy circumstance when $\alpha = 0.5$	39
Table 4.1 Descriptive statistics of inputs and outputs during 2008-2014.....	54
Table 4.2 Classical water environmental efficiencies of 15 monitoring areas in Hunan, China.....	55
Table 4.3 Average classical water environmental efficiencies of seven cities in Xiangjiang River Basin.....	56
Table 4.4 Water environmental efficiencies of the 15 monitoring areas from 2008 to 2014.....	57
Table 4.5 Water environmental efficiencies of seven cities in Xiangjiang River Basin.....	58
Table 4.6 Benchmarking analysis of the 15 monitoring areas in 2014.....	59
Table 5.1 Descriptive statistical analysis of inputs and outputs.....	74
Table 5.2 Four kinds of efficiencies of industry in 30 regions of China from 2006-2010.....	75
Table 5.3 Six administrative areas.....	78
Table 5.4 Average efficiency of six administrative areas during 2006-2010.....	79
Table 5.5 Benchmarks for China's industry.....	82
Table 6.1 Variables and descriptions.....	93
Table 6.2 CO ₂ emission factors by major carbonaceous fuel types in China.....	100
Table 6.3 Transformation coefficient to standard coal.....	101
Table 6.4 Distribution of 30 administrative regions in three areas of China.....	101
Table 6.5 The average metafrontier Malmquist-Luenberger index and its decompositions for each region 2007-2013.....	102
Table 6.6 Changes in MMPI and its decompositions of China's transportation sector 2007-2013.....	104

CHAPTER 1

Introduction

Contents

1.1 Background for the evaluation of environmental efficiency.....	1
1.2 Literature review: DEA-based environmental efficiency evaluation.....	3
1.3 Research topics.....	7
1.4 Structure and Contributions of the thesis	8
1.4.1 Structure	8
1.4.2 Contributions.....	9

1.1 Background for the evaluation of environmental efficiency

In recent years, the environmental problems, such as water pollution and air pollution, have seriously affected the sustainable development of economies of most countries, especially some developing countries, such as India and China. With the rapid industrialization, the environmental pollution is becoming more and more serious, causing direct damage to the ecosystems of these countries. Therefore, the dynamic balance between environment and economy has become an important social problem (Wu et al., 2014). Through the analysis of long-term practices, people have recognized that sustainable development of the economic and environment is the main way to solve this problem, which indicates the development should meet the needs of the present generation without compromising the ability of future generations. In order to achieve sustainable economic development, environmental protection has become a global consensus. In the year of 2015, 196 countries met in Paris for the United Nations Climate Change Conference and finally signed the “Paris Agreement” with the objective to alleviate environmental and climate change. The Paris Agreement aims at governing emission reductions from 2020 through commitments of countries to their nationally determined contributions. As an important member, China plays the critical

role in the global environmental improvement. Therefore, this thesis is mainly focused on the environmental issues in China.

Recently, China's economy has achieved rapid development. The GDP grows from 367.9 billion RMB in 1978 to 90.03 trillion RMB 2018. But the rapid economic growth mainly depends on high consumption of energy and resources at the cost of high pollution and low efficiency. In recent years, the contradiction between economic development and environmental protection has become increasingly prominent. Meanwhile people are facing increasingly serious environmental deterioration problems (Wu et al., 2014; An et al., 2017; Song et al., 2012). For example, heavy metal pollution in Xiangjiang River Basin of Hunan province, eutrophication pollution in Taihu Lake of Jiangsu province, and heavy winter haze of North China. With the increasing awareness of environmental protection, more attentions are paid to environmental protection (Glucker et al., 2013). The 13th Five-Year Plan clearly pointed out that China will increase the environmental supervision and protection to realize an overall improvement of the ecological environment (Xinhua News Agency, 2015). The report of the 19th National Congress of the Communist Party of China further clarified the basic strategy of "adhering to the harmonious coexistence of man and nature", and proposed to promote green development by focusing on solving environmental problems. Besides, this report proposed to strength and reform the ecological environment supervision system (Xi, 2017). With the extensive research on environmental problems, people have realized the importance of environmental protection in the sustainable development of the economy of a country. The sustainable development cannot be realized without effective management of the environment. To achieve effective environmental management, we require scientific and objective environmental performance evaluation methods. (Wu et al., 2014; Song et al., 2012). Environmental efficiency evaluation should provide a comprehensive evaluation of the performance of an organization in all aspects of resources consumption, economic output and environmental output. It should not only show tell us the environmental efficiency of the evaluated system on the macroscopic level, but also provides us with detailed benchmarking information for the design and implementation of environmental management policies (Song et al., 2012). Therefore, environmental efficiency evaluation is a key factor in solving environmental problems (Halkos and Tzeremes, 2013).

The environmental efficiency evaluation has attracted much attention of scholars and has been deeply investigated and applied in real life (Sueyoshi et al., 2017). Among various environmental efficiency evaluation methods, data envelopment analysis (DEA) is one of the most popular methods. The book of “2016 Research Fronts” jointly published by the Science and Technology Strategy Consulting Institute of the Chinese Academy of Sciences, the Literature Information Center of the Chinese Academy of Sciences, and Clarivate Analytics (formerly the Intellectual Property and Technology Division of Thomson Reuters) stated that environmental and energy efficiency evaluation based on data envelopment analysis is one of the two key hotspots in the fields of economics, psychology and other social sciences. The book especially emphasized that the 35 core papers in the field of environmental and energy efficiency evaluation all adopt the data envelopment analysis method*. Data envelopment analysis was proposed in 1978 by Charnes et al. (1978). It is a nonparametric method for evaluating the performance of a set of homogeneous decision making units (DMUs) based on linear programming models. Besides, it can deal with the performance evaluation of multi-input and multi-output systems, and the obtained results can provide benchmarking information for performance improvement (Boudreau, 2004). Recently, DEA has become one of the important research topics in management science. A large number of studies on the DEA methodological developments and applications have been conducted, such as Banker et al. (1984), Andersen and Petersen (1993) and Chen and Zhu (2019). DEA has been extended and applied to the evaluation of environmental efficiency considering environmental factors (undesirable outputs), and has gradually become one of the best and most popular environmental efficiency evaluation methods (Wang et al., 2013; Wang et al., 2016; Song and Guan, 2014). Thus, DEA is chosen as the basic methodology for the evaluation of environmental efficiency and further apply it to analyze the real environmental problems.

1.2 Literature review: DEA-based environmental efficiency evaluation

According to the theory of joint production, desirable outputs are always accompanied by undesirable outputs (Färe et al., 1989; Chen et al., 2016). Usually, the performance evaluation considering both economic factors (desirable outputs) and

* “2016 Research Fronts”. https://clarivate.com.cn/research_fronts_2017/2016research.pdf

environmental factors (undesirable outputs) is defined as environmental efficiency evaluation (see Song et al., 2013; Wu et al., 2014). Environmental factors, such as wastewater, carbon dioxide, sulfur dioxide, solid waste, etc. are usually undesirable outputs, so one key issue of environmental efficiency evaluation is how to deal with undesirable outputs. Due to the increased environmental concerns and government environmental policies, more and more attention has been paid to these undesirable outputs. Currently, there are two main methods for assessing environmental efficiency: stochastic frontier analysis (SFA) and data envelopment analysis (DEA) (Coelli et al., 2005). SFA is a parametric estimation method which uses the maximum likelihood estimation (MLE) to estimate the production function. This method uses a parametric modelling approach to measure a “frontier” value and thereby provides a measure to evaluate environmental efficiency through the frontier value. However, pre-determined production function form may not match the reality. Moreover, SFA will become much difficult when dealing with a multi-input and multi-output system. In contrast to SFA, DEA is a non-parametric programming technique for measuring the relative efficiency of a set of homogenous decision making units. It not only can deal with multiple-output multiple-input systems but also has the advantage of having no need to assume any particular functional forms relating to the inputs and outputs. Moreover, it has become one of the most popular methods for environmental efficiency evaluation. Usually, the real-life environmental systems are multi-input and multi-output systems that consider both desirable outputs and undesirable outputs, therefore, DEA is chosen as the basic method for measuring environmental efficiency in this thesis.

The research of environmental efficiency evaluation based on DEA has received much attention from researchers. Färe et al. (1989) is one of the important theoretical foundations of environmental efficiency evaluation. After that, the related theoretical methods have been largely developed. According to the addressing ways of undesirable outputs, the environmental efficiency evaluation studies can be classified into two categories: direct approaches and indirect approaches. Direct approaches can be further divided into three categories. The first one is based on Färe et al. (1989), which replaced strong disposability assumption of outputs by weakly disposable assumption. This work has been extensively developed (Seiford and Zhu, 2005; Zhou et al., 2013; Wang et al., 2016). The second one is based on slacks-based measure or Russell measure (Zhou et al., 2006; Bi et al., 2014; Chen and Jia, 2017; Liu and Wu, 2017). The third one is based

on the direction distance function (DDF) (Chung et al., 1997; Boyd et al., 2002; Picazo-Tadeo et al., 2012; Halkos and Tzeremes, 2013; Sueyoshi and Goto, 2017). Indirect approaches can be further divided into two categories. The first one treats undesirable outputs as inputs in performance evaluation (Liu and Sharp, 1999; Dyckhoff and Allen, 2001; Yang et al., 2015). This approach only needs the information on whether the data should be minimized or maximized, but it cannot reflect a real production process (Seiford and Zhu, 2002). The second one includes a non-linear monotonic decreasing transformation approach (Scheel, 2001) and a linear monotonic decreasing transformation approach (Seiford and Zhu, 2002; Wu et al., 2013).

Most of the above environmental efficiency works by DEA focused on single-stage system or considered the evaluated system as a “black box” without considering its internal structure. However, we cannot find the inefficiency in the internal production process of a system through this way, and thus it is hard to improve the system’s performance. With the increasing competition and relation among economic entities, the systems become more and more complex, it is urgent to propose the environmental efficiency evaluation for a network system. In recent years, the network DEA method becomes an effective method to measure the performance of multi-stage systems, which provides new ideas and breakthroughs for the study of complex environmental efficiency evaluation problems.

As mentioned above, the previous studies about environmental efficiency did not consider the internal structure of the system, and treated the system as a “black box” which overlooked the transformations to which the inputs are subject within the considered system (Ma, 2010; Yang et al., 2013). This simple way has been widely applied to environmental management (Song and Wang, 2013; Lin and Liu, 2015; Zhou et al., 2006; Halkos and Tzeremes, 2013; Liu and Wu, 2017). However, many evaluated systems cannot simply be considered as “black boxes”, otherwise, it may lead to biased results on the evaluation (Du and Huo, 2014; An et al., 2017; Färe and Grosskopf, 2000; Kao and Hwang, 2008). Kao and Hwang (2008) found that although the performance of each subsystem of a decision-making unit is worse than that of the corresponding subsystem of another decision-making unit, it is possible that the performance of the former is greater than that of the latter in the case of ignoring the internal structure of the systems. Wang et al. (1997) proposed that considering the intermediate production processes in the evaluation can identify all the sources that cause the inefficiency of the

whole system. In order to solve these problems, the network DEA method is proposed and widely used in environmental efficiency evaluation to consider the internal structure of the system. As the network DEA can measure the inefficiency of internal production process of the system, it has been widely concerned by scholars in recent years, and has become one of the research hotspots in environmental efficiency evaluation.

According to the types of network structure, the research on environmental efficiency evaluation based on network DEA can be classified into three categories. The first category is the series network DEA environmental efficiency evaluation which evaluates the DMUs with two or more internal subsystems in series which are linked with intermediate measures. Most of the existing studies on series network focus on two-stage network system. The two-stage network system specifically includes the traditional two-stage system and the extended general two-stage system. The former refers to the two-stage network system in which the intermediate measures are both the whole outputs of the first stage and the whole inputs of the second stage (Chen et al., 2012; Halkos et al., 2015), and the latter refers to a two-stage network system in which the intermediate measures are only partial or whole outputs of the first stage and partial or whole inputs of the second stage (Xie et al., 2012; Song et al., 2014; Bian et al., 2015; Song et al., 2015; Wu et al., 2015; Chen et al., 2016; Chu et al., 2016; Shi, 2016; Wu et al., 2016a; Lozano, 2017; Li et al., 2018; Zhou et al., 2018). The second category is the parallel network DEA environmental efficiency evaluation which evaluates the DMUs with two or more internal parallel subsystems. In the initial parallel network DEA environmental efficiency evaluation studies, each subsystem was operated independently. Färe et al. (1997) first studied the performance of such network structure systems. Later, this structure was further extended and applied to environmental efficiency evaluation (Bi et al., 2011; Gong et al., 2016). Now, the research on parallel network DEA environmental efficiency evaluation has been extended to non-independent parallel systems (Bian et al., 2014; Wu et al., 2016b; Liu et al., 2017; Li et al., 2018). The third category is the mixed network DEA environmental efficiency evaluation. The mixed network system which studies a kind of system with parallel and series sub-systems. Recently, the research on environmental efficiency evaluation based on mixed DEA is gradually increasing (Huang et al., 2014).

1.3 Research topics

The above literature review shows that environmental efficiency evaluation has been widely studied by scholars, but there are still some open problems. For example, how to evaluate the environmental efficiency of systems with fuzzy numbers? How to measure the environmental efficiency in order to set the closest target for an environmental inefficient system using least effort to achieve environmental efficient? How to measure the overall environmental efficiency and total factor energy efficiency of a complex two-stage system? and how to evaluate the dynamic change of environment efficiency of a parallel network system? Based on the theoretical investigation of these problems, effective environmental performance evaluation methods are developed and applied to some practical problems in this thesis. The main contents of this thesis are summarized as follows:

In chapter 3, an integrated Enhanced Russell measure model is proposed based on data envelopment analysis for evaluating the performance of decision making units in the presence of undesirable outputs under a fuzzy circumstance. In this chapter, a new model is applied to analyze the environmental efficiency and provide the benchmarks for thermal power firms in China, which can guide the decision makers of these firms to make suitable future production plans to improve their performance.

Considering the undesirable outputs, a new closest target DEA model based on Range Adjusted Measure (RAM) is established to measure the environmental efficiency of a single-stage system. The proposed model is used to measure the water environmental efficiency of the regions in Xiangjiang River Basin in China. Besides, the closest targets are set for these inefficient regions so that they can make the least effort to achieve efficient.

With the rapid development of industry, the problems of growing energy consumption and environmental pollution in industry attracted increasing attention of the government and scholars. In chapter 5, we divide an industrial system into two stages, i.e., an energy utilization stage and a pollution treatment stage, for accurately evaluating the total-factor energy efficiency of the system as well as its overall environmental efficiency. We build a new two-stage data envelopment analysis model with shared inputs to analyze the China's industry that was commonly considered as a

“black box” in traditional environmental efficiency methods. Based on the theoretical analysis of the model, some policy suggestions are given.

In chapter 6, we examine China’s transportation sector by dividing it into four main parallel subsystems: railway, highway, waterway, and civil aviation, and further build a network DEA model for performance measurement of China’s transportation sector with consideration of undesirable output- CO₂ emission. Moreover, considering regional heterogeneity of transportation sectors in different areas of China, a new metafrontier Malmquist-Luenberger productivity index is proposed based on the network DEA model, which is used to investigate the productivity growth of 30 regions’ transportation sectors during 2007-2013. Finally, some suggestions are given for guiding the development of China’s transportation sector.

1.4 Structure and Contributions of the thesis

1.4.1 Structure

This thesis is focused on environmental efficiency evaluation by data envelopment analysis and its applications. According to different systems studied, this thesis is organized as in figure 1.1.

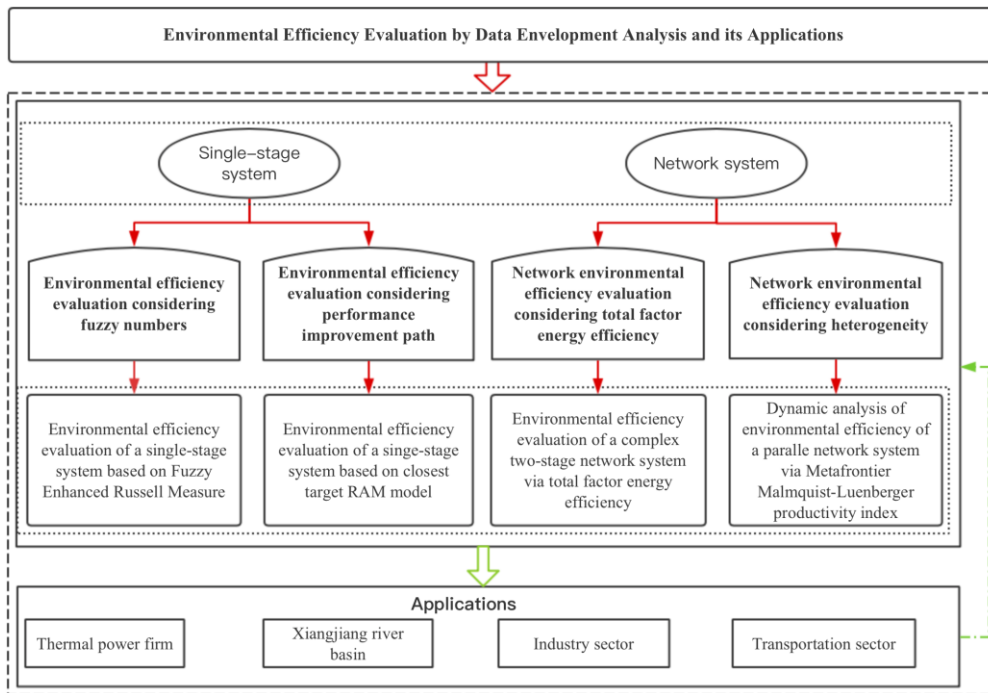


Figure 1.1 The organization of this thesis

This thesis will be divided into two parts according to the structure of the systems evaluated. The first part is dedicated to environmental efficiency evaluation methods and applications of single-stage systems, which contains two chapters. The second part is dedicated to environmental efficiency evaluation methods and applications of network systems, which also contains two chapters.

The environmental efficiency evaluation methods for single-stage systems and their applications are presented in Chapter 3 and Chapter 4. Chapter 3 studies the environmental efficiency evaluation of single-stage systems considering fuzzy numbers, and the proposed model is applied to China's thermal power firms. Chapter 4 presents an environmental efficiency evaluation method for a single-stage system considering performance improvement path, and the proposed method is applied to Xiangjiang River Basin in China.

Some environmental efficiency evaluation methods and their applications of network systems are described in Chapter 5 and Chapter 6. Chapter 5 investigates the environmental efficiency evaluation of a complex two-stage system in terms of total factor energy efficiency, and the proposed models are applied to China's industry sector. Chapter 6 studies the environmental efficiency evaluation of a parallel network system, and the proposed models are applied to China's transportation sector.

1.4.2 Contributions

(1) Considering environmental factors, a Fuzzy Enhanced Russell measure model is firstly built based on the Enhanced Russell measure and fuzzy theory. α -cut method is used to calculate the upper and lower bound values of environmental efficiencies. Finally, 30 thermal power firms in China are analyzed by the proposed method.

(2) Many previous works on the environmental efficiency evaluation provide methods for determining the benchmarks for the evaluated systems. However, the benchmarks determined by these methods are usually the furthest target for each inefficient system to achieve efficient. In order to make the evaluated system use the least effort to achieve environmental efficient, we proposed a closest target DEA model based on Range Adjusted Measure (RAM) to measure the water environmental efficiency and set the benchmarks for Xiangjiang River Basin in China.

(3) Most previous studies on environmental and energy efficiency consider an evaluated system as a "black box" without considering its internal structure, which

often leads to less reliable results. In order to overcome this problem, a two-stage DEA model is proposed to measure regional industrial overall environmental efficiency, energy utilization efficiency, pollution treatment efficiency, and the total-factor energy efficiency in chapter 5.

(4) Only few studies used a network DEA model to study the internal structure of China's transportation system previously. However, these studies lack a dynamic performance evaluation of the system. In chapter 6, China's transportation sector is divided into four parallel subsystems, and a new network DEA model is proposed to measure its environmental efficiency. Moreover, a metafrontier Malmquist-Luenberger productivity index is used to investigate the green productivity growth of provincial transportation sectors by considering the heterogeneity of transportation sectors in different regions of China.

CHAPTER 2

Basic DEA theory

Contents

2.1 Data envelopment analysis	11
2.2 Basic concepts	12
2.3 Basic DEA models	15
2.4 Basic concepts of environmental efficiency evaluation	17

This chapter mainly introduces the relevant preliminaries, including the basic concepts of data envelopment analysis (DEA), the basic DEA models and some basic concepts in environmental efficiency evaluation.

2.1 Data envelopment analysis

Data envelopment analysis (DEA) is a non-parametric programming method for efficiency evaluation of a set of entities called decision making units (DMUs) which convert multiple inputs to multiple outputs. It is a cross-research field of operational research, management science and mathematical economics. The seminal DEA model was proposed by Charnes, Cooper and Rhodes in 1978. So far, it has been widely developed and applied in many areas, such as business firms, hospitals, banks, thermal power firms, and others.

Through DEA method, the relative efficiency of the evaluated DMU can be obtained directly from the data without requiring a priori specification of weights and/or explicit delineation of assumed functional forms of relations between inputs and outputs. Compared with other methods, DEA has an evident advantage in dealing with the efficiency assessment of multi-input multi-output DMU. DEA can identify the best practice DMUs which form an efficient production frontier. Furthermore, it can provide some valuable management implications and useful information for decision makers to

improve the performance. For example, through horizontal comparison among DMUs, the efficiency performance of each decision-making unit can be measured, and the benchmarks can be found to guide the future development directions of the inefficient DMUs. The longitudinal comparison among DMUs can be used to derive the productivity level, the technological progress of each evaluated DMU. Besides, DEA can also be used for allocating resources or fixed-costs, measuring the returns to scale of DMU, and others.

More importantly, compared with another efficiency evaluation method, the Stochastic Frontier Analysis (SFA), DEA has evident advantages in dealing with multi-input and multi-output system while until recently SFA only allowed a single output, or multiple outputs with using a cost function if price data are available (Paradi et al., 2017).

2.2 Basic concepts

(1) Decision making unit

In real-life production and service activities, we often meet such management problem that we should evaluate the performance of some homogenous departments during a period, in which each department is called a decision making unit (DMU). It can be seen that DMU refers to any entity that converts inputs into outputs, such as universities, enterprises, hospitals, banks, etc. For these DMUs, the inputs can be labors, capital, fixed cost, the outputs show the effectiveness of the activity. For example, the evaluation of the operational efficiency of similar air-conditioning production enterprises in a certain area, each enterprise is a DMU, the employees of the enterprise, the investment in fixed assets, etc. are input indicators, and the number of air-conditioners and the quality of air-conditioning are output indicators.

When applying DEA for the efficiency evaluation of DMUs, we assume the DMUs are homogeneous, that is, all DMUs should have same external environment; all DMUs have the same input and output indicators; and all DMUs have the same production process. If the DMUs do not satisfy the homogeneity, it needs to be processed, please refer to related works such as Cook et al. (2013) and Imanirad et al. (2015).

(2) Performance evaluation

The performance evaluation of a DMU with single-input and single-output is generally based on the ratio of output to input. For the performance evaluation of multi-input and multi-output DMU, it is defined as the ratio of the weighted value of the outputs to the weighted value of the inputs. It should be noted that, without loss of generality, performance in this thesis refers to the relative efficiency of the DMU, that is, the relative efficiency of the evaluated DMU is obtained by comparing with the other DMUs' multiple inputs and multiple outputs.

(3) Production possibility set

Consider a set of n DMUs, with each, $DMU_j (j = 1, \dots, n)$, using m inputs $X_j = (x_{1j}, \dots, x_{mj})^T$ to produce s outputs $Y_j = (y_{1j}, \dots, y_{sj})^T$, where T in the superscript indicates transpose. Meanwhile, $X_j \geq 0$, $Y_j \geq 0$, $j = 1, \dots, n$, that is, the value of each input and output is greater than or equal to 0, and at least the value of one input indicator and one output indicator is positive. Besides, x_{ij} denotes the i th input of DMU_j , and y_{rj} denotes the r th output of DMU_j .

The production possibility set (PPS) is then defined as a set of all feasible production points, that is:

$$T = \{(X, Y) | X \text{ can produce } Y\} \quad (2.1)$$

Equivalently, technology T can be equivalently represented by its output sets $P(X) = \{Y | (X, Y) \in T\}$ or its input sets $P(Y) = \{X | (X, Y) \in T\}$.

For the PPS, based on Wei (2004), the axioms are given as follows.

Axiom 1. For an observed production activity $(X_j, Y_j) (j = 1, \dots, n)$, the input vector and output vector are $X_j = (x_{1j}, \dots, x_{mj})$ and $Y_j = (y_{1j}, \dots, y_{sj})$ respectively. Then, this production activity is feasible.

Axiom 2. For any two production activities in PPS, i.e., $(X, Y) \in T$, $(\hat{X}, \hat{Y}) \in T$, and any $\alpha \in [0, 1]$, then we have $\alpha(X, Y) + (1 - \alpha)(\hat{X}, \hat{Y}) = (\alpha X + (1 - \alpha)\hat{X}, \alpha Y + (1 - \alpha)\hat{Y}) \in T$.

Axiom 3. For any real production activity in PPS, i.e., $(X, Y) \in T$, if a production activity (\hat{X}, \hat{Y}) satisfies $\hat{X} \geq X$ and $\hat{Y} \leq Y$, then we have $(\hat{X}, \hat{Y}) \in T$.

Axiom 4a. For any real production activity in PPS, i.e., $(X, Y) \in T$, we have $\alpha(X, Y) = (\alpha X, \alpha Y) \in T$ for any $\alpha \in [0, +\infty)$.

Axiom 4b. For any real production activity in PPS, i.e., $(X, Y) \in T$, we have $\alpha(X, Y) = (\alpha X, \alpha Y) \in T$ any $\alpha \in [0, 1]$.

Axiom 4c. If any real production activity in PPS, i.e., $(X, Y) \in T$, we have $\alpha(X, Y) = (\alpha X, \alpha Y) \in T$ for any $\alpha \in [1, +\infty)$.

Based on the definition of Wei (2004), axiom 1 is called ordinary axiom, axiom 2 is called convex axiom, axiom 3 is called invalid axiom, axiom 4a is called cone axiom, and axiom 4b is called contraction axiom, axiom 4c is called expansion axiom. The axiom 3 means that using more input can always produce less output. The axiom 4a indicates that when the input increases (or decreases) by a multiple, the produced output can also increase (or decrease) by the same multiple. The axiom 4b shows that when the input is reduced by a certain ratio, the output reduced by the same proportion can be produced. The axiom 4c indicates that when the input is increased by a certain multiple, the output increased by the same multiple can be produced.

Based on the above axioms 1, 2, 3 and 4a, the production possibility set under constant returns to scale (CRS) can be formulated as follows.

$$T_{CRS} = \left\{ (X, Y): X_i \geq \sum_{j=1}^n \lambda_j x_{ij}, i = 1, \dots, m; Y_r \leq \sum_{j=1}^n \lambda_j y_{rj}, r = 1, \dots, s \right\} \quad (2.2)$$

Based on the axioms 1, 2 and 3, the production possibility set under variable returns to scale (VRS) can be expressed as

$$T_{VRS} = \left\{ (X, Y): X_i \geq \sum_{j=1}^n \lambda_j x_{ij}, i = 1, \dots, m; Y_r \leq \sum_{j=1}^n \lambda_j y_{rj}, r = 1, \dots, s; \sum_{j=1}^n \lambda_j = 1 \right\} \quad (2.3)$$

Based on the axioms 1, 2, 3, 4b, the production possibility set under non-increasing returns to scale (NIRS) can be formulated as follows.

$$T_{NIRS} = \left\{ (X, Y): X_i \geq \sum_{j=1}^n \lambda_j x_{ij}, i = 1, \dots, m; Y_r \leq \sum_{j=1}^n \lambda_j y_{rj}, r = 1, \dots, s; \sum_{j=1}^n \lambda_j \leq 1 \right\} \quad (2.4)$$

Based on axioms 1, 2, 3 and 4c, the production possibility set under non-decreasing returns to scale (NDRS) can be shown as follows.

$$T_{NDRS} = \left\{ (X, Y): X_i \geq \sum_{j=1}^n \lambda_j x_{ij}, i = 1, \dots, m; Y_r \leq \sum_{j=1}^n \lambda_j y_{rj}, r = 1, \dots, s; \sum_{j=1}^n \lambda_j \geq 1 \right\} \quad (2.5)$$

(4) Production frontier

The production frontier is a curved surface made of all efficient points in the PPS. It represents the boundary at which production may be set to obtain the maximum output of existing inputs or to obtain minimum inputs from existing outputs. Therefore, the combination of input and output of the decision making unit (DMU) on the production frontier is optimal. According to Wei (2004), the production frontier is defined as:

Definition 2.1. Assuming $\omega \geq 0$, $\mu \geq 0$, $L = \{(X, Y) | \omega^T X - \mu^T Y = 0\}$, $T \subset \{(X, Y) | \omega^T X - \mu^T Y \geq 0\}$ and $L \cap T \neq \emptyset$, then the weakly efficient surface of production possibility set T is L , and the corresponding weak production frontier is $L \cap T$. Especially, if $\omega \geq 0$, $\mu \geq 0$, then L is called the efficient surface of T , $L \cap T$ is the production frontier of production possibility set T .

2.3 Basic DEA models

In this section, two basic DEA models, i.e., CCR model and BCC model, are introduced. The former was proposed by Charnes, Cooper and Rhodes in 1978, is the earliest DEA model. According to the initials of the three authors, the model was named CCR model.

Assuming that there are n evaluated DMUs, each DMU uses the same inputs to produce the same outputs. $X_j = (x_{1j}, \dots, x_{mj})^T$ and $Y_j = (y_{1j}, \dots, y_{sj})^T$ are the input vector and output vector of DMU_j , respectively, where T in the superscript indicates transpose. The efficiency of each DMU is the ratio of the weighted outputs to the weighted inputs, the evaluated DMU is denoted as DMU_0 . The multiplier CCR model can be formulated as follows.

$$\begin{aligned}
 & \max \quad \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i=1}^m w_i x_{i0}} \\
 & s. t. \quad \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m w_i x_{ij}} \leq 1, \quad j = 1, \dots, n \\
 & \quad \quad u_r \geq 0, r = 1, \dots, s,
 \end{aligned} \tag{2.6}$$

$$w_i \geq 0, i = 1, \dots, m.$$

where u_r and w_i are the weights of the r th output and i th input, respectively. The first constraint means the ratio of weighted outputs to weighted inputs does not exceed 1 for each DMU. The objective is to seek a set of most favorable weights to maximize the ratio of DMU_0 . Model (2.6) is a fractional linear programming. By applying the Charnes-Cooper transformation, let $t = \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i=1}^m w_i x_{i0}}$, $\mu = tu$, $\omega = tw$, model (2.6) can be converted into model (2.7) as follows.

$$\begin{aligned}
 & \max \quad \sum_{r=1}^s \mu_r y_{r0} \\
 s. \ t. \quad & \sum_{r=1}^s \mu_r y_{rj} - \sum_{i=1}^m \omega_i x_{ij} \leq 0, \\
 & \sum_{i=1}^m \omega_i x_{i0} = 1, \\
 & \mu_r \geq 0, r = 1, \dots, s, \\
 & \omega_i \geq 0, i = 1, \dots, m.
 \end{aligned} \tag{2.7}$$

Definition 2.2. If the optimal value of model (2.7) is 1, the evaluated DMU_0 is efficient; if the optimal value of model (2.7) is less than 1, the evaluated DMU_0 is inefficient.

By duality, model (2.7) is equivalent to model (2.8), which is the envelopment form of CCR model.

$$\begin{aligned}
 & \min \quad \theta \\
 s. \ t. \quad & \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{i0}, i = 1, \dots, m, \\
 & \sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, \dots, s, \\
 & \lambda_j \geq 0, j = 1, \dots, n.
 \end{aligned} \tag{2.8}$$

Definition 2.3. If the optimal value of model (2.8) is 1, the evaluated DMU_0 is efficient; if the optimal value of model (2.8) is less than 1, the evaluated DMU_0 is inefficient.

According to the basic concepts in section 2.2, we know that CCR model is under the assumption of constant returns to scale. Banker, Charnes and Cooper (1984) extended the DEA model under the assumption of variable returns to scale, which is abbreviated as BCC model. The multiplier BCC model can be formulated as follows.

$$\begin{aligned}
 & \min \quad \theta \\
 & s. t. \quad \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{i0}, i = 1, \dots, m, \\
 & \quad \sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, \dots, s, \\
 & \quad \sum_{j=1}^n \lambda_j = 1, \\
 & \quad \lambda_j \geq 0, j = 1, \dots, n.
 \end{aligned} \tag{2.9}$$

Similarly, by duality, the envelopment form of BCC model is as follows.

$$\begin{aligned}
 & \max \quad \sum_{r=1}^s \mu_r y_{r0} - \mu_0 \\
 & s. t. \quad \sum_{r=1}^s \mu_r y_{rj} - \sum_{i=1}^m \omega_i x_{ij} - \mu_0 \leq 0, \\
 & \quad \sum_{i=1}^m \omega_i x_{i0} = 1, \\
 & \quad \mu_r \geq 0, r = 1, \dots, s, \\
 & \quad \omega_i \geq 0, i = 1, \dots, m
 \end{aligned} \tag{2.10}$$

2.4 Basic concepts of environmental efficiency evaluation

(1) Environmental efficiency

The traditional DEA model usually considers labor, capital as inputs and production yield, profit as outputs. These outputs that the DMU prefers to produce as much as possible in the production process are known as desirable outputs. However, according to the theory of joint production, desirable outputs are always accompanied by some outputs which are expected to be less in the process of production, such as carbon dioxide, sulfur dioxide, waste water, and solid waste. These outputs are defined as undesirable outputs. For example, when assessing the efficiency of paper mills, it is imperative to consider the paper products, as well as undesirable outputs such as wastewater discharge. Such comprehensive efficiency evaluation which consider both desirable outputs and undesirable outputs is called environmental efficiency evaluation.

Due to the existence of undesirable outputs in environmental efficiency evaluation, we cannot directly use the traditional DEA model to evaluate the environmental efficiency, so new processing method should be proposed. If undesirable outputs are considered in the DEA technology framework, the corresponding technology can be called the environmental DEA technology. Then, the efficiency obtained from the environmental DEA technology is defined by environmental efficiency (Zhou et al., 2008; Sueyoshi et al., 2017).

(2) Strong and weak disposability

Strong disposability includes strong disposability of inputs and strong disposability of outputs.

Strong disposability of inputs: If $(X, Y) \in T$ and $X' \geq X$, then $(X', Y) \in T$. This means if the inputs are not reduced, the original output can be produced.

Strong disposability of outputs: If $(X, Y) \in T$ and $Y' \leq Y$, then $(X, Y') \in T$. This means if the inputs do not change, it is feasible to produce all the reduced existing outputs in any directions (that is, some or all of the outputs are reduced).

Weak disposability includes weak disposability of inputs and weak disposability of outputs.

Weak disposability of inputs: if $(X, Y) \in T$ and $\beta \geq 1$, then $(\beta X, Y) \in T$. This states if inputs X can produce outputs, then it is possible to produce the outputs Y by increasing the inputs by a factor β .

Weak disposability of outputs: If $(X, Y) \in T$ and $0 \leq \theta \leq 1$, then $(X, \theta Y) \in T$. This represents that if inputs X can produce outputs Y , then it is possible to produce the reduced outputs θY using the original input.

According to the above definitions, under the assumption strong disposability of inputs, the increase of inputs will not cause the decrease of outputs. While under the assumption of weak disposability of inputs, the increase of inputs may lead to the decrease of outputs.

(3) Environmental production possibility set

Assume that both desirable and undesirable outputs are produced in the production process, denote $X_j = (x_{1j}, \dots, x_{mj})$, $U_j = (u_{1j}, \dots, u_{bj})$, $Y_j = (y_{1j}, \dots, y_{sj})$ as inputs, undesirable outputs and desirable outputs of $DMU_j (j = 1, \dots, n)$, respectively. The related production possibility set are expressed as follows.

$$T = \{(X, Y, U): X \text{ can produce } (Y, U)\} \quad (2.11)$$

Based on the definitions of weak disposability and strong disposability, for systems that considering environmental factors, if $(X, Y, U) \in T$, $Y' \leq Y$, $U' \geq U$ and $(X, Y', U') \in T$, then the outputs are strongly disposable. If $(X, Y, U) \in T$, $\mu \in [0, 1]$ and $(X, \mu Y, \mu U) \in T$, then the outputs are weakly disposable.

(4) DEA based methods for dealing with undesirable outputs

How to deal with undesirable outputs in the DEA model is crucial to assess the environmental efficiency of DMUs. After that, the model can take into account both desirable outputs (such as economic indicators) and undesirable outputs (such as pollution indicators). Since Färe et al. (1989) proposed the first DEA model to deal with undesirable outputs with the weak disposability, the environmental efficiency evaluation considering the undesirable outputs were largely extended. According to the existing DEA-related literature, the methods for dealing with undesirable outputs can be classified into two categories: direct method and indirect method.

a. Direct method

The first one is to treat the undesirable outputs under the weak disposability assumption and the desirable outputs under the strong disposability assumption. In this method, the PPS is usually assumed to satisfy the following two conditions:

If the production activity $(X, Y, U) \in T$ and $0 \leq \theta \leq 1$, then production activity $(X, \theta Y, \theta U) \in T$,

If the production activity $(X, Y, U) \in T$ and $U = 0$, then $\theta = 0$; (2.12)

The second direct method is to deal with undesirable outputs based on Russell measure which is shown as follows.

$$D_T(X, Y, U) = \inf\{f(\theta_i, \phi_r, \phi_k): (\theta_i x_i, \phi_r y_r, \phi_k u_k) \in T\} \quad (2.13)$$

The third direct method is to treat undesirable outputs based on the slack variables:

$$D_T(X, Y, U) = \inf\{f(s^-, s^+, s^{--}): (X - s^-, Y + s^+, U - s^{--}) \in T\} \quad (2.14)$$

The fourth direct method is to treat undesirable outputs based on the directional distance function (DDF) which measures the environment efficiency by simultaneously increasing desirable outputs and reducing undesirable outputs. The general form of DDF with undesirable outputs is defined as follows.

$$D_T(X, Y, U, g) = \sup\{\beta: (X - \beta g_X, Y + \beta g_Y, U - \beta g_U) \in T\} \quad (2.15)$$

b. Indirect method

The first indirect method is to treat the undesirable outputs as inputs (Liu and Sharp, 1999). The main idea behind this method is that the efficient DMU always prefers more desirable outputs and less inputs. Because of its simplicity and clarity, this method is widely used in the environment efficiency evaluation (Bian and Yang, 2010; Shi et al., 2010). However, treating undesirable outputs as inputs fails to reflect the true production process.

The second indirect method is conducting data transformation to undesirable outputs first, and then evaluating the environmental efficiency by using the traditional DEA model based on the transformed data. For example, Scheel (2001) and Seiford and Zhu (2002) suggested the linear monotonic decreasing transformation approach to transform undesirable output into a new variable like desirable output variable, that is, $f(U) = -U + \beta$. Golany and Roll (1989) and Lovell et al. (1995) used the reciprocals of the undesirable output as new output, the new output is modelled as $f(U) = 1/U$.

Each of the above methods has its own pros and cons. Therefore, which method is chosen for dealing with undesirable outputs depends on the specific research problem and research background.

CHAPTER 3

Environmental efficiency evaluation of a single-stage system with fuzzy numbers

Contents

3.1 Introduction	22
3.2 Review of Russell Measure, Fuzzy DEA, and undesirable outputs	24
3.2.1 Russell measure	24
3.2.2 Fuzzy DEA models	25
3.2.3 Undesirable outputs and Environmental efficiency	25
3.3 Modelling of a single-stage system with undesirable outputs and fuzzy numbers	27
3.3.1 Russell DEA model and enhanced Russell DEA model.....	27
3.3.2 Fuzzy enhanced Russell DEA model considering undesirable outputs	29
3.4 Application to the environmental efficiency evaluation of thermal power firms in China	34
3.5 Conclusions	40

Thermal power has accounted for the major part of the electricity generation over recent several decades in China. It plays an important role in supporting China's economic development while it also brings great pressure to the environment protection because of a large amount of pollution generated during its production. In order to solve or alleviate the environmental problem caused by thermal power firms, efficiency evaluation is the first important step. Since thermal power firm is a complex system with multiple inputs and multiple outputs, usually including fuzzy numbers and undesirable outputs in the production, in this chapter, we build an integrated Enhanced Russell measure model based on data envelopment analysis for evaluating the performance of decision making units in the presence of the undesirable outputs in fuzzy circumstance. Then, this new model is applied to analyze the environmental efficiency and provide the benchmarks for the thermal power firms in China which can

guide the decision makers to make suitable future production plans for improving their performance.

3.1 Introduction

In recent years, with the rapid development of China's economy, China is facing huge energy consumption and serious environmental pollution problems. In order to reduce environmental pollution, the Chinese government has put forward the strategic goal of building a resource-conserving and environment-friendly society to achieve sustainable economic, energy and environmental development. For example, in 2014, China promulgated a new important environmental law, “Environmental Protection Law of People's Republic of China”, which gives more punitive powers to environmental authorities and also defines geographical “red lines” where the area's ecology must require special protection (the NPC Standing Committee, 2014). Besides, the Chinese government has recognized the importance of environmental efficiency measurement and improvement and has taken a series of measures to deal with this issue, such as energy conservation assessment (ECA) and environmental impact assessment (EIA) (Hu, 2012). Among all kinds of energy types, electricity is the major resource of energy in China for many years. Furthermore, among various ways of electricity generation, China relies heavily on thermal power, hydropower and thermoelectricity. In particular, thermal power accounted for about 74.4% of all the electricity in 2016. Such a situation will be kept for a long time. As thermal power production usually produces a large amount of pollutions but with less treatment, it has become the major source resulting in the environmental problems of China. Thus, it is essential for us to measure the efficiency of thermal power firms so as to increase their productivity and reduce emissions.

Data envelopment analysis (DEA) is a non-parametric programming technique for evaluating the relative efficiency of a set of homogenous decision making units (DMUs) with multiple inputs and multiple outputs. It has been popularly applied in schools, hospitals, farms, banks and many other areas (Cook and Seiford, 2009; Cooper et al., 2004). Traditional DEA models aim at producing the maximum quantity of outputs for the given amount of inputs or consuming the minimum quantity of inputs for producing the given amount of outputs. Besides, all traditional DEA models are radial models,

such as CCR, BCC and their extensions, which are either input-oriented or output-oriented (Charnes et al., 1978; Banker et al., 1984). Comparing with these traditional DEA models, non-orientation modelling makes frontier efficiency studies more relevant to the production of thermal power firms because non-orientation ensures the analysis captures slacks on both input side and output side. Several non-orientation approaches have been built, such as the additive model, Russell measure (RM) model, slacks-based measure and so on. It should be noted that among these approaches, Russell measure (RM) model is a well-known non-orientation measure for evaluating DMUs' performance and has been applied to many areas, such as baseball batting performance, Taiwan's commercial banks (Lozano et al., 2011; Levkoff et al., 2012; Hsiao et al., 2011). Thus, in this chapter, we choose Russell measure as a basis for performance evaluation.

As we know, undesirable outputs, such as smoke pollution and waste, are usually produced with desirable outputs in the production processes of thermal power firms (Rivas and Magadan, 2010). These factors are expected to be as few as possible. Thus, the traditional DEA models are not applicable to measure the performance of the DMUs with undesirable outputs. Usually, the performance of DMUs with both desirable outputs and undesirable outputs is usually defined as environmental efficiency (Song et al., 2013; Wu et al., 2014). So far, many DEA models have been proposed to deal with undesirable outputs and finally obtain the environmental efficiency (Färe et al., 1989; Seiford and Zhu, 2002; Zhou et al., 2008).

Based on the above analysis, an approach by using the Russell measure considering the undesirable outputs is needed to measure the environmental efficiency of thermal power firm. However, according to our best knowledge, there are many theoretical works in Russell measure and undesirable outputs areas respectively but few works integrated them. Moreover, during our investigation on the thermal power firms, we found the undesirable output "solid waste" of the thermal power firm is so complex as it contains the garbage, refuse, sludge and other discarded materials including solid, liquid, semi-solid, or contained gaseous material that the data of undesirable output is difficult to be measured precisely. We can obtain a fuzzy description of the "solid waste". This requires us to further extend the above approach to be applicable to the fuzzy circumstance. But such kind of DEA work is not available in the previous works. In this chapter, we will propose a new enhanced Russell measure model which can well

address the fuzzy numbers and undesirable outputs problems simultaneously, and apply the new approach to analyze the thermal power firms in Anhui province of China. Our model can provide improvements for DMUs in more directions and in more realistic situation, and thus it can be flexibly applicable to other similar cases.

3.2 Review of Russell Measure, Fuzzy DEA, and undesirable outputs

In the following subsections, four streams of literature relevant to this research are briefly summarized. They include Russell measure, Fuzzy DEA methods, undesirable outputs and environmental efficiency. Based on the literature review, the research gap is pointed out.

3.2.1 Russell measure

Russell measure was first introduced by Färe and Lovell (1978). It was named as “Russell” because the scholar R.R. Russell subsequently contributed to its further development. Due to its non-radial property, it has a wide of applications. Lozano et al. (2011) proposed a Russell non-radial eco-efficiency measure to compute eco-efficiency scale elasticity bounds. Hsiao et al. (2011) introduced the entropy concept to Russell measure DEA model for eliminating the equal-weight effect in order to increase evaluation accuracy. Although this original Russell measure accounts for all the inefficiencies of an evaluated DMU in both input side and output side, there are some evident disadvantages of this measure. One is that RM models are usually non-linear programming problems, which makes the computation complicated. Another one is that RM models cannot be well interpreted because they are weighted average of arithmetic and harmonic means (Pastor et al., 1999).

In order to avoid the mentioned difficulties, Pastor et al. (1999) proposed a closely extended measure based on Russell measure which called Enhanced Russell measure (ERM). ERM can be interpreted as the ratio of the average efficiency of inputs and the average efficiency of outputs, which is a better interpretation of efficiency than Russell measure. Moreover, it can be decomposed into input component of average efficiency and an output one to analyze the performance of the evaluated DMUs. Besides, ERM has been studied by many other researchers because its advantage in calculation and interpretation. For example, Cooper et al. (2007) proposed an aggregate ERM that can

be formed with all the desirable properties of an aggregate measure. Ashrafi et al. (2012) built an Enhanced Russell measure model considering non-discretionary factors. Esmacili (2012) developed a new approach based upon the ERM for dealing with interval data in DEA.

3.2.2 Fuzzy DEA models

As we know, traditional DEA models assume that all the data for inputs and outputs are crisp, so they cannot deal with imprecise data. To solve this uncertain situation, fuzzy number theory is introduced in DEA area. The concept of fuzzy set was firstly proposed by Zadeh (1965) to deal with imprecise estimates in uncertain circumstance. Recent years, numerous DEA models have been developed in the fuzzy environments. For example, Kao and Liu (2000a, 2000b) developed a procedure to measure the efficiencies of DMUs with fuzzy observations by applying α -cut approach. Leon et al. (2003) built several DEA models in fuzzy form by using some ranking methods based on the comparison of α -cut. Lertworasirikul et al. (2001) developed DEA models considering imprecise data represented by fuzzy sets. They indicated that fuzzy DEA models taking the form of fuzzy linear programming are usually solved with the aid of some methods that can rank the fuzzy sets. Wen et al. (2009) employed a fuzzy DEA model based on credibility measure and proposed a method for ranking all the DMUs. However, these previous fuzzy DEA models were extended from CCR or BCC models, which are radial models and do not account for all the slacks of the inputs and outputs simultaneously. In order to solve these deficiencies, Wang and Li (2010) proposed a fuzzy DEA model to deal with efficiency evaluation problem with imprecise data based on ERM model. Later, Wang and Li (2014) extended it to super efficiency form for fully ranking DMUs. Hsiao et al. (2011) proposed a fuzzy super-efficiency slack-based measure DEA model (Fuzzy Super SBM) and a fuzzy slack-based measure DEA model (Fuzzy SBM DEA) to analyze the operational performance of parameters with fuzzy-numbered.

3.2.3 Undesirable outputs and Environmental efficiency

As we know, undesirable outputs are usually produced with desirable outputs in the production process, such as smoke pollution and waste (Perez-Calderon et al., 2011). These factors are expected to be as few as possible. Now, research on undesirable

outputs has become a popular topic in DEA. According to our best knowledge, the literature in this area may be classified into two categories: direct approaches and indirect approaches. Direct approaches are mainly based on Färe et al. (1989), which replaced strong disposability assumption of outputs by weakly disposability assumption. This work has been extensively developed (Färe et al., 1993; Seiford and Zhu, 2005; Färe et al., 2005; Zhou et al., 2007; Zhou et al., 2008; Tone, 2004). An important branch is employing directional distance function for addressing the undesirable outputs (Chung et al., 1997; Färe et al., 2005). Indirect approaches are based on extended strong disposability assumption of output, which can be further divided into three categories. The first one treats undesirable outputs as inputs for processing (Liu and Sharp, 1999; Haulu and Veeman, 2001; Dyckhoff and Allen, 2001; Oggioni et al., 2011). This approach only needs the information on whether the data has to be minimized or maximized, but it cannot reflect a real production process (Seiford and Zhu, 2002). The second one includes a non-linear monotonic decreasing transformation approach (Scheel, 2001) and a linear monotonic decreasing transformation approach (Seiford and Zhu, 2002). Some applications by using the second method can see Oggioni et al. (2011), Grubescic and Wei (2012) and Wu et al. (2013). The last one is slacks-based measure (SBM) approach, which deals with the undesirable outputs through the slacks of undesirable outputs (Tone, 2004).

Environmental efficiency refers to the efficiency of DMUs which consider both desirable outputs and undesirable outputs. A lot of environmental efficiency analysis by DEA approach has been taken. Korhonen and Luptacik (2004) proposed two different approaches to measuring the environmental efficiency of 24 power plants in a European country: one approach is to measure technical efficiency and ecological efficiency (the relation of the desirable output to the undesirable outputs) separately, the other approach treat the undesirable outputs as inputs. Barba-Gutierrez et al. (2009) used DEA model to evaluate the eco-efficiency of different commonplace household electric appliances. Bi et al. (2012) proposed a slacks-based environmental efficiency index based on data envelopment analysis and were applied to analyze the industry sector of China. Huang et al. (2014) built a new DEA model, combining global benchmark technology, undesirable output, super efficiency and slacks-based measure, for measuring the dynamic change of regional environmental efficiency in China. Li

and Shi (2014) applied an improved super-SBM model to measure the environmental efficiency of Chinese industrial sectors.

Even though environmental efficiency has already extensively applied in many areas, it is rarely seen in the fuzzy circumstance, including the theoretical and practical works. In this chapter, we will consider a more complex but common circumstance in thermal power firms where the decision making units have fuzzy numbers and undesirable outputs simultaneously. Combining fuzzy numbers and undesirable output, a new approach is proposed in this chapter for addressing this environmental scenario based on Enhanced Russell measure. This chapter not only inherits the advantages of data envelopment analysis, but also extends DEA approach theoretically to solve a more real and complex problem.

3.3 Modelling of a single-stage system with undesirable outputs and fuzzy numbers

3.3.1 Russell DEA model and enhanced Russell DEA model

Färe and Lovell (1978) introduced a non-radial model, which is called the Russell measure model. In order to address the complicated calculation of Russell measure, Pastor et al. (1999) extended the Russell measure model and proposed a new measure called the Enhanced Russell measure.

Assume that there are n DMUs in set N to be evaluated, each of which consumes the same inputs to produce the same outputs $X_j = (x_{1j}, \dots, x_{mj})^T$ and $Y_j = (y_{1j}, \dots, y_{sj})^T$ are inputs and outputs of DMU_j , respectively. $X_j \geq \mathbf{0}$ and $Y_j \geq \mathbf{0}$, at least one element in input vector and output vector is larger than 0.

Russell measure is a combination of the input and output measures of technical efficiency. For a given DMU, $DMU_0 (X_0, Y_0)$, the technical efficiency of Russell measure can be obtained by the following model:

$$\begin{aligned}
 \min R_g &= \frac{\sum_{i=1}^m \theta_i + \sum_{r=1}^s 1/\phi_r}{m+s} \\
 \text{s.t. } \theta_i x_{i0} &\geq \sum_{j=1}^n x_{ij} \lambda_j, \quad i=1, \dots, m, \\
 \phi_r y_{r0} &\leq \sum_{j=1}^n y_{rj} \lambda_j, \quad r=1, \dots, s, \\
 0 \leq \theta_i &\leq 1; 1 \leq \phi_r \quad \forall i, r, \\
 0 \leq \lambda_j &, j=1, \dots, n.
 \end{aligned} \tag{3.1}$$

Where λ_j are intensity variables (also called structure variables). This model is under the assumption of constant returns to scale (CRS). By adding the constraint $\sum_{j=1}^n \lambda_j = 1$ in the above model, we can deal with the variable returns to scale (VRS) case.

From model (3.1), we can find that R_g is a weighted average of arithmetic and harmonic means which is difficult to interpret and compute. Concerning these deficiencies, Pastor et al. (1999) proposed the Enhanced Russell measure which is represented in the following model.

$$\begin{aligned}
 \min R_e &= \frac{\sum_{i=1}^m \theta_{i0}/m}{\sum_{r=1}^s \phi_{r0}/s} \\
 \text{s.t. } \sum_{j=1}^n x_{ij} \lambda_j &\leq \theta_i x_{i0}, \quad i=1, \dots, m, \\
 \sum_{j=1}^n y_{rj} \lambda_j &\geq \phi_r y_{r0}, \quad r=1, \dots, s, \\
 \theta_i \leq 1; \phi_r &\geq 1; \lambda_j \geq 0, \quad i=1, \dots, m, r=1, \dots, s.
 \end{aligned} \tag{3.2}$$

Similarly, the VRS version of ERM can be obtained by adding the constraint $\sum_{j=1}^n \lambda_j = 1$. The objective of model (3.2) is minimizing the ratio of the average efficiency of inputs to the average inefficiency of outputs. When the optimal value of R_e is equal to 1, the DMU being evaluated is Koopmans-efficient (Koopmans, 1951). The above non-linear programming problem can be transformed into a linear one by employing the method in Charnes and Cooper (1962). Here, we omit the process of this transformation process. More details can be seen in Pastor et al. (1999).

3.3.2 Fuzzy enhanced Russell DEA model considering undesirable outputs

Fuzzy set theory has been proposed as a popular way to quantify imprecise and vague data in DEA models. The main types of fuzzy numbers are triangular fuzzy number, trapezoidal fuzzy number, rectangular fuzzy number and irregular fuzzy number. Among them, triangular fuzzy number is one of important and commonly used fuzzy numbers. Except for the triangular fuzzy number itself, the crisp number can also be treated as a degenerated interval fuzzy number with only one value in the domain. Thus, we can see all the variables of the DMUs as triangular fuzzy numbers.

Suppose Q is triangular fuzzy number, Q^L and Q^U are the least and most desirable bound values, respectively, Q^M is the center of fuzzy number, the triangular fuzzy number can be expressed by $Q = (Q^L, Q^M, Q^U)$ and the membership function is

$$\mu_Q(q) = \begin{cases} \frac{q - Q^L}{Q^M - Q^L}, & q \in [Q^L, Q^M] \\ \frac{Q^U - q}{Q^U - Q^M}, & q \in [Q^M, Q^U] \\ 0, & q \in (-\infty, Q^L) \cup (Q^U, +\infty) \end{cases} \quad (3.3)$$

Denote the α -cut of the triangular fuzzy number Q by Q_α which satisfies $Q_\alpha = \{q \mid \mu_Q(q) \geq \alpha\}$, where $(0 \leq \alpha \leq 1)$. Then, $Q_\alpha = [(Q)_\alpha^L, (Q)_\alpha^U]$. According to this, for any triangular fuzzy number, we can transform it into interval. Thus, the α -cut of the efficiencies of the evaluated DMU can be obtained accordingly.

In addition, it has been mentioned that there are four methods mentioned in section 3.2 for dealing with undesirable outputs. In fact, each way has its own strengths and weaknesses. All of them can be used to address the undesirable outputs as long as they reflect the meaningful economic trade-offs among undesirable outputs, desirable outputs and inputs, that is, one cannot reduce undesirable outputs for free. Whether one should assume an extended strong disposability or a weak disposability in a DEA model will much depend on the nature of the applications that it handles (Liu et al., 2010). As the undesirable outputs in the thermal power firms can be increased without reducing the amount of total industrial output value, thus the strong disposability of undesirable output is selected. Based on the chapter 2, the approach of Zhu and Seiford (2002) in extended strong disposability assumption group is used in the development of the new

model, that is, adding a big enough positive scalar w to the reciprocal additive transformation of the k th undesirable output u_{kj} .

Suppose that there are n DMUs in set N to be evaluated. For $DMU_j (j = 1, 2, \dots, n)$, it applies inputs $x_{ij} (i = 1, \dots, m) \geq 0$, to produce desirable outputs $y_{rj} (r = 1, \dots, s) \geq 0$ and undesirable outputs $u_{kj} (k = 1, \dots, g) \geq 0$. Denote \tilde{x}_{ij} , \tilde{y}_{rj} and \tilde{u}_{kj} as the fuzzy counterparts of x_{ij} , y_{rj} and u_{kj} , respectively. Fuzzy ERM model for measuring the efficiency of DMU_0 with undesirable outputs is as follows:

$$\begin{aligned}
 \min R_e &= \frac{\frac{1}{m} \sum_{i=1}^m \theta_i}{\frac{1}{s+g} \left(\sum_{r=1}^s \varphi_r + \sum_{k=1}^g \phi_k \right)} \\
 s.t. \quad &\sum_{j=1}^n \lambda_j \tilde{x}_{ij} \leq \theta_i \tilde{x}_{i0}; i = 1, \dots, m, \\
 &\sum_{j=1}^n \lambda_j \tilde{y}_{rj} \geq \varphi_r \tilde{y}_{r0}; r = 1, \dots, s, \\
 &\sum_{j=1}^n \lambda_j \tilde{u}_{kj} \geq \phi_k \tilde{u}_{k0}; k = 1, \dots, g, \\
 &\theta_i \leq 1, \forall i, \\
 &\varphi_r, \phi_k \geq 1, \forall r, k, \\
 &\phi_k \leq \frac{w}{\tilde{u}_{kj}}, \forall k, \\
 &\lambda_j \geq 0, j = 1, \dots, n.
 \end{aligned} \tag{3.4}$$

The model is clearly a non-linear programming with a fractional structure objective function. The variables of this model are θ_i , φ_r , ϕ_k , λ_j , wherein λ_j is intensity variable, m , s , g are the number of inputs, good outputs and undesirable outputs, respectively. $\tilde{u}_{kj} = -\tilde{u}_{kj} + w$, where w is big enough positive value. This is the second method in indirect approaches for addressing undesirable outputs. If $\tilde{u}_{kj} = [u_{kj}^L, u_{kj}^M, u_{kj}^U]$, then the transformed vector is $\tilde{u}_{kj} = [-u_{kj}^U + w, -u_{kj}^M + w, -u_{kj}^L + w] = [\bar{u}_{kj}^L, \bar{u}_{kj}^M, \bar{u}_{kj}^U]$. As the transformed undesirable output \tilde{u}_{kj} can be smaller than zero at its minimum level, thus $-u_{kj} + w \geq 0$, that is, u_{kj} cannot be larger than w . So, the proportion of k th undesirable output in model (3.4) cannot exceed than w/\tilde{u}_{kj} . For ease of illustration, denote w/\tilde{u}_{kj} by $\tilde{\ell}$. Then, through the Charnes-Cooper

transformation, the nonlinear model (3.4) can be converted into a linear programming formulation. Firstly, denote $\beta = \left(\frac{\sum_{r=1}^s \varphi_r + \sum_{k=1}^g \phi_k}{s+g} \right)^{-1}$, $b_i = \beta \theta_i$, $a_r = \beta \varphi_r$, $c_k = \beta \phi_k$, $t_j = \beta \lambda_j$, model (3.4) is transformed into the following linear program:

$$\begin{aligned}
 \min \tilde{R}_e &= \frac{\sum_{i=1}^m b_i}{m} \\
 \text{s.t.} \quad &\sum_{r=1}^s a_r + \sum_{k=1}^g c_k = s + g \\
 &\sum_{j=1}^n t_j \tilde{x}_{ij} \leq b_i \tilde{x}_{i0}; i = 1, \dots, m, \\
 &\sum_{j=1}^n t_j \tilde{y}_{rj} \geq a_r \tilde{y}_{r0}; r = 1, \dots, s, \\
 &\sum_{j=1}^n t_j \tilde{u}_{kj} \geq c_k \tilde{u}_{k0}; k = 1, \dots, g, \\
 &b_i \leq \beta, \forall i, \\
 &\beta \leq a_r, \forall r, \\
 &\beta \leq c_k, \forall k, \\
 &c_k \leq \tilde{\ell} \beta, \forall k, \\
 &t_j \geq 0, j = 1, \dots, n, \\
 &0 \leq \beta \leq 1.
 \end{aligned} \tag{3.5}$$

Then, we use the respective α – cut of x_{ij} , y_{rj} and \bar{u}_{kj} to calculate the efficiency of the DMU under evaluated. Firstly, we obtain the fuzzy number of x_{ij} , $(x_{ij})_\alpha = \{x_{ij} | \mu_{\tilde{x}_{ij}}(x_{ij}) \geq \alpha\} = [(x_{ij})_\alpha^L, (x_{ij})_\alpha^U] = [x_{ij}^L + \alpha(x_{ij}^M - x_{ij}^L), x_{ij}^U - \alpha(x_{ij}^U - x_{ij}^M)]$. Analogously, we can obtain $(y_{rj})_\alpha$ and $(\bar{u}_{kj})_\alpha$. By setting various values of $\alpha \in [0,1]$, the membership function of \tilde{R}_e is obtained correspondingly.

When evaluating DMU_0 , we can use the smallest input values $(x_{i0})_\alpha^L$ and the largest output values $(y_{r0})_\alpha^U$, $(\bar{u}_{k0})_\alpha^U$ of DMU_0 , while use the largest input values $(x_{ij})_\alpha^U$ and the smallest output values $(y_{rj})_\alpha^L$, $(\bar{u}_{kj})_\alpha^L$ of $DMU_j (j = 1, \dots, n, j \neq 0)$ in the evaluation to get the upper bound of DMU_0 's efficiency $(R_e)_\alpha^U$. In this situation, $\tilde{\ell}$ is set the value of $w/(\bar{u}_{k0})_\alpha^U$, denote $\tilde{\ell}_\alpha^U$. The model is as follow:

$$\begin{aligned}
 \min (R_e)_\alpha^U &= \frac{\sum_{i=1}^m b_i}{m} \\
 s.t. \quad &\sum_{r=1}^s a_r + \sum_{k=1}^g c_k = s + g \\
 &\sum_{\substack{j=1 \\ j \neq 0}}^n t_j (x_{ij})_\alpha^U + t_0 (x_{i0})_\alpha^L \leq b_i (x_{i0})_\alpha^L, i = 1, \dots, m, \\
 &\sum_{\substack{j=1 \\ j \neq 0}}^n t_j (y_{rj})_\alpha^L + t_0 (y_{r0})_\alpha^U \geq a_r (y_{r0})_\alpha^U, r = 1, \dots, s, \\
 &\sum_{\substack{j=1 \\ j \neq 0}}^n t_j (\bar{u}_{kj})_\alpha^L + t_0 (\bar{u}_{k0})_\alpha^U \geq c_k (\bar{u}_{k0})_\alpha^U, k = 1, \dots, g, \\
 &\beta \leq a_r, \forall r, \\
 &b_i \leq \beta, \forall i, \\
 &\beta \leq c_k, \forall k, \\
 &c_k \leq \tilde{\ell}_\alpha^U \beta, \forall k, \\
 &t_j \geq 0, \forall j, \\
 &0 \leq \beta \leq 1.
 \end{aligned} \tag{3.6}$$

Analogously, we use the largest input values $(x_{i0})_\alpha^U$ and the smallest output values $(y_{r0})_\alpha^L, (\bar{u}_{k0})_\alpha^L$ of DMU_0 , and use the smallest input values $(x_{ij})_\alpha^L$ and the largest output values $(y_{rj})_\alpha^U, (\bar{u}_{kj})_\alpha^U$ of $DMU_j (j = 1, \dots, n, j \neq 0)$ in the evaluation to get the lower bound of DMU_0 's efficiency $(R_e)_\alpha^L$. In this situation, $\tilde{\ell}$ is set the value of $w/(\bar{u}_{k0})_\alpha^L$, denote $\tilde{\ell}_\alpha^L$. The corresponding model is shown as below:

$$\begin{aligned}
\min (R_e)_\alpha^L &= \frac{\sum_{i=1}^m b_i}{m} \\
s.t. \quad &\sum_{r=1}^s a_r + \sum_{k=1}^g c_k = s + g \\
&\sum_{\substack{j=1 \\ j \neq 0}}^n t_j (x_{ij})_\alpha^L + t_0 (x_{i0})_\alpha^U \leq b_i (x_{i0})_\alpha^U, i = 1, \dots, m, \\
&\sum_{\substack{j=1 \\ j \neq 0}}^n t_j (y_{rj})_\alpha^U + t_0 (y_{r0})_\alpha^L \geq a_r (y_{r0})_\alpha^L, r = 1, \dots, s, \\
&\sum_{\substack{j=1 \\ j \neq 0}}^n t_j (\bar{u}_{kj})_\alpha^U + t_0 (\bar{u}_{k0})_\alpha^L \geq c_k (\bar{u}_{k0})_\alpha^L, k = 1, \dots, g, \\
&\beta \leq a_r, \forall r, \\
&b_i \leq \beta, \forall i, \\
&\beta \leq c_k, \forall k, \\
&c_k \leq \tilde{\ell}_\alpha^L \beta, \forall k, \\
&t_j \geq 0, \forall j, \\
&0 \leq \beta \leq 1.
\end{aligned} \tag{3.7}$$

The optimal values of model (3.6) and model (3.7) constitute the α -cut of the highest and lowest efficiency of DMU_0 . We treat our model as a parametric program related to the possible value of α -cut over the interval $[0, 1]$. Since the interval contains an infinite number of real values between 0 and 1, we cannot consider all the values. Instead, we discretize the interval by only considering a finite number of values $= k \times \Delta, k = 0, 1, \dots, K$, where K is the largest integer equal to $1/\Delta$, Δ is a step size, in this chapter, we set it 0.1. For each α , we can solve model (3.6) and (3.7) to obtain their corresponding objective values. In this way, we can obtain the lower bound efficiency and upper bound efficiency of the DMUs in each scenario. Then, the DMUs can be ranked through these interval efficiencies in different scenarios. Moreover, the possible rules of the efficiencies when α is located in some intervals can be found to guide the decision maker to make more suitable policy when the real α is unknown.

3.4 Application to the environmental efficiency evaluation of thermal power firms in China

In this section, we apply our approach to evaluate the environmental efficiencies of 30 thermal power firms in China in the year of 2010, which contain fuzzy number and undesirable output. According to the properties of this kind of firms, we select “production time” and “coal consumption” as inputs, “total industrial output value” as desirable output, and “solid waste” as undesirable output. The factor of “production time” chosen as an input is mainly because it can well reflect the workloads of workers and the cost of the firms’ machines. This indicator was also used in Song et al. (2014) for evaluating the thermoelectric firms which is very similar with the thermal power firms. “Solid waste” contains the garbage, refuse, sludge and other discarded materials including solid, liquid, semi-solid, or contained gaseous material, from the thermal power firms. Because of the complexity of solid wastes, a fuzzy description of the solid waste is obtained. Except “Solid waste”, the other indexes are precisely obtained. The units of these indexes are “hours”, “tons”, “10 thousand RMB” and “tons” respectively.

Denote “production time”, “coal consumption”, “total industrial output value” by x_1, x_2, y respectively, and the lower, middle and upper level of “solid waste” by u^L, u^M, u^U respectively. The statistical descriptions of these data are shown in Table 3.1.

Table 3.1 Statistical description

	x_1	x_2	y	u^L	u^M	u^U
Mean	6344.067	1311113	92971.06	918822.3	1020914	1123005
Standard. Deviation	1878.096	1230200	90928.34	2481782	2757536	3033289
Min	2000	24245	350	4470.3	4967	5463.7
Max	8760	3189931	243990.9	14096088	15662320	17228552

It can be seen from Table 3.1 that “coal consumption” had the largest mean value (expectation) while “production time” had the lowest mean value (expectation). Besides, all the data of these indexes had a large of variance, which can be indicated by the standard deviation of these indexes. Among them, “production time” data had the largest concentration, which can be calculated by the ratio of standard deviation and

mean. Moreover, the maximum and minimum values of each index had a large deviation.

Before applying our new model, we first transform the undesirable outputs into “desirable outputs” by $\tilde{u}_{kj} = -\tilde{u}_{kj} + w$, and let $w=17228652$. By using model (3.6) and model (3.7), the upper and lower bounds of the α – cut fuzzy efficiency of the DMUs under evaluated are obtained. Table 3.2 shows the upper and lower bounds of the fuzzy efficiency when α is set 0 to 1 with a step 0.1 respectively.

Table 3.2 The lower and upper bounds of the environmental efficiency

[illegible]

[illegible]

Table 3.2 (continued)

[illegible]

From Table 3.2, we can find that 6 of 30 thermal power firms were fully efficient whose upper and lower bound were all equal to 1 for any α , and the remaining 24 firms became inefficient when the value of α varies from 0 to 1. Moreover, when α increases, the upper bound efficiency of the evaluated DMU decreased and the lower bound increased. For example, for DMU5, when α varies from 0.1 to 0.9, the upper bound of the efficiency decreased from 0.9647 to 0.9644, while the lower bound efficiency increased from 0.9641 to 0.9644. There are two special cases, $\alpha = 1$ and 0, that should be mentioned. When α is equal to 1, there is only one value in the α -cut for the undesirable output of every DMU. In this case, the efficiency of the evaluated value is a crisp value. When $\alpha = 0$, the efficiency scores of a specific DMU has the largest interval between the upper and lower bounds. For instance, the efficiency of DMU_{12} was always 0.8828 when $\alpha = 1$, and the efficiency value varied between 0.8794 and 0.8883 when $\alpha = 0$.

Through the internal efficiencies in Table 3.2, we can rank the DMUs in each scenario by their geometric mean. For the sake of conciseness, we will not give the geometric average efficiency but just show the ranking of DMUs directly.

The first six DMUs were always efficient in all scenarios, they all rank No 1. A super efficiency method by Wang and Li (2014) may be used to further rank these efficient DMUs. Then, DMU 5, 2, 12, 3, 10, 8 followed one by one after the above efficient DMUs, which had the same ranking in all scenarios. DMU 20, 15, 7, 23, 27, 18, 19, 11, 21, 16, 17, 26 ranked differently in each scenario. Finally, DMU 25, 22, 24, 13, 4, 28 followed in the same order after the above DMUs in all scenarios.

It can be seen from Table 3.2 and Table 3.3 that DMU 13 and 24 had the worst performance among the enterprises, whose efficiencies were below 0.5, while all other enterprises' efficiencies were larger than 0.5. This means that DMU 13 and 24 had a large space for improvement in the future and they should take measures to solve the current inefficiencies. Through the results in Table 3.2, the average efficiencies of thermal power firms can be calculated. The average lower bound and upper bound efficiencies are around 0.73 to 0.74, which indicates that the average efficiencies of these firms are at a high level. This is probably because China (including Anhui province) has paid more attention to the environmental protection. Chinese government has introduced a series of laws for investigating and controlling the environment, such

29	4	4	4	4	4	4	4	4	4	4	4
30	28	28	28	28	28	28	28	28	28	28	28

Table 3.4 Proportion for firms to be efficient in the fuzzy circumstance when $\alpha = 0.5$

DMU	Production Time	Coal Consumption	Total industrial output value	Solid waste
1	1.0000	1.0000	1.0000	1.0000
2	0.9740	0.8838	1.0000	1.0017
3	0.8666	0.9269	1.0000	1.0594
4	0.4635	1.0000	2.6442	1.0000
5	0.9291	1.0000	1.0000	1.0000
6	1.0000	1.0000	1.0000	1.0000
7	0.6020	0.9505	1.0000	1.0252
8	0.7152	1.0000	1.1899	1.0000
9	1.0000	1.0000	1.0000	1.0000
10	0.8086	0.8784	1.0000	1.0731
11	0.4331	0.9187	1.0000	1.0078
12	0.8727	0.9650	1.0000	1.0740
13	0.6430	1.0000	2.6779	1.0000
14	1.0000	1.0000	1.0000	1.0000
15	0.6433	0.9461	1.0000	1.0503
16	0.5614	0.7618	1.0000	1.0018
17	0.4450	0.8624	1.0000	1.0287
18	0.5431	0.8718	1.0000	1.0565
19	0.4682	0.9570	1.0000	1.0788
20	0.6070	1.0000	1.0000	1.0524
21	0.4737	0.8958	1.0000	1.0412
22	0.3190	0.7244	1.0000	1.0141
23	0.5705	0.9764	1.0000	1.0609
24	0.2978	0.6410	1.0000	1.0200
25	0.2605	0.8638	1.0000	1.0059
26	0.8363	0.9733	1.0000	1.0218
27	0.5407	0.9516	1.0000	1.0725
28	0.2358	0.4205	1.0000	7.3331
29	1.0000	1.0000	1.0000	1.0000

30	1.0000	1.0000	1.0000	1.0000
----	--------	--------	--------	--------

Moreover, our approach can provide benchmarks for the evaluated firms to improve their efficiencies. In order to illustrate this, we take the scenario $\alpha = 0.5$ as an example. Denote the indexes of “Production time”, “Coal consumption”, “Total industrial output value”, “Solid waste” in model (3.6) by a , b_1 , b_2 and c respectively, and transform variables by β . Applying model (3.6), we can obtain their optimal value a^* , b_1^* , b_2^* , c^* , β^* respectively. Then the proportions of these indexes of evaluate DMUs for becoming efficient are $\theta^* = a^*/\beta^*$, $\varphi_1^* = b_1^*/\beta^*$, $\varphi_2^* = b_2^*/\beta^*$, and $\phi^* = c^*/\beta^*$. The results are shown as follows.

Based on the benchmarks in Table 3.4, we find that most of the improvements should be taken on the inputs. The total industrial output value and solid waste only need increase a small value at the current level. This indicates that if the firm wants to be environmental efficient, it should focus on its attention to its utilization of inputs. By these proportions of indexes, we can easily obtain the benchmarks (or targets) for evaluated DMUs when using the upper value of transformed “solid waste” under the best fuzzy circumstance. Similarly, through model (3.7), we can obtain the benchmarks (or targets) for evaluated DMUs when they obtain the lower value under the worst fuzzy circumstance. Because the limitation of contents, we omit this part to save space.

3.5 Conclusions

In this chapter, in order to measure the environmental efficiency of thermal power firms, we propose a fuzzy Enhanced Russell measure approach in the present of undesirable output. Firstly, the Fuzzy Enhanced Russell measure model is built based on the previous Enhanced Russell measure and fuzzy DEA models. Then, α -cut method is used to calculate the upper and lower bound environmental efficiencies. Finally, 30 thermal power firms in China are analyzed by our approach. Six efficient firms are determined, which coincides with the common sense about the situation of these firms. The average environmental efficiency of 30 firms is good. We believe that with “the environmental law abiding guideline for thermal power firms” published by the Ministry of Environmental Protection of China in March 2013, these firms will have a better environmental efficiency because they are forced to enhance the pollution

prevention and increase the environmental management level under this law. Furthermore, the benchmarks for DMUs under a certain fuzzy circumstance are given.

It should be noted that α -cut based method is chosen to solve the fuzzy programming problem in this chapter. Actually, there are several other methods, such as tolerance approach (Sengupta, 1992), possibility approach (Lertworasirikul et al., 2003), that can be used to address this problem. In the future, we will compare these methods in solving the problem. Moreover, how to apply our approach to more applications, such as real example with the ordinal data, is also an interesting research topic.

CHAPTER 4

Environmental efficiency evaluation of a single-stage system considering performance improvement path

Contents

4.1 Introduction	44
4.2 Traditional RAM model and the closest target	46
4.3 Closest target RAM model considering undesirable outputs	48
4.4 Application to the water environmental efficiency evaluation of Xiangjiang River Basin in China	52
4.4.1 Data and variables	53
4.4.2 Results analysis	55
4.5 Conclusions	60

In recent decades, with the rapid economic development of Xiangjiang River Basin in China, the discharge of industrial waste gas, wastewater and domestic waste gas, wastewater also increased significantly, which caused great damage to the ecological environment of Xiangjiang River Basin and violated the sustainable development of economy. In order to solve the environmental pollution problem, many scholars have adopted data envelopment analysis (DEA) to measure and improve the environmental efficiency of various industries and entities in China. However, as the target (benchmark) set by these works is usually the furthest one for a decision making unit (DMU) to be efficient, thus it may be hardly accepted by the DMU. In this chapter, considering the undesirable outputs, a new closest target DEA model based on range adjusted measure (RAM) is proposed. Finally, the proposed model is applied to the water environmental efficiency evaluation of Xiangjiang River basin in China. The results show that the environmental efficiency of Xiangjiang River basin has an increasing trend during the year of 2008-2014, but the deviations among the areas are still at a larger value. Compared to the “furthest” target methods, the targets by our

approach are more acceptable for DMUs to improve the performance on their economy and environment.

4.1 Introduction

Xiangjiang River, as the largest river in Hunan Province in China, is the mother river of Hunan province. Xiangjiang River Basin is the most densely populated region with the highest level of urbanization and the most developed economy in Hunan Province. However, the large population and rapid economic development have resulted in the greatest pressure on resources and environment. Recently, with the gradual acceleration of the modernization process, many environmental pollution problems, such as haze, water resources shortage, water and atmospheric pollution, heavy metal pollution, have seriously threatened the ecological environment of Xiangjiang River Basin. Environmental pollution seriously restricts the sustainable development of economy and society. The Chinese government and the local government of Hunan Province issued many related environmental laws and regulations to promote the implementation of cleaner production technology and pollution reduction, so as to achieve sustainable economic and environmental development (Li and Lin, 2016). While scientific evaluation of environmental efficiency can provide reasonable basis for enterprises or local governments to implement specific solutions for performance improvement.

However, due to the lack of professional environmental efficiency evaluation and scientific targets for efficiency improvement, Xiangjiang River Basin is still facing water resources shortage, water and atmospheric pollution and heavy metal pollution. Therefore, it is urgent to measure the water environmental efficiency and set the benchmarks for Xiangjiang River Basin. Environmental efficiency can comprehensively reflect the ecological situation because it considers both the economic factors and environmental factors in the efficiency evaluation (Song et al., 2012; Fang et al., 2013). In this chapter, data envelopment analysis (DEA) approach with the closest target is applied to measure the environmental efficiency and set the closest targets for Xiangjiang River Basin.

DEA, as a non-parametric programming technique, has become more and more popular in evaluating the performance of a set of homogenous decision making units (DMUs) (An et al., 2016; Li and Lin, 2016). So far, it has been widely applied in

evaluating the environmental efficiency or ecological efficiency (Färe et al., 1989; Tone, 2004; Leleu, 2013; Zhou et al., 2012). Song et al. (2012) reviewed the DEA models for environmental efficiency when considering a system as a “black box”. In that review, environmental efficiency evaluation methods are classified into three categories according to their ways for addressing the undesirable outputs. In fact, several other methods should be added now. One is slacks-based measure (SBM) approach by Tone (2004) which deals with the undesirable outputs through the slacks of undesirable outputs. This method can simultaneously measure the inefficiencies in the inputs and outputs while the traditional method only can radial measure the efficiency improvement. Among the previous methods, an important and popular method is on weakly disposability assumption which is based on Färe et al. (1989) where undesirable outputs are treated as their original forms. Several works have been developed in this direction (Leleu, 2013; Zhou et al., 2012; Miao et al., 2016). Another important category of approaches treat pollution as a free disposable input (Hailu and Veeman, 2001; An et al., 2017). Each method has its own strengths and weaknesses. All of them can be used to address the undesirable outputs as long as they reflect the meaningful economic trade-offs among undesirable outputs, desirable outputs and inputs, that is, one cannot reduce undesirable outputs for free (Liu et al., 2010). Whether one should assume a strong disposability or a weakly disposability in a DEA model is mainly depend on the nature of the applications that it handles.

However, the previous studies almost set the “furthest” target for a DMU to reach efficient while measuring the environmental efficiency. Thus, the benchmark (target) may be not easily acceptable by the DMU. Recently, some developments focus on finding the “closest” target so that the DMU under evaluation can achieve efficient with the “least” effort. The idea behind the closest target is that the closer target suggests directions of improvement for the inputs and outputs of the inefficient unit that will lead the DMU to be efficient with least effort. There are two ways for finding the closest target. One is minimizing the selected distance. Frei and Harker (1999) gave the closest targets by minimizing the Euclidean distance or weighted Euclidean distance to the efficient frontier, more extensions in this direction see Baek and Lee (2009), Amirteimoori and Kordrostami (2010), Aparicio and Pastor (2014a). Gonzalez and Alvarez (2001) gained the relative targets by minimizing the sum of input contractions required to reach the frontier of the technology. Portela et al. (2004) applied directional

distance function approach to determine the targets for the DMUs. Jahanshahloo et al. (2012) conducted a DEA method to obtain the minimum distance of DMUs to the frontier by $\|\bullet\|_1$. Briec and Lemaire (1999), and Briec and Leleu (2003) used Hölder distance functions to obtain the evaluated DMU' minimum distance to the frontier. Ando et al. (2012) pointed out that least distance measures based on Hölder norms meet neither weak nor strong monotonicity on the strongly efficient frontier and provided a method to guarantee the function is weak monotonicity. To realize the strong monotonicity, Aparicio and Pastor (2014b) provided a solution for output-oriented models based on an extended production possibility set which is strongly monotonic; Fukuyama et al. (2014) employed least distance p -norm inefficiency measures that satisfy strong monotonicity over the strongly efficient frontier to obtain the targets for the DMUs. The other category is minimizing (or maximizing) the efficiency measure. Portela et al. (2003) maximized the BRWZ measure proposed by Brockett et al. (1997) to obtain the closest targets. Aparicio et al. (2007, 2013) proposed several mathematical programming problems to find the closest targets where some efficiency measures, such as range adjusted measured, Russell measure, slacks-based measure, are chosen as criterion of similarity. These programming problems can be easily solved, and the results guarantee the evaluated DMU can reach the closest projection point on the Pareto-efficient frontier.

To measure the environmental efficiency of the water system in Xiangjiang River Basin and set the closest target for the evaluated DMU to be efficient, in this chapter, considering the undesirable outputs, we propose a new closest target model based on Range Adjusted Measure (RAM). The RAM is chosen as the basic model because it is not only a non-radial DEA model, but also can deal with non-positive data in the input and output indicators (Ding et al., 2018). Then, the new closest target model is applied to environmental efficiency evaluation of the water system in Xiangjiang River Basin.

4.2 Traditional RAM model and the closest target

In this section, we firstly introduce the approach of RAM, and then show Aparicio et al.'s (2007) approach which finds the closest targets. As two representative approaches in DEA for measuring efficiency and finding the closest targets, these two approaches have been largely studied and extended respectively (Sueyoshi and Sekitani, 2007; Tavassoli et al., 2016; Aparicio and Pastor, 2014b; Wu et al., 2018).

Consider we have n DMUs, and each $DMU_j (j = 1, \dots, n)$ uses m inputs to produce s outputs which are denoted by $(X_j, Y_j), j = 1, \dots, n$. It is assumed that $X_j = (x_{1j}, \dots, x_{mj}) \geq 0, X_j \neq 0, j = 1, \dots, n$, and $Y_j = (y_{1j}, \dots, y_{sj}) \geq 0, Y_j \neq 0, j = 1, \dots, n$. The range adjusted measure (RAM) model (Cooper et al., 1999) under constant returns to scale is shown as follows.

$$\begin{aligned}
 \text{Min } & 1 - \frac{1}{m+s} \left(\sum_{i=1}^m \frac{s_{i0}^-}{R_i^-} + \sum_{r=1}^s \frac{s_{r0}^+}{R_r^+} \right) \\
 \text{s.t. } & \sum_{j=1}^n \lambda_j x_{ij} + s_{i0}^- = x_{i0}, i = 1, \dots, m \\
 & \sum_{j=1}^n \lambda_j y_{rj} - s_{r0}^+ = y_{r0}, r = 1, \dots, s \\
 & \lambda_j, s_{i0}^-, s_{r0}^+ \geq 0; j = 1, \dots, n.
 \end{aligned} \tag{4.1}$$

where λ_j represents unknown variable (often referred to as “structural” or “intensity” variables) for connecting the input and output vectors by a convex combination. $R_i^- = \max_j \{x_{ij}\} - \min_j \{x_{ij}\}$ is the range of i th input and $R_r^+ = \max_j \{y_{rj}\} - \min_j \{y_{rj}\}$ is the range of r th output; s_{i0}^- and s_{r0}^+ are the slacks of the i th input and the r th output of DMU_0 , respectively. Denote $(\lambda_j^*, s_{i0}^{-*}, s_{r0}^{+*})$ be an optimal solution of the model (4.1), when the optimal value of the model (4.1) is 1, then DMU_0 is efficient; otherwise, DMU_0 is inefficient. It should be noted that this model is different from the SBM model

whose objective function is $\text{Min } (1 - \frac{1}{m} \sum_{i=1}^m \frac{s_{i0}^-}{x_{i0}}) / (1 + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^+}{y_{r0}})$ (Tone, 2001).

Compared with the SBM model, the RAM model is not only a non-radial model that can simultaneously measure the inefficiency of inputs and outputs, but also can deal with also non-positive data in the input and output indicators. Thus, RAM is more suitable for the general environmental efficiency evaluation problem.

Definition 4.1. Denote $(X_j, Y_j) (j = 1, \dots, n)$ by the production activities of all DMUs, the production possibility set T is

$$T = \left\{ (x, y) \mid x \geq \sum_{j=1}^n \lambda_j x_{ij}, y \leq \sum_{j=1}^n \lambda_j y_{rj}, \lambda_j \geq 0 \right\}.$$

By Definition 4.1, we can character the efficient frontier of the PPS, $\partial(T)$, which consists of the non-dominated points of T , as

$$\partial(T) = \{(X, Y) \in P | X' \leq X, Y' \geq Y \Rightarrow (X', Y') = (X, Y)\} \quad (4.2)$$

or

$$\partial(T) = \{(X, Y) | -vX + wY = 0, -vX_j + wY_j \leq 0, j = 1, \dots, n, v > 0_m, w > 0_m\} \quad (4.3)$$

in the multiplier form with input and output weights (Ruiz et al., 2014).

Denote the set of extreme efficient points in the PPS by E . The following theorem from Aparicio et al. (2007) provides a useful characterization of $\partial(T)$, which will be used in the formulation of the closest target setting model:

Theorem 4.1

$$\partial(T) = \left\{ (X, Y) \in \mathbb{R}_+^{m+s} \left| \begin{array}{l} X = \sum_{j \in E} \lambda_j X_j, Y = \sum_{j \in E} \lambda_j Y_j, \\ -vX_j + wY_j + d_j = 0, j \in E \\ v > 1_m, w > 1_s \\ d_j \leq Mb_j, j \in E \\ \lambda_j \leq M(1 - b_j), j \in E \\ d_j, \lambda_j \geq 0, b_j \in \{0, 1\}, j \in E \end{array} \right. \right\}$$

where M is a big positive quantity.

Proof. The proof is similar with Aparicio et al. (2007). We omit it here.

Theorem 4.1 shows the points on a Pareto-efficient face of the technology, which are dominating the evaluated $DMU_0(X_0, Y_0)$, can be expressed as a combination of extreme efficient units lying on the same efficient face of the production possibility set. More importantly, the set of infeasible points in which the minimum distance to the Pareto-efficient frontier is attained can be represented by a set of linear constraints. Then, by applying it to the closest target model, we can find the closest target for inefficient DMU_0 , such as Aparicio et al.'s (2007) mADD model.

4.3 Closest target RAM model considering undesirable outputs

Assume that n DMUs will be evaluated. Each of them $DMU_j (j = 1, \dots, n)$ uses m inputs to produce s desirable outputs while generating q undesirable outputs. The notations are given as follows. $x_{ij} (i = 1, \dots, m)$ is the i th input of DMU_j , $y_{rj} (r = 1, \dots, s)$ is the r th desirable output of DMU_j and $z_{pj} (p = 1, \dots, q)$ is the p th undesirable

output of DMU_j . Based on the notations, the related definition of production possibility set is given.

Definition 4.2. The production possibility set considering undesirable outputs is defined as follows.

$$T_{env} = \left\{ (x, y, z) \mid x \geq \sum_{j=1}^n x_{ij} \lambda_j, y \leq \sum_{j=1}^n y_{ij} \lambda_j, z \geq \sum_{j=1}^n z_{ij} \lambda_j, \lambda_j \geq 0 \right\}$$

where λ_j stands for unknown variables (often referred to as “structural” or “intensity” variables) for connecting the input and output vectors by a convex combination. This production possibility set is under the constant variables to scale, by adding $\sum_{j=1}^n \lambda_j = 1$, the production possibility set will become under the variable returns to scale. In Definition 4.2, undesirable outputs are treated as inputs, which is similar to the way in Liu and Sharp (1999). The efficient DMUs always wish to minimize desirable inputs and undesirable outputs, and to maximize desirable outputs and undesirable inputs. As Liu et al. (2010) pointed out that if one only wishes to investigate operational efficiency from this point of view, there is no need to distinguish between inputs and outputs, but only minimum and maximum.

Based on the RAM model, we firstly construct the RAM model considering undesirable outputs, and then measure the environmental efficiency of the evaluated DMU_0 . The model is expressed as follows.

$$\begin{aligned} \text{Min } & 1 - \frac{1}{m+p+s} \left(\sum_{i=1}^m \frac{s_{i0}^-}{R_i^-} + \sum_{p=1}^q \frac{s_{p0}^{--}}{R_p^{--}} + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^+}{R_r^+} \right) \\ \text{s.t. } & \sum_{j=1}^n \lambda_j x_{ij} + s_{i0}^- = x_{i0}, i = 1, \dots, m, \\ & \sum_{j=1}^n \lambda_j y_{rj} - s_{r0}^+ = y_{r0}, r = 1, \dots, s, \\ & \sum_{j=1}^n \lambda_j z_{pj} + s_{p0}^{--} = z_{p0}, p = 1, \dots, q, \\ & \lambda_j, s_{i0}^-, s_{r0}^+, s_{p0}^{--} \geq 0, j = 1, \dots, n, i = 1, \dots, m; r = 1, \dots, s; p = 1, \dots, q. \end{aligned} \tag{4.4}$$

where $R_i^- = \max_j \{x_{ij}\} - \min_j \{x_{ij}\}$, $R_p^{--} = \max_j \{z_{pj}\} - \min_j \{z_{pj}\}$ and $R_r^+ = \max_j \{y_{rj}\} - \min_j \{y_{rj}\}$ are the range of i th input, the range of p th undesirable output

and the range of r th desirable output, respectively. s_{i0}^- , s_{r0}^+ , and s_{p0}^{--} are the slacks of the i th input, the r th desirable output and the p th undesirable output of DMU_0 . It can be seen that model (4.4) can measure the distance between the evaluated DMU and the benchmark (reference point) from the perspective of input and output. Assume $(\lambda_j^*, s_{i0}^{-*}, s_{r0}^{+*}, s_{p0}^{--*})$ is an optimal solution of the model (4.4), based on the results of the model (4.4), we can obtain the *classical environmental efficiency* for DMU_0 , which can then be computed through formula (4.5).

$$\rho_e = 1 - \frac{1}{m + p + s} \left(\sum_{i=1}^m \frac{s_{i0}^{-*}}{R_i^-} + \sum_{p=1}^q \frac{s_{p0}^{--*}}{R_p^{--}} + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^{+*}}{R_r^+} \right) \quad (4.5)$$

When the optimal value of model (4.4) is equal to one, DMU_0 is classical environmental efficient, otherwise, it is classical environmental inefficient. It is clear that classical environmental efficiency of a DMU calculated from model (4.4) is based on the furthest targets (maximum input and output slacks) for the DMU to be efficient.

Denote the set of all extreme classical environmental efficient points by Set H. By Definition 4.2, we can similarly character the efficient frontier $\partial(T_{env})$ of the PPS, which consists of the non-dominated points, as

$$\partial(T_{env}) = \{(X, Y, Z) \in P | X' \leq X, Y' \geq Y, Z' \leq Z \Rightarrow (X', Y', Z') = (X, Y, Z)\} \quad (4.6)$$

Or

$$\partial(T_{env}) = \{(X, Y, Z) | -vX + wY - \pi Z = 0, -vX_j + wY_j - \pi Z_j \leq 0, j = 1, \dots, n, v > 0, w > 0, \pi > 0\} \quad (4.7)$$

in multiplier form with input and output weights.

Different from the model (4.4), based on the set H, we build the following closest target model for measuring the environmental efficiency of the evaluated DMU , i.e., DMU_0 , and meanwhile set the closest target for it to be efficient.

$$\begin{aligned}
Max \quad & 1 - \frac{1}{m+p+s} \left(\sum_{i=1}^m \frac{s_{i0}^-}{R_i^-} + \sum_{p=1}^q \frac{s_{p0}^{--}}{R_p^{--}} + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^+}{R_r^+} \right) \\
s.t. \quad & \sum_{j \in H} \lambda_j x_{ij} + s_{i0}^- = x_{i0}, i = 1, \dots, m, \\
& \sum_{j \in H} \lambda_j y_{rj} - s_{r0}^+ = y_{r0}, r = 1, \dots, s, \\
& \sum_{j \in H} \lambda_j z_{pj} + s_{p0}^{--} = z_{p0}, p = 1, \dots, q, \\
& - \sum_{i=1}^m v_i x_{ij} - \sum_{p=1}^q \pi_p z_{ij} + \sum_{r=1}^s w_r y_{rj} + d_j = 0, j \in H, \\
& v_i \geq \frac{1}{(m+q+s)R_i^-}, \quad i = 1, \dots, m, \\
& \pi_p \geq \frac{1}{(m+q+s)R_p^{--}}, \quad p = 1, \dots, q, \\
& w_r \geq \frac{1}{(m+q+s)R_r^+}, \quad r = 1, \dots, s, \\
& d_j \leq M b_j, j \in H, \\
& \lambda_j \leq M(1 - b_j), j \in H, \\
& b_j \in \{0, 1\}, d_j \geq 0, \lambda_j \geq 0, j \in H, \\
& s_{i0}^-, s_{r0}^+, s_{p0}^{--} \geq 0, i = 1, \dots, m; r = 1, \dots, s; p = 1, \dots, q.
\end{aligned} \tag{4.8}$$

where s_{i0}^- , s_{r0}^+ and s_{p0}^{--} are the slacks of the i th input, the r th desirable output and the p th undesirable output of DMU_o . M is a big enough positive quantity. The first three constraints are used to calculate the slacks to the linear combination of extreme efficient units and dominate DMU_o . The fourth to seventh constraints are the constraints corresponding to the multiplier formulation of RAM DEA model, but it only considered the extreme efficient DMUs in H , which can ensure that we consider all the possible points in T_{env} lie on or below these the hyperplanes. The eighth to tenth constraints are the key conditions that determine which DMU is active as a peer for the evaluation of DMU_o . If $\lambda_j > 0$, then $b_j = 0$, $d_j = 0$. Thus, if DMU_j participates actively as a peer

then it necessarily belongs to the hyperplane $-\sum_{i=1}^m v_i x_{ij} - \sum_{p=1}^q \pi_p z_{ij} + \sum_{r=1}^s w_r y_{rj} + d_j = 0$. If

$\lambda_j = 0$, then $d_j \geq 0$, which indicates DMU_j is not a peer for evaluating DMU_o .

Considering the constraints of the model (4.4) and model (4.8), the following theorem can be easily derived. We state Theorem 4.2 without proof.

Theorem 4.2. The optimal value of model (4.8) must not be larger than that of the model (4.4).

Assume $(\lambda_j^*, s_{i0}^{--*}, s_{r0}^{+*}, s_{p0}^{--*}, v_i^*, \pi_p^*, w_r^*, d_j^*, b_j^*)$ is an optimal solution of the closest target model (4.8). Then, the closest target for the evaluated DMU_o can be expressed as:

$$(\hat{x}_{i0} = x_{i0} - s_{i0}^{--*}, \hat{y}_{r0} = y_{r0} + s_{i0}^{+*}, \hat{z}_{p0} = z_{p0} - s_{p0}^{--*}) \quad (4.9)$$

The *environmental efficiency* for the evaluated DMU_o based on the closest target can be obtained by computing the following formula.

$$\rho_{env} = 1 - \frac{1}{m + p + s} \left(\sum_{i=1}^m \frac{s_{i0}^{--*}}{R_i^-} + \sum_{p=1}^q \frac{s_{p0}^{--*}}{R_p^-} + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^{+*}}{R_r^+} \right) \quad (4.10)$$

Without the specific illustration, the environmental efficiency in the later part of this chapter are all refer to the environmental efficiency based on the closest target model, model (4.8), and the classical environmental inefficient refers to the efficiency based on the model (4.4). It should be noted that DMU_o is environmental efficient if and only if all slacks s_{i0}^{--*} , s_{r0}^{+*} and s_{p0}^{--*} in model (4.8) are zero, that is $\rho_{env} = 1$. Based on the model (4.4) and model (4.8), we have the following theorem.

Theorem 4.3. If the evaluated DMU_o is classical environmental efficient, the DMU_o must be environmental efficient.

Proof. According to the definition of classical environmental efficient, an optimal slack vector $(s_{i0}^{--*}, s_{r0}^{+*}, s_{p0}^{--*})$ in model (4.4) for a classical environmental efficient DMU_o must be zero. From the constraints of model (4.4) and (4.8), we can find slacks $(s_{i0}^{--*} = 0, s_{r0}^{+*} = 0, s_{p0}^{--*} = 0)$ for the classical environmental efficient DMU_o in model (4.4) must be a feasible solution of model (4.8). As the constraints $s_{i0}^{--*} \geq 0, s_{r0}^{+*} \geq 0$ and $s_{p0}^{--*} \geq 0$, the optimal slacks in model (4.8) must be equal to zero too. Thus, the DMU_o must be environmental efficient.

4.4 Application to the water environmental efficiency evaluation of Xiangjiang River Basin in China

In this section, we apply the proposed model to evaluate the environmental efficiency of water system in Xiangjiang River Basin in China. The results show that the water environmental efficiency obtained from model (4.8) is higher than the

classical water environmental efficiency obtained from model (4.4) and the target set by the closest target model is easily realized.

4.4.1 Data and variables

Based on the research purpose and the validity of the data, we investigate the water environmental efficiency of 15 monitoring areas in seven cities of Xiangjiang River basin in China from 2008-2014. In this chapter, labor force, capital stock, and energy consumption of each monitoring area are selected as input variables. The indexes of water pollution generally include dissolved oxygen, total phosphorus, ammonia nitrogen, PH, permanganate and other indicators. As DEA requires the number of decision making units to be more than twice of the number of indicators, and there is also a strong correlation between the above indexes. In order to achieve the distinction and validity of the assessment results, dissolved oxygen (DO) and total phosphorus (TP) are selected as water pollution indexes. Since the environmental factors are usually undesirable, here, we use the reciprocal of dissolved oxygen (DO) denoted by DO' as the undesirable output. Besides, gross domestic product (GDP) of each area is selected as desirable output. All the data are collected from the "China Statistical Yearbook", "Hunan Statistical Yearbook", and "Water Quality Monitoring Station" covering the years of 2009-2015. The descriptive statistics of inputs and outputs are shown in Table 4.1.

Table 4.1 Descriptive statistics of inputs and outputs during 2008-2014

	Labor (10 thousands person)	Capital (100 million RMB)	Energy (10 thousands of TCE)	DO (mg/L)	TP (mg/L)	GDP (100 million RMB)
2008						
Mean	325.084	443.3067	532.8767	7.752	0.0583	1105.261
Variance	9570.854	263485.7	31145.79	1.4982	0.0013	622951.1
Max	422.84	1702.3	888.24	11.14	0.139	3000.98
Min	159.63	174.55	184.26	6.1	0.01	528.4
2009						
Mean	334.9227	637.028	557.576	7.9013	0.0639	1303.315
Variance	407564.7	10825.21	32527.86	1.5125	0.0012	1031122
Max	440.03	2200.62	891.75	11.18	0.138	3744.76
Min	175.66	242.05	196.76	5.89	0.007	568.31
2010						
Mean	344.5127	833.5107	592.6167	7.6727	0.0794	1588.619
Variance	12402.9	638096.8	37822.98	0.5239	0.0016	1517310
Max	458.31	2785.99	969.25	9.16	0.146	4547.06
Min	172.72	305.1	219.62	6.15	0.007	678.71
2011						
Mean	341.3636	1100.734	498.0357	7.7936	0.0683	1974.079
Variance	13321.07	990766.4	27342.7	0.8571	0.0014	2489730
Max	466.39	3433.33	804.04	9.93	0.141	5619.33
Min	169.33	425.25	168.43	6.82	0.005	847.26
2012						
Mean	354.9207	1373.709	570.002	7.6893	0.0715	2220.991
Variance	13447.33	1123715	39811.78	0.3275	0.0019	3009651
Max	470.18	3956.06	1052.41	8.47	0.161	6399.91
Min	175.46	581.91	225.09	6.27	0.005	1002.65
2013						
Mean	360.392	1741.072	532.8767	7.5767	0.0653	2472.869
Variance	13443.71	1332636	31145.79	0.3448	0.0013	3768624
Max	475.44	4539.39	888.24	8.75	0.143	7153.13
Min	184.48	787.57	184.26	6.5	0.008	1118.17
2014						
Mean	361.268	2116.535	557.576	7.4107	0.0653	2718.79
Variance	13709.77	1882373	32527.86	0.3259	0.002	4494915
Max	476.45	5435.75	891.75	8.54	0.172	7824.81
Min	180.3	938.94	196.76	6.68	0.005	1210.86

From Table 4.1, it can be observed that the mean values of labor force, capital, and energy consumption increased year by year, which means that the investments of each area increased year by year. Meanwhile, the overall downward trend of the average dissolved oxygen and the overall growth trend of the average total phosphorus indicated the overall water quality had deteriorated during this period. Although GDP of all areas increased greatly, but from the large variance of GDP, we can know economic development among different areas were largely different.

4.4.2 Results analysis

In this section, we evaluate the water environmental efficiency of 15 monitoring areas in 7 cities. In order to assess the annual water environmental efficiency of each area, each area of each year is treated as a DMU. The classical water environmental efficiency of each area can be derived by using model (4.4) and formula (4.5). The results are shown in table 4.2.

Table 4.2 Classical water environmental efficiencies of 15 monitoring areas in Xiangjiang river basin

City	Area	2008	2009	2010	2011	2012	2013	2014	Mean
Yongzhou	Xiaoshui	1.0000	0.6755	0.6754	0.6952	0.6952	0.6704	0.6771	0.7270
	Trunk	0.9941	0.6695	0.6634	0.6894	0.6894	0.6718	0.6593	0.7196
Hengyang	Chunlingshui	0.9674	1.0000	0.9965	1.0000	1.0000	0.5784	0.5606	0.8719
	Zhengshui	0.9666	0.9391	1.0000	0.9752	0.9752	0.5306	0.5676	0.8506
	Leishui	0.9560	0.8722	0.9359	0.9615	0.9615	0.5711	0.5663	0.8321
	Mishui	1.0000	0.9456	1.0000	\	\	0.5610	0.5659	0.8145
	Trunk	0.9836	0.9521	0.9864	0.9800	0.9800	0.5590	0.5567	0.8568
Zhuzhou	Lushui	0.8982	0.7253	0.6245	0.7205	0.7205	0.6548	0.6567	0.7144
	Trunk	1.0000	0.7586	0.7150	0.8424	0.8424	0.6713	0.7125	0.7917
Xiangtan	Lianshui	0.7409	0.7129	0.6545	0.7098	0.7098	0.6717	0.6483	0.6926
	Trunk	0.7094	0.6209	0.5922	0.6513	0.6513	0.6559	0.6641	0.6493
Changsha	Liuyanghe	0.8693	0.9060	0.7856	1.0000	1.0000	0.9459	0.8951	0.9146
	Trunk	0.8860	0.8713	0.8367	1.0000	1.0000	1.0000	1.0000	0.9420
Chenzhou	Leishui	1.0000	0.7939	0.7799	1.0000	1.0000	0.8781	1.0000	0.9217
Loudi	Lianshui	0.6062	0.5503	0.5284	0.5596	0.5596	0.5126	0.4563	0.5390
	Mean	0.9052	0.7996	0.7850	0.8418	0.8418	0.6755	0.6791	

In Table 4.2, the areas with the efficiency value of 1 are classical water environmental efficient. Due to the data of Mishui area of Hengyang in 2011 and 2012

is unavailable, the classical water environmental efficiency of this area could not be obtained. From table 4.2, it can be found that the overall classical water environmental efficiency of Xiangjiang River Basin was decreasing year by year. Liuyanghe area of Changsha, Trunk area of Changsha, and Leishui area of Chenzhou performed well, and their water environmental efficiencies were all greater than 0.9. Lianshui area of Loudi performs the worst. According to the locations of the 15 monitoring areas, we can get the classical water environmental efficiencies of the seven cities in Xiangjiang River Basin, which were shown in table 4.3.

Table 4.3 Average classical water environmental efficiencies of seven cities in Xiangjiang river basin

	2008	2009	2010	2011	2012	2013	2014	Mean
Yongzhou	0.9971	0.6725	0.6694	0.6923	0.6923	0.6711	0.6682	0.7233
Hengyang	0.9747	0.9418	0.9838	0.9792	0.9792	0.5600	0.5634	0.8546
Zhuzhou	0.9491	0.7420	0.6698	0.7814	0.7814	0.6631	0.6846	0.7530
Xiangtan	0.7252	0.6669	0.6234	0.6805	0.6805	0.6638	0.6562	0.6709
Changsha	0.8776	0.8886	0.8112	1.0000	1.0000	0.9730	0.9475	0.9283
Chenzhou	1.0000	0.7939	0.7799	1.0000	1.0000	0.8781	1.0000	0.9217
Loudi	0.6062	0.5503	0.5284	0.5596	0.5596	0.5126	0.4563	0.5390

It can be seen from table 4.3, the overall classical water environmental efficiencies of Xiangjiang River Basin had become worse and worse from 2008 to 2014. Changsha performed the best, followed by Chenzhou and Loudi performs the worst. As the capital city of Hunan province, Changsha has the largest economy and pays more attention to environmental protection than other cities. For the worst performance city Loudi, the local government needs to coordinate the development of economy and the environment. Besides, the classic water environmental efficient areas in table 4.2 forms the efficient set H of model (4.8), by model (4.8), the water environmental efficiency and the closest target of each area of each year can be obtained.

Table 4.4 Water environmental efficiencies of the 15 monitoring areas from 2008 to 2014

City	Area	2008	2009	2010	2011	2012	2013	2014	Mean
Yongzhou	Xiaoshui	1.0000	0.9857	0.9943	0.9086	0.9086	0.9142	0.8631	0.9392
	Trunk	0.9941	0.9806	0.9836	0.9000	0.9000	0.9171	0.8692	0.9349
Hengyang	Chunlingshui	0.9674	1.0000	0.9987	1.0000	1.0000	0.9916	0.9751	0.9904
	Zhengshui	0.9666	0.9996	1.0000	0.9814	0.9814	0.9896	0.9642	0.9833
	Leishui	0.9560	0.9839	0.9925	0.9771	0.9771	0.9969	0.9969	0.9829
	Mishui	1.0000	0.9805	1.0000	\	\	0.9898	0.9962	0.9933
	Trunk	0.9836	0.9996	1.0000	0.9929	0.9929	0.9855	0.9778	0.9903
Zhuzhou	Lushui	0.8982	0.9548	0.8768	0.9038	0.9038	0.9111	0.8718	0.9029
	Trunk	1.0000	0.9751	0.9340	0.9291	0.9291	0.9143	0.8693	0.9358
Xiangtan	Lianshui	0.7433	0.7339	0.7729	0.7695	0.7695	0.7814	0.7787	0.7642
	Trunk	0.8682	0.8300	0.7759	0.7898	0.7898	0.7588	0.7515	0.7948
Changsha	Liuyanghe	1.0000	1.0000	0.9845	1.0000	1.0000	0.9459	0.8951	0.9751
	Trunk	0.9875	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9982
Chenzhou	Leishui	1.0000	0.9634	0.9531	1.0000	1.0000	0.9951	1.0000	0.9874
Loudi	Lianshui	0.6267	0.6558	0.7080	0.8678	0.8678	0.8610	0.8616	0.7784
	Mean	0.9328	0.9362	0.9316	0.9300	0.9300	0.9302	0.9114	

The water efficiencies of the 15 monitoring areas are shown in table 4.4. The areas in a certain year having the efficiency of 1 are water environmental efficient. It can be seen from table 4.4 that the average water environmental efficiencies of these areas tended to be the same, with an efficiency value of about 0.93, which was obviously different from the classical water efficiency. During this period, the best performing year is 2009, and the worst year is 2014, while the efficiency difference is small and can be ignored. Comparing the efficiencies of the 15 areas, we find the Trunk area of Changsha, the Mishui area of Hengyang, the Trunk area of Hengyang, and the Chuling area of Hengyang performed well, and the efficiencies were all higher than 0.99. From the average efficiency of each area listed in the last column of table 4.4, except the Lianshui area of Xiangtan, the Trunk area of Xiangtan and the Lianshui area of Loudi, other 12 areas' average efficiencies were above 0.9 which indicated that the overall ecological environment level of water system in Xiangjiang River Basin were all at a higher level. The results indicated that Hunan Province had made some achievements in the control of water quality pollution in Xiangjiang River.

Comparing the results in tables 4.2 and 4.4, it is found the average water environmental efficiency of each area based on the closest target model (4.8) was higher than the average classical water environmental efficiency. Compared with the classical environmental efficiency evaluation model (4.4), the water environmental inefficient areas can achieve efficient with the “least” effort through our proposed model (4.8), besides, the closest target for each water environmental inefficient area can be obtained. Furthermore, the water environmental efficiencies of seven cities in Xiangjiang river basin from 2008-2014 were listed in table 4.5.

Table 4.5 Water environmental efficiencies of seven cities in Xiangjiang river basin

	2008	2009	2010	2011	2012	2013	2014	Mean
Yongzhou	1.0000	1.0000	0.9803	1.0000	1.0000	1.0000	0.9455	0.9894
Hengyang	1.0000	0.8609	1.0000	1.0000	0.6969	0.7604	0.6946	0.8590
Zhuzhou	1.0000	0.9858	0.9436	1.0000	1.0000	1.0000	0.9591	0.9841
Xiangtan	1.0000	0.9546	0.9363	1.0000	0.9811	0.9287	1.0000	0.9715
Changsha	0.8884	0.9207	0.9044	0.9752	1.0000	1.0000	1.0000	0.9555
Chenzhou	1.0000	1.0000	0.9244	0.9911	0.8847	0.9203	0.8915	0.9446
Loudi	1.0000	0.9093	0.8789	0.8639	0.8803	0.9016	0.8623	0.8995

It can be clearly seen that the average water environmental efficiency was very high during this period. Compared with the classical water environment efficiency, we find that the water environment efficiency was more stable and the difference between cities was much smaller. The results showed that the closest target of each inefficient city was stable and more easily achieved.

Since the benchmarking analysis of the 15 monitoring areas of each year was similar, we only analyze the closest targets of the areas in 2014 to illustrate the proposed model.

The benchmarks in Table 4.6 provided the closest targets for the 15 monitoring areas to balance the development of economic growth with water environmental protection so as to achieve water environmental efficient. The areas marked in bold were water environmental efficient in 2014, that is the Trunk area of Changsha, and the Leishui area of Chenzhou. Except these areas, the other areas were water environment inefficient that needed to reduce inputs (labour, capital stock and energy consumption) or increase GDP and dissolved oxygen or reduce total phosphorus in order to be efficient. Taking Lianshui area of Loudi as an example, in order to achieve efficient,

we should reduce the labor force of 406.68 units and the energy consumption of 374.551 units, besides, the dissolved oxygen should be increased by 0.140 units and the total phosphorus should be decreased by 0.043 units, while maintaining the gross domestic product (GDP) and capital stock. It is noted that through the proposed method, we can not only measure the water environmental efficiency of each area but also provide the closest target for each inefficient area. Therefore, the proposed method has a strong appeal for guiding local government to formulate relevant economic and environmental policies. For example, if the environmental efficiency of an area performs badly, the government should issue policies to stimulate companies to use high-tech to reduce pollution, or shut down heavily polluted enterprises to reduce environmental pollution.

Table 4.6 Benchmarking analysis of the 15 monitoring areas in 2014

City	Area	Labor	Capital	Energy	DO	TP	GDP
Yongzhou	Xiaoshui	550.068	41.792	0.000	1.903	0.030	0.000
	Trunk	550.068	41.792	0.000	1.445	0.037	0.000
Hengyang	Chunlingshui	184.384	35.211	0.000	0.000	0.000	0.000
	Zhengshui	424.333	41.332	0.000	0.000	0.000	0.000
	Leishui	0.000	0.000	0.000	0.000	0.000	135.443
	Mishui	0.000	0.000	0.000	0.000	0.000	168.212
	Trunk	281.390	24.594	0.000	0.000	0.000	0.000
Zhuzhou	Lushui	540.097	0.000	46.880	2.883	0.011	0.000
	Trunk	174.354	0.000	89.065	3.583	0.000	0.000
Xiangtan	Lianshui	532.808	0.000	380.547	4.686	0.000	0.000
	Trunk	562.859	0.000	377.081	6.703	0.001	0.000
Changsha	Liuyanghe	0.000	0.000	0.000	0.433	0.091	0.000
	Trunk	0.000	0.000	0.000	0.000	0.000	0.000
Chenzhou	Leishui	0.000	0.000	0.000	0.000	0.000	0.000
Loudi	Lianshui	406.680	0.000	374.551	0.140	0.043	0.000

4.5 Conclusions

The previous studies almost set the “furthest” target for a DMU to reach the environmental efficient while measuring the environmental efficiency. In this chapter, in order to make the evaluated DMU to achieve environmental efficiency with least effort, we construct a closest target environmental efficiency evaluation method based on RAM. Besides, the proposed method is applied to investigate the water environmental efficiency of Xiangjiang River Basin in China.

The results show that the average water environmental efficiency of the water system in Xiangjiang River Basin remained at a higher level from 2008-2014. This indicates that Hunan Province had made certain achievements in building a harmonious society with coordinated development of economy and environment. Compared with the classical environmental efficiency method, the water environmental efficiency obtained by the proposed method was higher than the classical method. Moreover, the proposed method can provide the closest target for the inefficient DMU to achieve efficient.

In addition, we find that most water environmental efficient areas are economically developed cities, such as Changsha and Zhuzhou. Therefore, the other inefficient areas can learn from these efficient areas and formulate corresponding policies according to their economic level and environmental conditions to improve the environmental efficiency.

CHAPTER 5

Environmental efficiency evaluation of a two-stage system via total-factor energy efficiency

Contents

5.1 Introduction	61
5.2 Modeling of environmental efficiency evaluation of the two-stage system of China's industry	66
5.3 Application to the environmental efficiency evaluation of China's industry	73
5.3.1 Data and variables	73
5.3.2 Results analysis	74
5.3.3 Benchmarking analysis	81
5.4 Conclusions	83

With the rapid development of China's industry, the problems of growing energy consumption and environmental pollution are drawing increasing attention from government managers and scholars. In this chapter, we divide the industrial system into two stages, i.e., an energy utilization stage and a pollution treatment stage, for accurately evaluating the total-factor energy efficiency as well as the overall environmental efficiency. Based on the two-stage structure of the industrial system, we build a new two-stage data envelopment analysis (DEA) model with shared inputs and apply this model to China's industry.

5.1 Introduction

China has achieved tremendous success in economic development during the past several decades, meanwhile, the government is coping with current internal challenges of energy shortage and environmental degradation. The degradation includes, for example, a shortage of water resources in the western area and desertification in the northwest of the country. China is also facing an urgent problem of environmental

degradation caused by waste gas emissions, such as the heavy haze environmental problem in most of China's provinces (Wang et al., 2014). In order to realize sustainable development, China has to consider how to reduce energy consumption and pollutant emissions while maintaining rapid economic growth. China's 12th Five-Year Plan announced several new energy and CO₂ emission targets to be reached by 2015, reducing China's energy usage by 16%, SO₂ emissions and Chemical Oxygen Demand (COD) by 8%, and CO₂ emissions per unit of GDP by 17%. Targets for each China's provinces have also been announced. One of the critical tools to reduce final energy consumption, improve industrial competitiveness, and reduce pollutant emission is to measure and improve energy and environmental efficiency (Oikonomou et al., 2009). In order to realize the goals of China's 12th Five-Year Plan, it is necessary to analyze the implementation situation of China's 11th Five-Year Plan, so the policymakers can take better measures to improve performance based on the analysis of previous energy and environmental efficiencies.

The literature mainly contains two methods for evaluating energy and environmental efficiency. One is the parametric method stochastic frontier approach (SFA) and the other is non-parametric method data envelopment analysis (DEA). SFA is a parametric estimation method making use of maximum likelihood estimation (MLE). This method uses a parametric modelling approach to measure a "frontier" value and thereby provide a measure to evaluate energy efficiency through the frontier value. Boyd (2005) and Boyd et al. (2008) used SFA method in the American Energy Star Program to calculate an energy performance indicator. Lin and Wang (2014) used the excessive energy-input SFA to analyze the total factor energy efficiency and the corresponding energy conservation potential of China's iron and steel industry. However, pre-determined production functions may not match the reality, and SFA faces challenges when dealing with a multi-output problem. In contrast to SFA, DEA is a non-parametric programming technique for measuring the relative efficiency of a set of homogenous decision making units (DMUs). It was first proposed by Charnes, Cooper and Rhodes in 1978, and not only can deal with multiple outputs and multiple inputs but also has the advantage of having no need to assume any particular functional forms relating to input and output (Charnes et al., 1978; Yang et al., 2011; Johnson and Ruggiero, 2014). A great number and variety of DEA applications and research projects

have led to many new developments related to DEA efficiency. As a result, DEA is a capable method to evaluate energy efficiency and environmental efficiency.

Recently, a growing number of studies have employed conventional DEA models (Hu and Wang, 2006), non-radial DEA models (Fukuyama and Weber, 2009; Zhou et al., 2012; Zhang and Choi, 2013), range-adjusted measure-based DEA (RAM-DEA) models (Wang et al., 2013), and directional distance function (DDF) models (Wang et al., 2013; Zhou et al., 2012) to evaluate energy and environmental efficiency. It is well accepted that the conventional energy efficiency index is actually the partial-factor energy productivity (partial-factor energy efficiency) in which energy is the single input, while non-energy inputs (e.g., labor and capital stock) are neglected and undesirable outputs are not considered. Patterson (1996) gave a detailed discussion of this concept. However, all real-life industrial economic production activities are joint-production processes where both energy resources (e.g., coal, oil, natural gas) and other resources (e.g., labor, capital) are used simultaneously to produce desirable outputs (e.g., GDP) and undesirable outputs such as the emission of pollutants (e.g., solid waste, SO₂, waste water). Therefore, when applied to real-life examples, the methods which only use partial-factor energy productivity to evaluate energy consumption may obtain implausible results (Han et al., 2007; Hu and Wang, 2006). Therefore, it is necessary to take into account total-factor inputs instead of a single energy input while also considering undesirable outputs so as to more exactly evaluate the energy and environmental efficiency. This issue can be well addressed by DEA technique because DEA is applicable to multiple inputs and multiple outputs problems. Based on this idea, some total-factor energy efficiency (TFEE) approaches have been proposed recently. Hu and Wang (2006) used total-factor energy efficiency to evaluate the energy efficiencies of 29 administrative regions in China for the period 1995-2002 and found a U-shape relation between TFEE and per capita income in these regions of China. Zhang et al. (2011) used DEA window analysis to investigate the dynamic trends in the total-factor energy efficiency of a sample of developing countries. Zhao et al. (2014) applied a total-factor energy efficiency index to evaluate the changes of TFEE at the sector and provincial levels. They found that technology progress, energy price and economic development have a positive influence on TFEE based on Tobit regression. In this category of research, not only energy inputs but also non-energy inputs (e.g., labor, capital) are considered when analyzing the desirable outputs. Considering

undesirable outputs, Zhou and Ang (2008) proposed several DEA-type linear programming models which consider both desirable and undesirable outputs in measuring economy-wide total-factor energy efficiency performance. Shi et al. (2010) developed an extended DEA model by treating undesirable outputs as inputs to evaluate the industrial energy efficiency and investigated the maximum energy-saving potential in 28 administrative regions in China. After that, Bai et al. (2012) used a super efficiency DEA method to measure the energy efficiency of 11 provinces in western China from 1989 to 2009, under the framework of total-factor energy efficiency where both desirable outputs and undesirable outputs are considered. Wang et al. (2013) applied the Range-Adjusted Measure (RAM)-based nonparametric approach to evaluate the regional energy and environmental efficiency of China over the period 2006-2010. In their efficiency evaluation models, the energy and non-energy inputs, as well as the desirable and undesirable outputs, are considered to characterize the energy consumption and economic production of several Chinese regions.

Most of the above-mentioned studies investigated the sector or regional total-factor energy efficiency, while rare work has focused on the industrial total-factor energy efficiency and industrial environmental efficiency in China. Industry plays a vital role in the development of the economy in China, as evidenced by the fact that the gross industrial output value (GIOV) accounted for about 38.5% of China's gross domestic product (GDP) in 2012. More importantly, the industrial sector is an energy intensive sector which accounted for 70% of total final energy consumption in 2012 (NBSC, 2013, 2014). Industrial pollution is also the main source of Chinese pollution. Thus, it is urgent and meaningful to study the industrial total-factor energy efficiency and industrial environmental efficiency in China. In addition, the industrial system not only creates economic outputs, but also produces industrial pollution, such as industrial solid waste, industrial waste water, and industrial waste gas. Therefore, the environmental efficiency evaluation of the industrial system can not only evaluate the operation of the industrial system, but also obtain specific measures to improve the environmental efficiency so as to realize the sustainable development of the economy and the environment. However, almost all previously published works considered the industrial system as a "black box" when they measured the environmental efficiency of industrial system, which probably has resulted in ignorance of some deficiencies in the system. In this chapter, we divide the process of energy consumption and utilization in

China's industry into two stages: the industrial energy utilization stage and the industrial pollution treatment stage. In the energy utilization stage, the main work is to produce the industrial products, while in industrial pollution treatment stage, the main work is to dispose of the pollution produced in the first stage. Accordingly, the provincial industrial overall environmental efficiency is decomposed into two parts, industrial energy utilization efficiency and industrial pollution treatment efficiency. Through analyzing the two-stage structure of China's industry's energy consumption process, we can effectively investigate the inefficiencies of the internal structure of the system and provide valuable managerial insights when assessing the dual impacts of operating and business strategies for China's industrial sector.

So far, many published works have studied two-stage structure systems. Hampf (2014) proposed a model that described a two-stage process to measure the environmental efficiency and applied the model to an analysis of US power plants. Cook et al. (2010) reviewed related DEA publications on two-stage systems, i.e., two-stage DEA models, where the outputs from the first stage are intermediate measures and taken as the inputs for the second stage. Halkos et al. (2014) reviewed the DEA works for an extensive two-stage systems which allow "exogenous" inputs as intermediate measures. Based on these two reviews, we briefly overview the works on two-stage systems as follows. i) The standard two-stage DEA approach proposed by Wang et al. (1997) and Seiford and Zhu (1999). ii) The network DEA approach proposed by Färe and Grosskopf (1996). iii) The relational two-stage DEA approach proposed by Kao and Hwang (2008) and Chen et al. (2009), which assumes a multiplicative or additive relationship between overall efficiency and divisional efficiencies. iv) The game-theoretic two-stage DEA approach proposed by Liang et al. (2008), which considers the two stages as two players in a game. Because we want to obtain benchmarks of the evaluated DMUs while measuring their environmental efficiencies, we chose the network DEA approach. Based on this approach, a new two-stage DEA model is built to firstly obtain the overall environmental efficiency and the benchmark for each province's industry. Then, according to the benchmarks, we can further obtain the industrial total factor energy efficiency by the ratio of the expected energy consumption and the actual energy consumption.

5.2 Modeling of environmental efficiency evaluation of the two-stage system of China's industry

Currently, most studies on environmental efficiency have considered the evaluated system as a single stage without considering its internal structure. As a result, there is no clear evidence of the transformations to which the inputs are subject within the considered units (Castelli et al., 2010). In contrast to the single-stage DEA model, two-stage DEA models show the performance of the individual stages and thus are more informative for decision-makers. For our study of the industrial environmental efficiency evaluation in China, we divide the industrial production process into two sub-processes: the energy utilization process and the pollution treatment process. The former sub-process focuses on using energy and non-energy inputs to produce the desirable outputs and undesirable outputs, while the latter sub-process focuses on the recycling and disposing of the pollution and wastes which are produced in the former.

In keeping with previous works for measuring energy and environmental efficiency and the characteristics of China's industry, for the first stage we select the indices of industrial labor force (ILF), industrial capital (IC), and industrial energy consumption (IEC) as the inputs, and choose the indices of gross industrial output value (GIOV), industrial solid wastes generated (ISWG), industrial waste water discharged (IWWD), and industrial waste gas emitted (IWGE) as the outputs (Wu et al., 2014; Shi et al., 2010). Here, we employ "the net value of fixed assets" to reflect the "capital" which is the same as in the previous work of Wang and Wei (2014). It is clear that other than GIOV, all outputs are undesirable outputs. In addition, we consider industrial capital (IC) and industrial labor force (ILF) as non-energy inputs and the industrial energy consumption (IEC) as the energy input in the first stage. For the second stage, we select industrial labor force (ILF), industrial capital (IC), investment in industrial pollution treatment (IIPT), and the undesirable outputs from the first stage as its inputs, and product output value by disposing of and utilizing solid waste, waste water, and waste gas (POVW) as its outputs. The structure can be seen in Figure 5.1.

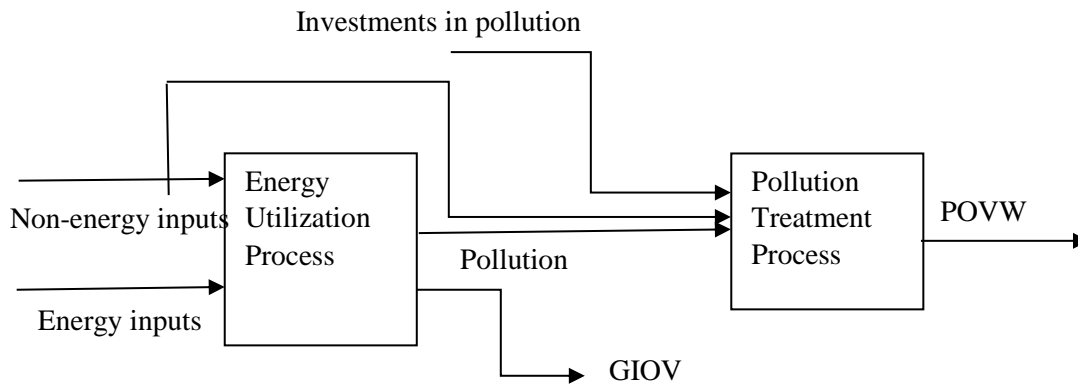


Figure 5.1 Two-stage structure system of China's industry

It is evident that in the industrial system, industrial labor force and industrial capital are used in both the energy utilization stage and the pollution treatment stage. For example, some labors work in both stages by repairing equipment such as lights and machines. Thus, these resources are shared inputs for both sub-processes. In regard to shared inputs, so far there are several approaches, such as weighted restrictions (Beasley, 1995; Cook et al., 2000) and an additive objective function (Cook and Hababou, 2001). Notably, these works did not consider the internal structure of the processes. In dealing with shared inputs in the network production, Yu and Lin (2008) evaluated the railway performances in a multi-activity network framework with shared inputs. Zha and Liang (2010) developed an approach to measure the performance of a two-stage production process in series, where the shared inputs could be freely allocated among different stages.

As we have mentioned, the industrial energy consumption in China can be divided into an energy utilization process and a pollution treatment process, in which the undesirable outputs in the energy utilization process are part of the inputs of the pollution treatment process. Assume there are n DMUs, each of which represents the industry of an administrative region of China ($DMU_j, j = 1, \dots, n$). Denote the shared inputs by $X_j = (x_{1j}, \dots, x_{Mj})$ and energy inputs by $Z_j = (z_{1j}, \dots, z_{Kj})$ in the first stage. The desirable outputs of the first stage are denoted by $D_j = (d_{1j}, \dots, d_{Sj})$, and the undesirable outputs of the first stage by $U_j = (u_{1j}, \dots, u_{Fj})$ which are also the inputs of the second stage, the new inputs of the second stage by $I_j = (i_{1j}, \dots, i_{Gj})$ and the outputs of the second stage by $Y_j = (y_{1j}, \dots, y_{Hj})$. Denote the DMU being evaluated by DMU_0 .

In our study of industrial environmental efficiency, the undesirable outputs (pollutants) are mainly generated by energy inputs in the production process and should be reduced if energy consumption is reduced. Therefore, we apply the weak disposability assumption to deal with undesirable outputs. As expressed in Färe and Grosskopf (2004), weak disposability indicates that a Null-Joint relationship exists between desirable outputs and undesirable outputs in the production process, which means desirable outputs and undesirable outputs should be reduced in a proportional way (see more details about this assumption in Färe et al., 1989; Tone, 2004; Zhou et al., 2008). The assumption of weak disposability is important because it enables us to model undesirable outputs in DEA models, considering the possible tradeoffs between the desirable outputs and the undesirable outputs. Analogous to Kuosmanen (2005)'s way of defining production technology under the variable return to scale that satisfies weak-disposability assumption, the related production possibility set (PPS) of the industrial two-stage system shown in Figure 5.1 is given as follows.

$$T_{two-stage} = \left\{ \begin{array}{l} (x, z, d, u, i, y) | \\ \text{Stage 1 constraints:} \\ \sum_{j=1}^n (\rho^j + \mu^j) \alpha^j x_m^j \leq \alpha^{j'} x_m, \quad m = 1, \dots, M \\ \sum_{j=1}^n (\rho^j + \mu^j) z_k^j \leq z_k, \quad k = 1, \dots, K \\ \sum_{j=1}^n \rho^j d_s^j \geq d_s, \quad s = 1, \dots, S \\ \sum_{j=1}^n \rho^j u_f^j = u_f, \quad f = 1, \dots, F \\ \text{Stage 2 constraints:} \\ \sum_{j=1}^n \rho^j u_f^j = u_f, \quad f = 1, \dots, F \\ \sum_{j=1}^n (\rho^j + \mu^j) i_g^j \leq i_g, \quad g = 1, \dots, G \\ \sum_{j=1}^n (\rho^j + \mu^j) (1 - \alpha^j) x_m^j \leq (1 - \alpha^{j'}) x_m, \quad m = 1, \dots, M \\ \sum_{j=1}^n (\rho^j + \mu^j) y_h^j \geq y_h, \quad h = 1, \dots, H \\ \text{generic constraints:} \\ \sum_{j=1}^n (\rho^j + \mu^j) = 1 \\ \rho^j, \mu^j \geq 0, \quad j = 1, \dots, n \end{array} \right\} \quad (5.1)$$

In this formula, α^j ($0 < \alpha^j < 1$) is the portion of shared inputs used by the first stage of DMU_j , while $1 - \alpha^j$ is the portion of shared inputs consumed by the second stage of DMU_j . This system is expressed in terms of the unknown parameters ρ^j, μ^j . $\sum_{j=1}^n \rho^j u_f^j = u_f$ represents the weak disposability assumption about the undesirable outputs. $\sum_{j=1}^n (\rho^j + \mu^j) = 1$ models our requirement of the variable returns to scale assumption. It should be noted that the production possibility set uses the same intensity variables ρ^j, μ^j in the two stages. That is because we want the two sub-processes of the industry to cooperate to achieve the overall environmental efficiency of the system, with the two stages working under the control of a centralized decision-maker. Thus, the two stages jointly determine one optimal plan to maximize the overall environmental efficiency of the system. This way of addressing the intensity vector in PPS can be also found in Maghbouli et al. (2014). Based on this production possibility

set, we can build the following centralized model, which integrates the two stages under the control of a centralized decision-maker, for measuring the overall environmental efficiency of the two-stage system.

$$\begin{aligned}
 \min e_0 &= \frac{1}{2} \left[\frac{1}{M+K+F} \left[\sum_{m=1}^M \beta_m + \sum_{k=1}^K \delta_k + \sum_{f=1}^F \theta_f \right] + \frac{1}{F+G+M} \left[\sum_{f=1}^F \theta_f + \sum_{g=1}^G \phi_g + \sum_{m=1}^M \varphi_m \right] \right] \\
 \text{s.t.} \\
 \text{Stage 1 constraints:} \\
 \sum_{j=1}^n (\rho^j + \mu^j) \alpha^j x_m^j &\leq \beta_m \alpha^0 x_m^0, & m = 1, \dots, M \\
 \sum_{j=1}^n (\rho^j + \mu^j) z_k^j &\leq \delta_k z_k^0, & k = 1, \dots, K \\
 \sum_{j=1}^n \rho^j d_s^j &\geq d_s^0, & s = 1, \dots, S \\
 \sum_{j=1}^n \rho^j u_f^j &= \theta_f u_f^0, & f = 1, \dots, F \\
 \text{Stage 2 constraints:} \\
 \sum_{j=1}^n \rho^j u_f^j &= \theta_f u_f^0, & f = 1, \dots, F \\
 \sum_{j=1}^n (\rho^j + \mu^j) i_g^j &\leq \phi_g i_g^0, & g = 1, \dots, G \\
 \sum_{j=1}^n (\rho^j + \mu^j) (1 - \alpha^j) x_m^j &\leq \varphi_m (1 - \alpha^0) x_m^0, & m = 1, \dots, M \\
 \sum_{j=1}^n (\rho^j + \mu^j) y_h^j &\geq y_h^0, & h = 1, \dots, H \\
 \text{generic constraints:} \\
 \sum_{j=1}^n (\rho^j + \mu^j) &= 1 \\
 LW^j &\leq \alpha^j \leq UP^j & j = 1, \dots, n \\
 \rho^j; \mu^j &\geq 0, & j = 1, \dots, n \\
 0 \leq \beta_m, \delta_k, \theta_f, \phi_g, \varphi_m &\leq 1, & \text{for all } m, k, f, g, m.
 \end{aligned} \tag{5.2}$$

In this formula, we treat the two stages as equally important, and the constraints $0 \leq \beta_m, \delta_k, \theta_f, \phi_g, \varphi_m \leq 1$ are the limitation for improvement. Constraint $LW^j \leq \alpha^j \leq UP^j$ is used to avoid extreme and unrealistic values being chosen. The optimal value e_0^* is defined as the overall environmental efficiency of DMU_0 . When e_0^* is 1, the whole system is environmental efficient; otherwise, it is environmental inefficient. The overall environmental efficiency can be decomposed into two terms: the first term

$e_{10} = \frac{1}{M+K+F} \left[\sum_{m=1}^M \beta_m + \sum_{k=1}^K \delta_k + \sum_{f=1}^F \theta_f \right]$ is the efficiency of the first stage, i.e.,

energy utilization efficiency; the second one $e_{20} = \frac{1}{F + G + M} \left[\sum_{f=1}^F \theta_f + \sum_{g=1}^G \phi_g + \sum_{m=1}^M \varphi_m \right]$

is the efficiency of the second stage, i.e., pollution treatment efficiency. If the optimal value of the first term $e_{10}^* = 1$, the first stage is efficient; If the optimal value of the second term $e_{20}^* = 1$, the second stage is efficient. It can be easily known that the system is overall environmental efficient if and only if the two stages are both efficient.

This model is a non-linear programming model. Let $\rho^j \alpha^j = a^j$, $\mu^j \alpha^j = b^j$, we can transform the model as follows:

$$\begin{aligned} \min e_0 &= \frac{1}{2} \left[\frac{1}{M + K + F} \left[\sum_{m=1}^M \beta_m + \sum_{k=1}^K \delta_k + \sum_{f=1}^F \theta_f \right] + \frac{1}{F + G + M} \left[\sum_{f=1}^F \theta_f + \sum_{g=1}^G \phi_g + \sum_{m=1}^M \varphi_m \right] \right] \\ \text{s.t.} \\ \text{Stage 1 constraints:} \\ \sum_{j=1, j \neq j_0}^n (a^j + b^j) x_m^j + (a^0 + b^0) x_m^0 &\leq \beta_m \alpha^0 x_m^0, & m = 1, \dots, M \\ \sum_{j=1}^n (\rho^j + \mu^j) z_k^j &\leq \delta_k z_k^0, & k = 1, \dots, K \\ \sum_{j=1}^n \rho^j d_s^j &\geq d_s^0, & s = 1, \dots, S \\ \sum_{j=1}^n \rho^j u_f^j &= \theta_f u_f^0, & f = 1, \dots, F \\ \text{Stage 2 constraints:} \\ \sum_{j=1}^n \rho^j u_f^j &= \theta_f u_f^0, & f = 1, \dots, F \\ \sum_{j=1}^n (\rho^j + \mu^j) i_g^j &\leq \phi_g i_g^0, & g = 1, \dots, G \\ \sum_{j=1, j \neq j_0}^n (\rho^j + \mu^j - a^j - b^j) x_m^j + (\rho^0 + \mu^0 - a^0 - b^0) x_m^0 &\leq \varphi_m (1 - \alpha^0) x_m^0, & m = 1, \dots, M \\ \sum_{j=1}^n (\rho^j + \mu^j) y_h^j &\geq y_h^0, & h = 1, \dots, H \\ \text{generic constraints:} \\ \sum_{j=1}^n (\rho^j + \mu^j) &= 1 \\ LW^0 &\leq \alpha^0 \leq UP^0 \\ LW^j * \rho^j &\leq a^j \leq UP^j * \rho^j & j = 1, \dots, n, \\ LW^j * \mu^j &\leq b^j \leq UP^j * \mu^j & j = 1, \dots, n, \\ \rho^j, \mu^j; a^j, b^j &\geq 0, & j = 1, \dots, n, \\ 0 \leq \beta_m, \delta_k, \theta_f, \phi_g, \varphi_m &\leq 1, & \text{for all } m, k, f, g, m. \end{aligned} \tag{5.3}$$

Model (5.3) is still non-linear since $\beta_m \alpha^0$ and $\varphi_m \alpha^0$ exist in some constraints. If we fix the value of variable α^0 , model (5.3) becomes a parametric linear program which can be efficiently solved by the following algorithm.

- a. In computation, the initial value for α^0 will be set as the value LW^0 , and then its corresponding linear program can be solved. If it is feasible, its corresponding objective optimal value can be obtained.
- b. Increase α^0 by a very small positive number ε ($=0.00001$ for example) for each step t , resulting in $\alpha_t^0 = LW^0 + t \times \varepsilon, t = 1, \dots$, until the upper bound of UP^0 is reached. For each α_t^0 , we can obtain a corresponding objective optimal value ed_0^t if its corresponding model is feasible.
- c. Comparing all the optimal objective values, $ed_0^t, t = 1, 2, \dots$, we can obtain the smallest value, denoted by e_0^* . Then e_0^* is just the optimal objective value of model (5.3). At the same time, we can obtain the efficiency of the first stage by e_{10}^* and the second stage by e_{20}^* .

By using the above algorithm, the non-linear model can be solved and the optimal values $\rho^{j*}, \mu^{j*}, \alpha^{j*}, b^{j*}, \beta_m^*, \delta_k^*, \theta_f^*, \phi_g^*, \varphi_m^*$, the overall environmental efficiency of the system e_0^* and the efficiency of the first stage by e_{10}^* and the second stage by e_{20}^* are obtained. Besides, according to Hu and Wang (2006), the total-factor energy efficiency (TFEE) index is defined as the ratio of the expected energy consumption to the actual energy consumption in a multi-factor production progress. Based on this, we can derive the TFEE index of DMU_0 by the proposed model in this chapter as follows:

$$TFEE_0 = \frac{\text{Expected Energy Consumption of } DMU_0}{\text{Actual Energy Consumption of } DMU_0} = \frac{1}{K} \sum_{k=1}^K \delta_k^* \quad (5.4)$$

5.3 Application to the environmental efficiency evaluation of China's industry

In this section, we will use the proposed two-stage DEA model to evaluate the industrial energy efficiency, industrial overall environmental efficiency, industrial energy utilization efficiency, and industrial pollution treatment efficiency of 30 provinces in China. The corresponding strategy and policy implications are discussed in order to propose guidelines for the improvement of the industrial performance of different provinces.

5.3.1 Data and variables

This study uses the data of 30 provinces in China to estimate their energy and environmental efficiencies during the 11th Five-Year plan period (2006-2010). It should be noted that after the year of 2011, indicators of statistical system, method of survey and related technologies were revised by the Ministry of Environmental Protection, so the data in these years are not included for our analysis. As mentioned in Section 5.2, the input and output variables employed in this study include industrial labor force (ILF), industrial capital (IC), industrial energy consumption (IEC), investment on industrial pollution treatment (IIPT), gross industrial output value (GIOV), industrial solid wastes generated (ISWG), industrial waste water discharged (IWWD), industrial waste gas emitted (IWGE), and product output value by disposing of and utilizing solid waste, waste water, and waste gas (POVW). The dimension of these variables are in Ten thousand employees, Billion RMB, Ten thousand tons of standard coal, Billion RMB, Million tons, Tons, Million tons, Million RMB, and Billion RMB, respectively. The data are collected from the China Statistical Yearbook, China Energy Statistical Yearbook, and China Statistical Yearbook on Environment for each of the years 2007-2011. Because many data of Tibet are not available in the statistics, Tibet is not considered in our analysis. Descriptive statistical analysis on these variables are shown in Table 5.1.

Table 5.1 Descriptive statistical analysis of inputs and outputs

	Variables	ILF	IC	IEC	GLOV	ISWG	IWGE	IWWD	IIPT	POVW
2006	Mean	172.3	1690.9	6779.2	3418.4	5051.1	74.4	80038.5	161311.9	342258.6
	Std.dev.	124.8	1543.9	4391	3296.7	3759.6	44.7	70312.9	142217.9	377342.1
	Max	496.4	6894.8	18731.3	12500.2	14229	168.7	287181	596643.1	1497950.1
	Min	13	134.8	644	217.6	147	2.3	7168	7773.2	10369.2
2007	Mean	178.4	2021.7	7442.7	4110.4	5854.2	71.3	82187.9	184123	450404.5
	Std.dev.	130.3	1734.1	4816	3872.2	4503.9	42	72683.2	159263.5	523786
	Max	505.9	7177.8	20423.9	14910	18688	158.3	268762	673420	2240597.9
	Min	14.1	83.3	739.9	278.4	158	2.5	5960	3889	20431.2
2008	Mean	178.4	2541.7	7879.7	4965.1	6337.3	66.4	80519.6	180880	540441.2
	Std.dev.	132.5	2053.4	5032.7	4517	4857.2	38.9	71152.9	168893.4	592634.8
	Max	498	8342.4	21399	17254	19769	146.6	259999	844159	2409843
	Min	14.7	119.5	794.5	321.2	220	2.1	5991	3774	41309
2009	Mean	184.3	3176.9	8335.6	5248.8	6797.7	62.2	78097.2	147540.3	536073.5
	Std.dev.	139.6	2502.9	5293.6	4750.7	5160.8	36.3	67539.6	108913	581425.5
	Max	528.5	10304.6	22694	18091.6	21975.8	136.6	256160	515832	2513210
	Min	16	144	863.1	300.6	200.9	2.1	7031	3563	24440
2010	Mean	192.5	3903.5	9088.6	6442.6	8031	62.1	79133.2	132325.7	592826.5
	Std.dev.	150	2978	5720.7	5475.8	6635.8	36.1	70357.6	105065.6	650121.4
	Max	563.2	12463.1	24365.6	21462.7	31688	138.3	263760	456759	2863867.2
	Min	17.1	191.6	951.3	385.2	212	2.8	5782	4354	31623.2

From Table 5.1, it can be observed that the mean values of labor force, capital, and industrial energy consumption increase year by year, which means that the industrial investments of each province increased these years. The standard deviations of all the nine variables are high, which implies that there may be uneven economic and social development across different provinces.

5.3.2 Results analysis

Through our models (5.3) and (5.4) in Section 5.3, we can obtain the overall environmental efficiency, the efficiency of two stages, and the total factor energy efficiency of the industrial system in each Chinese province when setting the lower bound and upper bounds of α^j to 3% and 97% respectively. The results are shown in Table 5.2.

Table 5.2 Four kinds of efficiencies of industry in 30 regions of China from 2006-2010

	Total factor energy efficiency					Overall environmental efficiency				
	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010
Beijing	0.934	0.957	1.000	1.000	1.000	0.737	0.759	1.000	1.000	1.000
Tianjin	0.606	0.680	1.000	0.933	1.000	0.662	0.663	1.000	0.947	1.000
Hebei	0.578	0.955	1.000	0.822	1.000	0.416	0.516	1.000	0.634	1.000
Shanxi	0.701	0.715	0.895	0.500	0.732	0.312	0.415	0.458	0.394	0.453
Inner Mongolia	0.604	0.665	0.921	0.932	1.000	0.296	0.451	0.646	0.807	1.000
Liaoning	0.424	0.662	0.643	0.669	0.635	0.313	0.404	0.458	0.471	0.579
Jilin	0.264	0.484	0.626	0.625	1.000	0.413	0.445	0.524	0.567	1.000
Heilongjiang	0.347	0.390	0.967	0.603	0.800	0.485	0.489	0.662	0.500	0.843
Shanghai	0.975	0.734	0.850	1.000	1.000	0.814	0.735	0.842	1.000	1.000
Jiangsu	0.835	1.000	1.000	1.000	1.000	0.646	0.759	1.000	0.912	1.000
Zhejiang	0.904	1.000	1.000	0.923	1.000	0.683	1.000	0.938	0.876	1.000
Anhui	0.735	0.675	0.660	0.674	0.758	0.360	0.398	0.514	0.503	0.666
Fujian	0.478	0.319	0.499	0.612	0.338	0.396	0.423	0.455	0.505	0.550
Jiangxi	0.751	0.567	0.649	0.665	0.705	0.376	0.416	0.477	0.549	0.642
Shandong	0.579	0.729	1.000	1.000	1.000	0.520	0.596	0.797	0.931	1.000
Henan	0.485	0.712	0.657	0.599	0.829	0.403	0.436	0.554	0.563	0.740
Hubei	0.546	0.549	0.636	0.800	0.754	0.431	0.475	0.516	0.541	0.609
Hunan	0.937	0.938	0.863	0.758	0.785	0.394	0.445	0.515	0.529	0.655
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guangxi	0.439	0.834	0.789	0.786	0.871	0.362	0.408	0.455	0.443	0.543
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chongqing	0.279	0.653	0.571	0.759	0.736	0.312	0.327	0.388	0.491	0.579
Sichuan	0.667	0.834	0.545	0.563	0.745	0.345	0.354	0.400	0.464	0.640
Guizhou	0.575	0.804	0.836	0.752	0.808	0.371	0.408	0.457	0.402	0.436
Yunnan	0.908	0.990	1.000	0.975	1.000	0.507	0.585	1.000	0.634	1.000
Shaanxi	0.840	0.594	0.599	0.613	0.707	0.359	0.383	0.415	0.432	0.520
Gansu	0.889	0.719	0.884	0.762	0.725	0.349	0.436	0.484	0.495	0.527
Qinghai	1.000	0.921	1.000	0.972	1.000	1.000	0.896	1.000	0.771	1.000
Ningxia	0.278	0.592	0.702	0.628	0.862	0.320	0.331	0.375	0.373	0.557
Xinjiang	0.671	0.398	0.744	0.582	0.721	0.391	0.399	0.457	0.407	0.559
Average	0.674	0.736	0.818	0.784	0.850	0.499	0.545	0.660	0.638	0.770

Table 5.2 (continued)

	Efficiency of the first stage					Efficiency of the second stage				
	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010
Beijing	0.771	0.811	1.000	1.000	1.000	0.702	0.707	1.000	1.000	1.000
Tianjin	0.672	0.732	1.000	0.975	1.000	0.652	0.593	1.000	0.920	1.000
Hebei	0.383	0.556	1.000	0.600	1.000	0.448	0.477	1.000	0.667	1.000
Shanxi	0.398	0.422	0.517	0.368	0.469	0.227	0.408	0.399	0.420	0.438
Inner Mongolia	0.353	0.464	0.638	0.806	1.000	0.239	0.437	0.654	0.809	1.000
Liaoning	0.329	0.452	0.491	0.514	0.562	0.296	0.356	0.424	0.429	0.595
Jilin	0.341	0.439	0.545	0.583	1.000	0.485	0.451	0.504	0.550	1.000
Heilongjiang	0.403	0.432	0.720	0.505	0.816	0.566	0.546	0.603	0.495	0.870
Shanghai	0.807	0.745	0.843	1.000	1.000	0.822	0.725	0.841	1.000	1.000
Jiangsu	0.661	0.809	1.000	0.939	1.000	0.631	0.709	1.000	0.885	1.000
Zhejiang	0.744	1.000	0.948	0.900	1.000	0.621	1.000	0.927	0.852	1.000
Anhui	0.454	0.471	0.536	0.545	0.670	0.266	0.325	0.492	0.461	0.662
Fujian	0.432	0.406	0.499	0.554	0.513	0.359	0.439	0.411	0.457	0.588
Jiangxi	0.470	0.438	0.508	0.549	0.657	0.282	0.394	0.446	0.548	0.626
Shandong	0.542	0.628	0.840	0.948	1.000	0.498	0.564	0.753	0.914	1.000
Henan	0.404	0.512	0.562	0.539	0.723	0.402	0.359	0.547	0.586	0.757
Hubei	0.415	0.442	0.511	0.604	0.650	0.447	0.507	0.520	0.478	0.569
Hunan	0.514	0.545	0.581	0.565	0.660	0.275	0.346	0.449	0.493	0.650
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guangxi	0.309	0.454	0.462	0.473	0.553	0.416	0.361	0.448	0.414	0.532
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chongqing	0.263	0.414	0.427	0.555	0.619	0.362	0.240	0.350	0.427	0.540
Sichuan	0.400	0.472	0.415	0.455	0.602	0.291	0.237	0.386	0.473	0.679
Guizhou	0.343	0.442	0.490	0.439	0.478	0.399	0.375	0.424	0.364	0.394
Yunnan	0.536	0.606	1.000	0.664	1.000	0.479	0.563	1.000	0.605	1.000
Shaanxi	0.499	0.435	0.467	0.492	0.592	0.219	0.331	0.362	0.371	0.449
Gansu	0.489	0.448	0.528	0.531	0.565	0.210	0.424	0.441	0.460	0.488
Qinghai	1.000	0.873	1.000	0.849	1.000	1.000	0.919	1.000	0.693	1.000
Ningxia	0.258	0.363	0.423	0.395	0.617	0.381	0.299	0.327	0.351	0.497
Xinjiang	0.430	0.346	0.495	0.410	0.555	0.352	0.451	0.419	0.403	0.564
Average	0.521	0.572	0.682	0.659	0.777	0.478	0.518	0.638	0.617	0.763

Firstly, we focus on the total factor energy efficiencies of China's industrial sector. It can be seen from Table 5.2 that average total factor energy efficiency of industry increased from 0.674 in 2006 to 0.850 in 2010. Guangdong and Hainan province were energy efficient during this period. In addition to these total factor energy efficient regions, Beijing city and Jiangsu province had high total factor energy efficiencies. This indicates that the performance in terms of energy utilization in these regions was relatively good. Analyzing these regions, we find that Guangdong, Beijing, Jiangsu are well-developed regions. Maybe the good local economy encouraged these regions to introduce more new high technology and incorporate advanced machinery in production, with the result that the energy was used more effectively. In the future, the low-energy-efficiency regions could investigate the techniques in these high-energy-efficiency regions and learn from others' experience to improve their own performance in energy utilization.

Returning to Table 5.2, we can also see that the overall environmental efficiency as well as the efficiency of stage 1 and the efficiency of stage 2 improved significantly from 2006 to 2010 for the most provinces. It should be noted that using our approach, the three kinds of efficiencies of any region in Table 5.2 are relative efficiencies which are obtained by comparison with other regions' performances. In this chapter, the overall environmental efficiency measures the efficiency of a whole industrial production process, considering both the first and second stages. The overall environmental efficiency of a region's industry is calculated as the average of the efficiencies of its two stages. The overall environmental efficiencies listed from column 7 to 11 show four kinds of scenarios. 13 regions' overall environmental efficiencies of industry increased year by year, namely Inner Mongolia, Liaoning, Jilin, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Chongqing, Sichuan, Shaanxi, and Gansu. Two other regions improved their industrial overall environmental efficiencies to be efficient and then maintained that efficiency, namely Beijing and Shanghai. Two other provinces, namely Guangdong and Hainan, were efficient for the whole study period. All the other regions' industrial overall environmental efficiencies fluctuated during these years.

The average value of overall environmental efficiencies of all regions increased year by year from 0.499 in 2006 to 0.770 in 2010, which shows that China's industrial performance became better during the "11th Five-Year Plan". Similar phenomena can also be seen in the divisional efficiencies in Table 5.2. Comparing the efficiencies of

two stages, we find that the first stage efficiencies were better than the second stage, but the gap decreased. At the end of 2010, the average efficiencies of two stages were at almost the same level. This phenomenon was because Chinese government paid more and more attention to environmental pollution. During this period, the government enacted many policies for environment protection which encouraged green industry and punished polluting enterprises. Examples of such policies are the “China National Environmental Protection Plan in the Eleventh Five-Years (2006-2010)” and the “Measures for the Administrative Penalties for Environmental Protection (2010)”.

In order to analyze the efficiency trends of provinces from a larger scale viewpoint, we classify these 30 regions into six administrative areas: North China, Northeast China, East China, South Central China, Southwest China, and Northwest China, according to the administrative area division of China. The provinces of each area are shown in Table 5.3.

Table 5.3 Six administrative areas

Area	Provinces
North China	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia
Northeast China	Liaoning, Jilin, Heilongjiang
East China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
South Central China	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan
Southwest China	Chongqing, Sichuan, Guizhou, Yunnan
Northwest China	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Based on the area division, we can obtain the total factor energy efficiencies, overall environmental efficiencies, efficiencies of stage 1, and efficiencies of stage 2 of the six areas during 2006-2010 by averaging all corresponding provincial efficiencies. The results are shown in Figure 5.2.

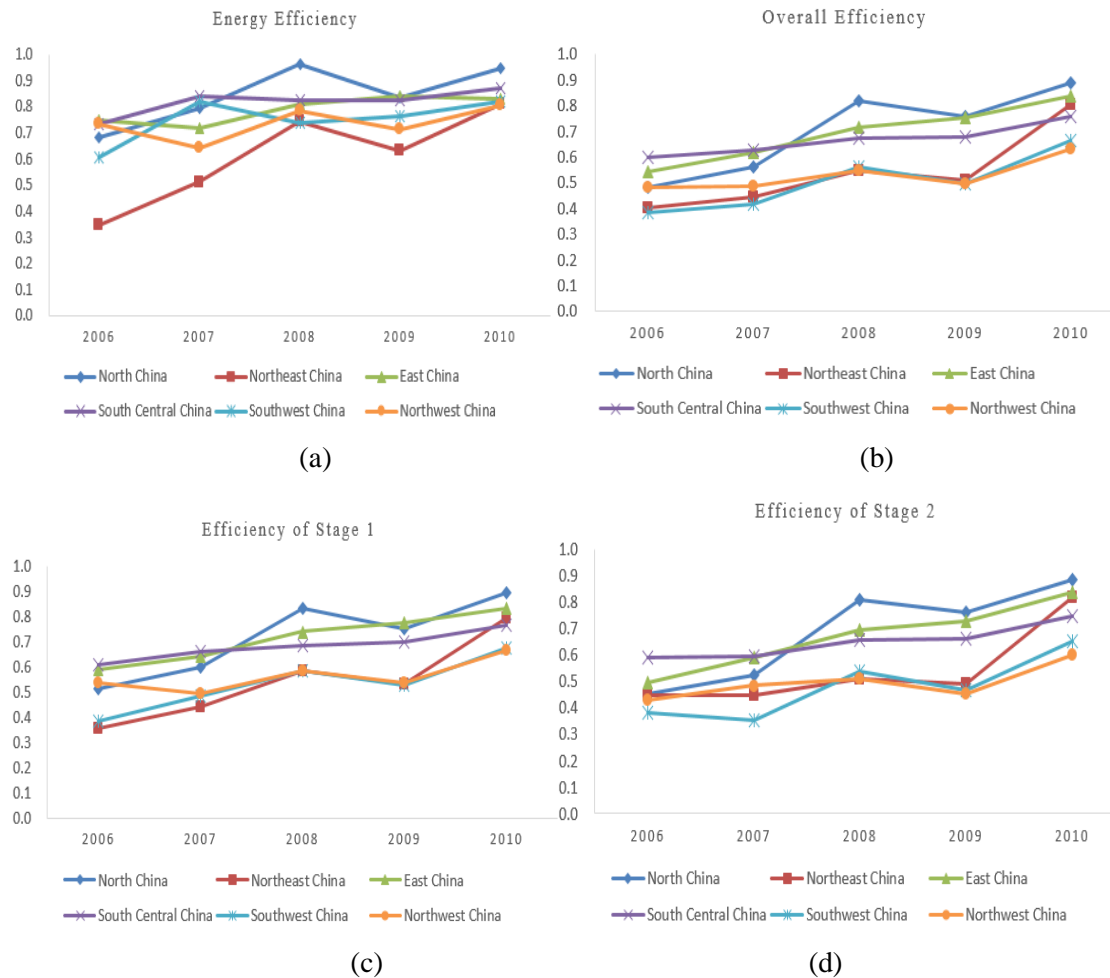


Figure 5.2 The industrial efficiencies of different areas in China

To analyze the differences among the four kinds of efficiencies in the six areas, we average all the values of the same kind of efficiency during the period. The results are shown in Table 5.4.

Table 5.4 Average efficiency of six administrative areas during 2006-2010

	Total factor energy efficiency	Overall environmental efficiency	Efficiency of stage 1	Efficiency of stage 2
North China	0.8452	0.7026	0.7174	0.6879
Northeast China	0.6094	0.5435	0.5422	0.5448
East China	0.7889	0.6936	0.7159	0.6714
South Central China	0.8189	0.6673	0.6826	0.6519
Southwest China	0.7500	0.5051	0.5310	0.4792
Northwest China	0.7362	0.5294	0.5624	0.4964

Through Figure 5.2 (a), we know that Northeast China's total factor energy efficiencies increased the most, being only 0.345 in 2006 but 0.812 in 2010. The other areas' total factor energy efficiencies were fluctuant with an increasing trend. North China had the largest total factor energy efficiency starting in 2008. Combining the data in Table 5.4, we see that North China also had the largest average total factor energy efficiency, followed by South Central China, East China, Southwest China, Northwest China and Northeast China. North China had the best performance because many industrial enterprises there, such as enterprises in Beijing and Tianjin, employed high technology instead of the traditional technology for production. As for the Northwest area, although it has a large amount of natural resources, its average total factor energy efficiency was the lowest, which may be because the local government did not pay enough attention to the technology of energy utilization.

From Figure 5.2 (b), we can also see that the overall environmental efficiencies of the six areas all had an increasing trend during those years. In addition, the overall environmental efficiencies of North China, East China, and South Central China were higher than other areas on average. North China, Southwest China, and Northwest China had a significant decline in 2009, which may have been caused by the global economic crisis in 2008. Different from these three areas, East China maintained steadily growth during 2006-2010, which showed that their industry had strong ability to resist economic difficulties. This is consistent with the real situation of industry in East China and reflects the validity of our approach. Looking at the two stages' efficiencies shown in (c) and (d) of Figure 5.2, we find that they had the same situation as the overall environmental efficiencies. Besides, most of the first stage efficiencies were larger than the second stage efficiencies in the same year for these six areas. This indicates that the main inefficiencies of the industrial system were caused by the second stage, i.e., the pollution treatment stage. In 2010, however, these two stages' efficiencies were nearly at the same level which indicated that the work of pollution treatment had made great progress in those years.

To sum up, four kinds of efficiencies of the six areas all had an increasing trend. North China, East China, and South Central China had relatively better performances than the other areas. This phenomenon indicates that the efficiency in China has a regional character. Compared with the areas of Northeast, Southwest, and Northwest China, the areas of North China, East China, and South Central China are more

attractive for skilled laborers and qualified enterprises. Many skilled laborers in Northwest China migrate to other regions seeking employment in places such as Beijing in North China, Shanghai in East China, and Guangzhou in South Central China. Moreover, the natural resources in the Northeast and Southwest were limited, which can be seen from the China Energy Statistical Yearbook 2007-2011. With the development of China's domestic transportation system, the disadvantages of location for Northeast and Southwest areas becomes weaker since they can get resources more easily. Based on these results, we suggest that the Chinese government should pay attention to the differences among areas to balance the development of China's industry.

5.3.3 Benchmarking analysis

Through our models, we can also obtain benchmarks for these industries to become overall environmental efficient. In other words, we can set the targets of inputs and outputs so that achieving those goals would make the industry overall efficient. Because our model is a two-stage input-oriented model, if the evaluated DMU intends to achieve efficiency, the DMU can reduce its two sub-processes' inputs and undesirable outputs simultaneously. For ease of illustration, we take only the year 2010 as an example. The benchmarks of provinces are shown in Table 5.5.

Table 5.5 Benchmarks for China's industry

	ILF	IC	IEC	ISWG	IWGE	IWWD	ILF	IC	IPT
Beijing	58.382	200.886	6954	1269	5.684	8198	92.866	319.543	19340
Tianjin	25.217	733.129	6818	1862	21.762	19680	72.523	2108.457	164684
Hebei	64.432	2093.505	27531	31688	99.418	114232	139.467	4531.512	108588
Shanxi	82.572	742.873	9941.777	1744.545	15.783	26151.07	89.597	797.413	80172.53
Inner Mongolia	59.409	3299.688	16820	16996	119.298	39536	20.015	1111.660	132400
Liaoning	113.473	1025.251	13544.2	2922.899	34.153	63624.26	113.714	1028.993	124530.2
Jilin	56.150	2608.266	8297	4642	30.064	38656	41.843	1943.682	63366
Heilongjiang	75.186	863.894	9853.724	4714.134	22.853	38921	75.186	1155.685	49494
Shanghai	147.556	1306.324	11201	2448	22.148	36696	10.596	93.809	94107
Jiangsu	243.422	7340.785	25774	9064	100.245	263760	169.858	5122.347	185995
Zhejiang	143.657	1318.511	16865	4268	65.389	217426	402.567	3694.840	119568
Anhui	79.927	1384.349	8542.741	2265.759	24.257	61897.79	79.927	940.203	58895
Fujian	53.963	496.542	9809	2135.6	26.334	55004.01	125.710	1129.996	87267.1
Jiangxi	59.730	1032.312	6291.003	1929.706	22.432	62606.46	59.730	1391.847	42065.72
Shandong	48.808	1043.426	34808	16038	138.287	208257	464.957	9940.008	456759
Henan	163.112	2712.498	17475.43	4734.086	59.950	136763	163.112	2782.342	125120
Hubei	116.360	1050.719	10545.13	2400.085	28.466	74670.56	110.001	995.362	81824.4
Hunan	104.675	1171.939	9390.738	2416.616	29.579	82909.01	104.675	1325.357	69105.21
Guangdong	77.158	719.879	26908	5456	98.909	187031	486.040	4534.710	310584
Guangxi	53.176	950.303	5782.762	1744.672	19.985	54994.36	53.176	1190.213	38642.68
Hainan	2.489	27.017	1359	212	2.817	5782	15.161	164.593	4354
Chongqing	62.960	563.021	6570.865	1352.422	14.078	30830.37	50.484	447.059	50810.5
Sichuan	122.602	1350.966	12295.81	3107.189	33.172	74944.66	115.704	1852.948	71627
Guizhou	39.470	349.880	4072.245	568.1118	5.140	8516.107	29.028	253.859	29163.46
Yunnan	77.827	1148.954	8674	9392	43.955	30926	42.276	624.123	106272
Shaanxi	69.215	618.611	7918.749	1677.669	16.866	34821.22	61.630	546.276	63052.76
Gansu	33.281	345.834	3773.662	585.1506	6.618	15352	33.281	314.605	31768.91
Qinghai	7.249	197.721	2568	1783	13.315	9031	9.807	267.504	9747
Ningxia	11.527	262.327	2501.79	1253.212	8.693	10575.18	11.527	114.641	14924.62
Xinjiang	32.282	367.586	3779.761	931.4257	10.001	25375.37	32.282	476.851	25419.72

These benchmarks provide the targets for China's local governments to balance the development of the industrial economic growth with environmental protection so as to achieve overall environmental efficient. For example, if Shanxi province intends to

be efficient, it should reduce its industrial labor force to 82.572 ten thousand employees, its net value of fixed assets to 742.873 billion RMB, and its industrial energy consumption to 9941.777 ten thousand tons of standard coal in the first stage. In addition, it should reduce industrial solid wastes generated, industrial waste gas emitted, industrial waste water discharged to 1744.545 million tons, 15.783 tons, and 26151.07 million tons respectively. In the second stage, it should reduce the industrial labor force to 89.597 ten thousand employees, the net value of fixed assets to 797.413 billion RMB, and its investments in industrial pollution treatment to 80172.528 million RMB. By analyzing the change proportion of each variable, we can find that the main cause of inefficiencies in China's industry are the industrial solid wastes generated and the industrial waste water discharged. Thus, the government policy makers should take more and better measures to control these pollutants.

5.4 Conclusions

Efficiency improvement is one of the most cost-effective ways to achieve the goals of energy saving and environment protection. Most of the previous analysis approaches for energy efficiency and environmental efficiency consider the evaluated system as a black box system without considering the internal structure, which often results in less reliable and more imprecise results. In order to overcome this problem, this chapter proposes a two-stage DEA model to measure regional industrial overall environmental efficiency, energy utilization efficiency, pollution treatment efficiency, and the total-factor energy efficiency. We apply this model to the statistics for 30 Chinese provinces for the years 2006-2010. In addition, we group the 30 provinces into six areas (North China, Northeast China, East China, South Central China, Southwest China, and Northwest China) to analyze the efficiencies of larger scale areas. The results indicate that China's industrial performance was greatly improved during the study period but the six areas had a notable degree of distinct differences. According to these results, we give the following policy recommendations for improving industrial performance, especially overall environmental efficiency and total factor energy efficiency.

Firstly, fully utilize the industrial energy resources such as coal and crude oil. In terms of the average industrial energy efficiency in areas, North China performs the best while Northeast China performs the worst. These relatively low efficiency areas can be improved by (a) introducing new technology to reduce industrial energy intensity

(i.e., industrial energy consumption for per unit gross industrial output value); and (b) retiring backward technology and equipment, adopting new high-technology equipment with lower pollution, and saving electricity to achieve continuous and efficient progress. Applied well, these will allow industries to realize comprehensive utilization of all kinds of energy.

Secondly, the best way to improve overall environmental efficiency in the studied regions and areas is to enhance the industrial pollution treatment. Compared with the first stage industrial energy utilization efficiency, the second stage industrial pollution treatment efficiency is lower. Furthermore, according to our results, we found most of the inefficiency of the second stage came from the poor treatment of the solid waste and waste water. Thus, the government should take more measures to control these pollutants to improve the overall environmental efficiency of industry, which will simultaneously improve the industrial energy and environmental efficiency.

Environmental efficiency evaluation of a parallel network system considering regional heterogeneity

Contents

6.1 Introduction	86
6.2 Environmental efficiency evaluation of a parallel transportation network considering regional heterogeneity	90
6.2.1 Network DEA model	90
6.2.2 Metafrontier Malmquist-Luenberger productivity index	95
6.3 Application to the environmental efficiency evaluation of China's transportation sector considering regional heterogeneity	99
6.3.1 Data and variables	99
6.3.2 Results Analysis	101
6.4 Conclusions	108

Environmental efficiency measurement of the transportation sector is crucial for guiding central or local governments to realize green transportation without sacrificing too much its economic value. In this chapter, we examine the China's transportation sector by dividing it into four main subsystems: railway, highway, waterway, and civil aviation, and further build a parallel network data envelopment analysis model for environmental efficiency measurement of the sector with an undesirable factor-CO₂ emission. Moreover, considering the heterogeneity of transportation sectors in different areas of China, a new metafrontier Malmquist-Luenberger productivity index (MMPLI) is proposed for considering the undesirable outputs and network structure of transportation sector so as to investigate the dynamic changes in environmental efficiencies of 30 regions' transportation sectors during 2007-2013. The results indicate that Eastern China had the strongest catching-up effect, Western China had the largest innovation effect, and Central China had the strongest technology leading effect during these years.

6.1 Introduction

As an important part of human social and economic activities, transportation is to realize the physical location movement of people and goods by organizing various resources such as tools, staff, funds, etc. According to the means of transport, transportation services are mainly carried railway transportation, highway transportation, waterway transportation, civil aviation transportation and pipeline transportation. As pipeline transportation is only suitable for liquid transportation, and its application range is limited. We will not study it in this chapter. In 2016, the number of civil aviation airports reached 218 and the passenger volume reached 1016.357 million journeys; the railway mileage (i.e. distance traveled on railway lines) had reached about 124 thousand kilometers, which ranked the second place in the world, as did the electrified railway mileage. Besides, the operational mileage (i.e. total length of railway lines) of high-speed rail reached 22 thousand kilometers, which ranked first over the world, and the scale under construction exceeded 10,000 kilometers. Meanwhile, the number of high-speed railways under construction exceeds 10000 km; the total national highway mileage is 4.6963 million km, with an increase of 119000 km over the previous year; and the length of navigation of inland waterways nationwide is 127,100 km, with an increase of 100 km over the previous year. National ports have 30,388 berths for production and 2,317 berths of 10, 000 tonnage or above (MTPRC, 2017).

Although China's transportation sector has developed rapidly, this progress has been accompanied by problems. a) In China, the transportation sector accounted for 8% of total energy consumption and 10% of total carbon emission in 2013, according to China Statistical Yearbook 2015. b) The overall scale of China's transportation infrastructure is large now, but the construction mainly leans towards Eastern China, and the disparity between Eastern China, Central China, and Western China is enlarging. Thus, lowering energy consumption and carbon emissions of the transportation sector in these three different areas is crucial for long-term sustainable development of transportation, resources, and environment. In order to establish a green transportation sector, when we evaluate the evolution of the performance of the transportation sector, we should consider green factors so as to find its inefficiency and its efficiency changes in terms of both productivity growth and emission reduction.

Many single indicators, such as transportation intensity effect (TIE), and energy use per turnover (EUT), are used to evaluate the performance of transportation (Wang et al., 2011; Chung et al., 2013) without taking into consideration other factors involved in the transportation process. To deal with this problem, data envelopment analysis (DEA) has been employed to evaluate the transportation performance by considering more factors, which is more appropriate than any single-factor indicators. DEA as a non-parametric approach can well evaluate a system with multiple inputs and multiple outputs and does not need a functional form assumption of the production (Charnes et al., 1978), so it has been widely used for measuring the performance of transportation (Wu et al., 2016; Viton 1997; Adler et al., 2013).

So far, many DEA research works have focused on the transportation sector. These works can be classified into two categories: one is the static performance evaluation which measures the efficiency of a transportation system in a year or a period; and the other is the dynamic performance evaluation, which usually uses the Malmquist productivity index and its extensions to investigate the efficiency changes or productivity growth over multiple periods. In the first category, the research usually applied DEA models, such as conventional DEA models, slacks-based measure models, and network DEA models, to evaluate the performance of transportation in a year or a period without analyzing the technical process and efficiency changes involved in the development of the transportation sector (Adler et al., 2013; Zhou et al., 2013; Song et al., 2015). Zhou et al. (2013) employed output-oriented DEA models with different returns to scale assumptions to study the carbon emissions performance of China's transport sector from 2003 to 2009; the results indicated that the number of efficient regions decreased starting in 2004, bottomed out in 2006, and improved slightly afterwards. Chang et al. (2013) measured the carbon emissions and potential reductions of these in the regional transport sector in 2009 by using the SBM-DEA model; the results showed that the transportation sector in most provinces of China were not eco-efficient. Zhou et al. (2014) presented an application of DEA approach with consideration of undesirable outputs to analyze energy efficiency and potential energy savings for the Chinese transport industry during 2003-2009. Adler et al. (2013) proposed a new DEA approach named the directional economic-environmental distance function (DEED) approach to compute the relative efficiency of aircraft-engine combinations which accounted for the production of both desirable and undesirable

outputs such as noise and air pollutant emissions. Song, Hao, and Zhu (2015) used an undesirable-output-oriented data envelopment analysis (DEA) model with slacks-based measure (SBM) to evaluate the changes in the environmental efficiency of the transportation sector in 30 Chinese administrative regions between 2003 and 2012. Since ignoring the internal structure of a system probably overestimates the system's efficiency, recently, some scholars have built or applied network DEA models to recognize the internal inefficiency of transportation sectors. Wanke (2013) analyzed the efficiency in Brazilian ports by using a two-stage network-DEA approach to simultaneously optimize physical infrastructure and shipment consolidation efficiency levels through considering shipment frequency per year as the critical intermediate output. Tavassoli et al. (2014) developed a two-stage network SBM model with shared inputs to assess the performance of 11 domestic airlines in Iran by introducing linking activities between components. In that paper, the first stage evaluated airline technical efficiency and the second stage measured the service effectiveness. Lu et al. (2012) examined the production efficiency and marketing efficiency of 30 US airline companies by a two-stage DEA model. In addition, they conducted a regression analysis of the effect of corporate governance mechanisms on airlines performance. Yu et al. (2015) proposed a multi-activity network data envelopment analysis model to assess the performance in terms of individual activities, individual processes, individual periods, and overall operation. Wu et al. (2016) divided the transportation into passenger transportation and freight transportation, and then used a parallel network DEA model for measuring the energy and environmental efficiency of Chinese provincial transportation sectors in 2012. Liu et al. (2017) analyzed the land transportation sector of China (including railway transportation and road transportation) during 2009-2012 by using a parallel slack-based measure data envelopment analysis model.

In the second category, the performance of transportation sectors was dynamically analyzed using the Malmquist productivity index or its extended forms, which can measure the productivity growth and the growth's determinants in the transportation sector over multiple periods. Besides this, the index is capable of reflecting progress or regress in efficiency along with progress or regress of the frontier technology over time under the multiple inputs and multiple outputs framework. The Malmquist productivity index was first introduced by Malmquist (1953), and Caves et al. (1982) extended it by

applying the ratio of two distances. After Färe and Grosskopf (1992) introduced the non-parametric technique DEA to the Malmquist productivity index measurement, the index began to receive much attention from scholars. Nicola et al. (2013) measured the productivity of 20 Italian airport management companies during 2006-2008 using a DEA Malmquist index that included a quality component. Scotti and Volta (2015) used a Biennial Malmquist-Luenberger (BML) index to measure the productivity of European airlines during 2000-2010. They compared the BML index with the traditional index and found the environment-sensitive productivity growth was lower than that given by the traditional index. Zhang et al. (2015) employed a non-radial Malmquist carbon dioxide (CO₂) emission performance index (NMCPI) to analyze the changes in the total-factor CO₂ emission performance of the regional transportation sector in China for the period 2002 to 2010. Gitto and Mancuso (2012) evaluated the productivity evolution, from 2000 through 2006, of Italian airports by applying the Malmquist index to a sample of 28 airports covering about 96%, 99%, and 99% respectively of the total number of passengers, movement, and cargo. Zhang and Wei (2015) measured the dynamic changes in carbon emission performance within regional transportation sectors by incorporating regional heterogeneity and arithmetic measure into the non-radial Malmquist carbon emissions index.

Based on this literature review, we can see that most works treat the transportation sector as a “black box”, considering only the initial inputs and final outputs. Few works investigate the internal structure by using network DEA models, but the main limitation of these works is that they do not analyze the performance dynamically, thus information about productivity growth and its decompositions is missed even though it is very important for guiding local government investments (see more details in Chen and Yu, 2014; Wang and Feng, 2015). In this chapter, we will build a new framework for measuring the performance evolution of transportation sectors taking the internal structure into consideration. According to the means of transport, we classify the whole transportation sector into four parallel subsystems: railway transportation, highway transportation, waterway transportation, and civil aviation transportation. So far, few papers have considered the transportation efficiency evaluation of this network structure. Moreover, considering the heterogeneity of Chinese provincial transportation sectors, we classify them into three regions according to their location: Eastern China, Central China, and Western China. To consider green factors in the performance

evaluation, we firstly build a new parallel DEA model for measuring the environmental efficiency of transportation sectors considering the undesirable output carbon dioxide. Then, a new metafrontier Malmquist-Luenberger productivity index (MMLPI) based on our network DEA model is derived to investigate the productivity growth.

6.2 Environmental efficiency evaluation of a parallel transportation network system considering regional heterogeneity

In this section, we first look at the conventional DEA model and then develop a new network DEA model for a transportation sector. Further, we define the metafrontier Malmquist-Luenberger productivity index for the transportation sector. Since the transportation sector (system) in China is mainly composed of four subsystems: railway transportation, highway transportation, waterway transportation, and civil aviation transportation, we formulate the system using a parallel network DEA model.

6.2.1 Network DEA model

At the beginning, we assume each administrative region's transportation sector is a "black box", ignoring the internal structure, so conventional DEA model can be applied to measure the performance of transportation. Using the traditional denotations in DEA, we assume that there is a set of n DMUs (which are provincial transportation sectors here), and each $DMU_j (j = 1, 2, \dots, n)$ produces b different outputs using m different inputs which are denoted as $y_{rj} (r = 1, 2, \dots, b)$ and $x_{ij} (i = 1, 2, \dots, m)$, respectively. Charnes et al. (1978) presented the output-oriented CCR model for measuring the efficiency of DMU_0 as follows. (By convention, " DMU_0 " is used to denote the DMU currently under consideration.)

$$\begin{aligned}
 \phi = \min \quad & \sum_{i=1}^m \omega_i x_{i0} \\
 \text{s.t.} \quad & \sum_{r=1}^b \mu_r y_{rj} - \sum_{i=1}^m \omega_i x_{ij} \leq 0, j = 1, 2, \dots, n \\
 & \sum_{r=1}^b \mu_r y_{r0} = 1 \\
 & \mu_r, \omega_i \geq \varepsilon, r = 1, 2, \dots, b, i = 1, 2, \dots, m.
 \end{aligned} \tag{6.1}$$

where u_r, ω_i are the prices and multipliers associated with the r th output and the i th input respectively. When ϕ is equal to 1, the DMU_0 is efficient, otherwise, the DMU_0 is inefficient. The dual problem of model (6.1) is

$$\begin{aligned}
 \phi = \max \quad & \delta + \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^b s_r^+ \right) \\
 \text{s.t.} \quad & \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = x_{i0}, i = 1, 2, \dots, m \\
 & \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = \delta y_{r0}, r = 1, 2, \dots, b \\
 & \lambda_j \geq 0, j = 1, 2, \dots, n.
 \end{aligned} \tag{6.2}$$

It can be seen that model (6.2) seeks the maximal increase of outputs for a DMU by using its inputs. Thus, the reciprocal of the optimal values of models (6.1) and (6.2), $1/\phi$, defines an output distance (also called efficiency) to the production frontier formed by the best-performing (efficient) DMUs, and is widely used for Malmquist productivity index measurement (Pastor and Lovell, 2005; Oh and Lee, 2010). Since ignoring the internal structure of a system will result in the overestimation of the performance, we should delve further into the transportation sector. According to the means of transport, we divide the transportation sector into four main subsystems: railway transportation, highway transportation, waterway transportation, and civil aviation transportation. Following previous works (Chang et al., 2013; Halkos and Tzeremes, 2009; Lv et al., 2012; Song et al., 2016) for analyzing the transportation sector, we select energy consumption and capital stock as the inputs of the four subsystems. Because these inputs for the overall transportation system are difficultly distributed to each subsystem of each province, according to the same analysis in Chen (2017), we also consider the variables as shared inputs since they are variables for the local transportation government for general purposes, and also, their exact data for each subsystem in Chinese provinces are not available from statistical yearbooks. As there are no statistics in China about the capital stock of each transportation industry, the amount of fixed capital investment is used to represent capital stock, as other authors have done (e.g., Lee, 2005; Bian and Yang, 2010; Chang et al., 2013). We choose the number of employees in railway, highway, waterway, civil aviation, the emissions of carbon dioxide and the gross product as outputs. Among them, the number of

employees in railway, highway, waterway, civil aviation can be obtained from the statistical year books so that it is defined as the individual inputs of these subsystems, while the values of the gross product and the emissions of carbon dioxide of the whole transportation system are available but the detail value in each subsystem are not known as the values cannot be easily split into each subsystem. For example, the transportation tasks for generating the gross products of transportation are usually attributed to the integration of several or all the transportation subsystems not just an individual subsystem, thus the values cannot be easily decomposed into each subsystem. Therefore, analogous to Chen et al. (2010), the emissions of carbon dioxide and the gross product are considered as the shared undesirable output and shared desirable output of these four subsystems. For these shared outputs, we only know their total values of the whole system but do not know that of each subsystem. Different from these shared outputs measures, the passenger volume and freight volume transported by each transportation subsystem are the individual outputs whose values can be obtained from the statistical yearbook. The corresponding structure for the transportation sector is given in Figure 6.1 as follows.

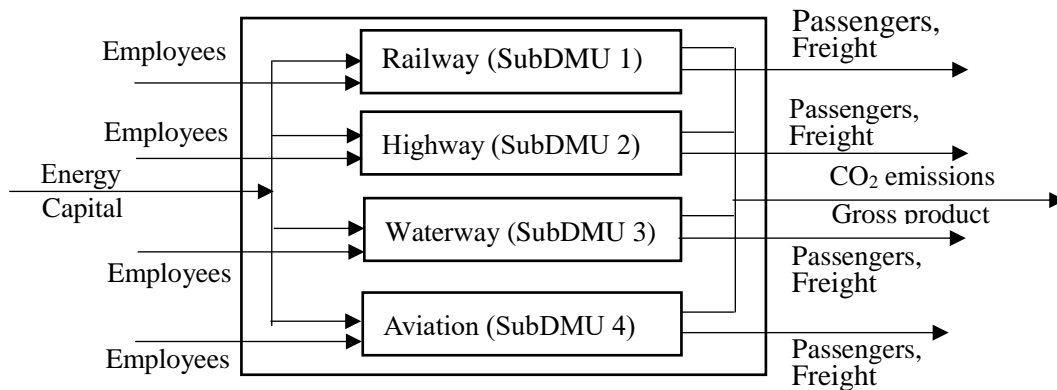


Figure 6.1 The network structure of China's transportation sector

Consider a provincial transportation sector in one year as a decision making unit (DMU). For ease of illustration in building the network model, the notations are defined as the follows.

Table 6.1 Variables and descriptions

Notation	Description
<i>Indexes</i>	
j	Index of the j^{th} DMU
p	Index of the p^{th} SubDMU
l	Index of the l^{th} individual input
r	Index of the r^{th} individual desirable output
i	Index of the i^{th} shared input
g	Index of the g^{th} shared desirable output
h	Index of h^{th} shared undesirable output
<i>Inputs/outputs</i>	
X_j	The shared input vector of DMU $_j$
\tilde{X}_j^p	The individual input vector of SubDMU $_p$ within DMU $_j$
Y_j	The shared desirable output vector of DMU $_j$
\tilde{Y}_j^p	The individual desirable output vector of SubDMU $_p$ within DMU $_j$
Z_j	The shared undesirable output vector of DMU $_j$
\tilde{x}_{lj}^p	The l^{th} individual input of subDMU $_p$ of DMU $_j$ within DMU $_j$
\tilde{y}_{rj}^p	The r^{th} individual desirable output of subDMU $_p$ within DMU $_j$
x_{ij}	The i^{th} shared input of DMU $_j$ for its four subsystems
y_{gj}	The g^{th} shared desirable output of DMU $_j$ for its four subsystem
z_{hj}	The h^{th} shared undesirable output of DMU $_j$ for its four subsystems
<i>Variables</i>	
α_i^p	The proportion of i^{th} shared input of subDMU $_p$ of DMU $_j$ to x_{ij}
β_h^p	The proportion of h^{th} shared undesirable output of subDMU $_p$ of DMU $_j$ to z_{hj}
γ_g^p	The proportion of g^{th} shared desirable output of subDMU $_p$ of DMU $_j$ to y_{gj}

To evaluate the performance of the above structure system, we must deal with the shared inputs and shared outputs. So far, there have been several approaches proposed for solving shared inputs, such as weighted restrictions (Beasley, 1995; Cook et al., 2000) and additive objective functions (Cook and Hababou, 2001). Note that these works neither specified the sharing proportions of shared inputs nor considered the inner structure of the system. Recently, some researchers have dealt with shared inputs in the network system. Yu and Lin (2008) evaluated railway performances in a multi-activity network framework with shared inputs. Zha and Liang (2010) developed an approach to measure the performance of a two-stage production process in series, where

the shared inputs could be freely allocated among different stages. Chen et al. (2010) used a multiple DEA model to evaluate the performance of a two-stage network process with non-splittable shared inputs to both stages. Yu et al. (2015) estimated the production efficiency, service efficiency, and operational efficiency of multimode transit firms with shared technicians and ticket agents by using a dynamic network DEA model. Similarly, shared outputs could be addressed although such works are rare. Jahanshahloo et al. (2004) measured the efficiency of thirty-nine branches of a commercial Iranian bank with shared inputs and shared outputs. Recently, Kao (2016) built a network DEA model to reanalyze these bank branches. However, all these previous works did not consider shared undesirable outputs and shared inputs simultaneously in the measurement of the total factor productivity, thus they cannot be applied to measure the transportation sector as modeled in Figure 6.1. In this section, we proposed a new network DEA model for measuring the transportation sector with the structure in Figure 6.1, which has not only shared inputs, shared desirable outputs, and shared undesirable outputs, but also individual inputs and individual outputs. The model is as follows:

$$\begin{aligned}
\phi = \min & \sum_{i=1}^m \omega_i x_{i0} + \sum_{l=1}^d (\theta_l \sum_{p=1}^q \tilde{x}_{l0}^p) + \sum_{h=1}^k v_h z_{h0} \\
s.t. & \sum_{r=1}^b \mu_r \tilde{y}_{r0} + \sum_{g=1}^f \xi_g y_{g0} = 1, \\
& \sum_{r=1}^b (\mu_r (\sum_{p=1}^q \tilde{y}_{rj}^p)) + \sum_{g=1}^f \xi_g y_{gj} - \sum_{i=1}^m \omega_i x_{ij} - \sum_{l=1}^d (\theta_l (\sum_{p=1}^q \tilde{x}_{lj}^p)) - \sum_{h=1}^k v_h z_{hj} \leq 0, j \in PPS, \\
& \sum_{r=1}^b \mu_r \tilde{y}_{rj}^p + \sum_{g=1}^f \xi_g \gamma_g^p y_{gj} - \sum_{i=1}^m \omega_i \alpha_i^p x_{ij} - \sum_{l=1}^d \theta_l \tilde{x}_{lj}^p - \sum_{h=1}^k v_h \beta_h^p z_{hj} \leq 0, p = 1, \dots, q, j \in PPS, \\
& \sum_{p=1}^q \alpha_i^p = 1, i = 1, \dots, m, \\
& \sum_{p=1}^q \beta_h^p = 1, h = 1, \dots, k, \\
& \sum_{p=1}^q \gamma_g^p = 1, g = 1, \dots, f, \\
& \omega_i, \mu_r, v_h, \theta_l, \xi_g, \alpha_i^p, \beta_h^p, \gamma_g^p \geq 0, \\
& i = 1, 2, \dots, m; r = 1, \dots, b; h = 1, \dots, k; l = 1, \dots, d; g = 1, \dots, f; p = 1, \dots, q.
\end{aligned} \tag{6.3}$$

In model (6.3), ω_i, v_h and θ_l denote the multipliers corresponding to shared input, individual input and shared undesirable output, respectively. μ_r and ξ_g are the

multipliers of individual desirable output and shared desirable output, respectively. This model can be seen as an extension of Chen et al. (2010) for the network system shown in Fig.6.1 which considering the parallel network, undesirable output, shared input and shared output. The second constraint in this model requires the aggregate output to be less than or equal to the aggregate input which implies the efficiency of the whole system no more than 1, and the second constraint implies the efficiency of the $SubDMU_p (p = 1, \dots, q)$ no more than 1. The constraints $\sum_{p=1}^q \alpha_i^p = 1, \sum_{p=1}^q \beta_h^p = 1$ and $\sum_{p=1}^q \gamma_g^p = 1$ represent the total values of shared inputs and shared undesirable output and shared desirable output are fully divided into four subsystems. $j \in PPS$ refers to all the DMUs which operate in the production possibility set (or technology set) PPS .

Model (6.3) is a non-linear programming model. By substituting $\xi_g \gamma_g^p, \omega_i \alpha_i^p$, and $v_h \beta_h^p$ by ζ_g^p, w_i^p , and u_h^p respectively, it can be transformed into the following linear model.

$$\begin{aligned}
 \phi = \min \quad & \sum_{i=1}^m \omega_i x_{i0} + \sum_{l=1}^d (\mathcal{G}_l \sum_p^q \tilde{x}_{l0}^p) + \sum_{h=1}^k v_h z_{h0} \\
 \text{s.t.} \quad & \sum_{r=1}^b \mu_r \tilde{y}_{r0} + \sum_{g=1}^f \xi_g y_{g0} = 1, \\
 & \sum_{r=1}^b \mu_r \tilde{y}_{rj} + \sum_{g=1}^f \xi_g y_{gj} - \sum_{i=1}^m \omega_i x_{ij} - \sum_{l=1}^d \mathcal{G}_l \sum_{p=1}^q \tilde{x}_{lj}^p - \sum_{h=1}^k v_h z_{hj} \leq 0, j \in PPS; \\
 & \sum_{r=1}^b \mu_r \tilde{y}_{rj}^p + \sum_{g=1}^f \zeta_g^p y_{gj} - \sum_{i=1}^m w_i^p x_{ij} - \sum_{l=1}^d \mathcal{G}_l \tilde{x}_{lj}^p - \sum_{h=1}^k u_h^p z_{hj} \leq 0, j \in PPS, p = 1, \dots, q; \\
 & \sum_{p=1}^q w_i^p = \omega_i, i = 1, \dots, m, \\
 & \sum_{p=1}^q u_h^p = v_h, h = 1, \dots, k, \\
 & \sum_{p=1}^q \zeta_g^p = \xi_g, g = 1, \dots, f, \\
 & \omega_i, \mu_r, v_h, \mathcal{G}_l, \xi_g, w_i^p, u_h^p, \zeta_g^p \geq 0, \\
 & i = 1, 2, \dots, m; r = 1, \dots, b; h = 1, \dots, k; l = 1, \dots, d; g = 1, \dots, f; p = 1, \dots, q.
 \end{aligned} \tag{6.4}$$

By solving model (6.4), the output distance $1/\phi$ (or environmental efficiency) of DMU_0 under the technology set PPS can be obtained for computing productivity index.

6.2.2 Metafrontier Malmquist-Luenberger productivity index

It is well known that the ratio of the efficiencies of a DMU in two different periods can be viewed as a measure of performance change. Because using different periods as the base period may yield inconsistent results, researchers such as Kao (2010) and Färe et al. (1994) have suggested using the geometric mean of the performance changes calculated from the two base periods as the Malmquist Productivity Index (MPI). Since this seminal work of Färe et al. (1994), MPI has been used in many empirical studies. However, this productivity index did not consider the undesirable outputs and the heterogeneity among the DMUs, that is, it assumed all DMUs operate under the same production technology and produced all good outputs. In fact, a DMU under a given production technology cannot be directly compared with those operating under different technologies. This is because DMUs in one specific technology group have different production possibilities from those in other groups. Within China's transportation sector, there is much more high-speed railway in Eastern China than that in Western China. Thus, the productivity analysis with the conventional MPI approach may not be directly applicable to China's transportation sector for measuring performance changes. Oh and Lee (2010) proposed a metafrontier Malmquist-Luenberger productivity index (MMLPI) which introduces a metaproduction function to the nonparametric analysis of productivity growth in order to compare productivity changes and the decomposed components for economic agents under different technologies. Based on Oh and Lee (2010), a new metafrontier Malmquist-Luenberger productivity index (MMLPI) which considers the undesirable output is proposed. For analyze the productivity, in the context of China's transportation sector divided into three regions (Eastern China, Central China, and Western China), we illustrate the MMLPI as follows.

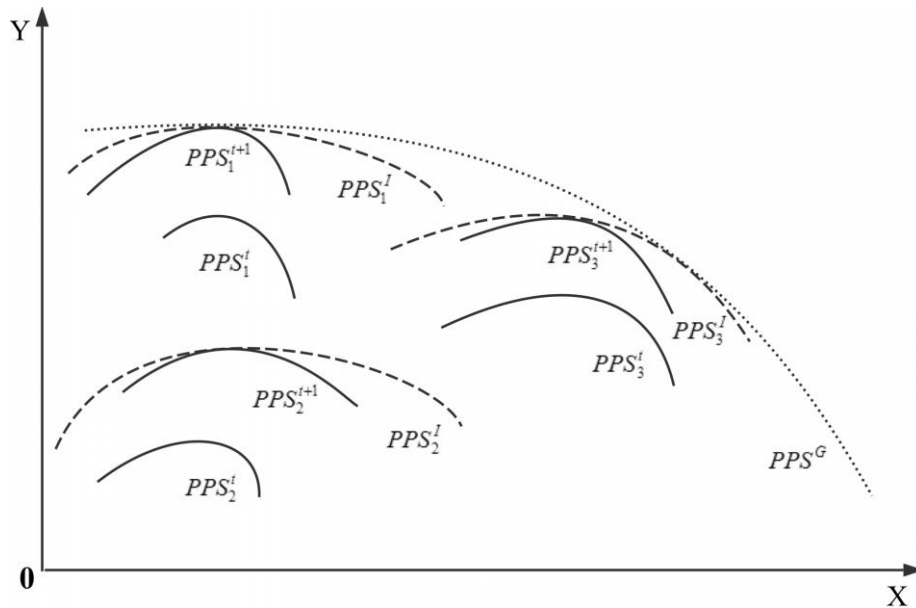


Figure 6.2 Metafrontier in a Malmquist-Luenberger productivity index framework for Transportation sector

It should be noted that only one input and one desirable output are included in Figure 6.2 to introduce the concept intuitively in two-dimension figure without loss of generality.

Definition 6.1. (a) The contemporaneous technology set of DMUs within Group R in time s is defined by PPS_R^s . When $PPS = PPS_R^s$ in model (6.4), the output distance $1/\phi$ of (x, y) is denoted by $D^s(x, y)$.

(b) The intertemporal technology set which is formed by all the DMUs in Group R at all the production time $t, t+1$, etc. is defined by PPS_R^I . When $PPS = PPS_R^I$ in model (6.4), the output distance $1/\phi$ of (x, y) is denoted by $D^I(x, y)$.

(c) The global technology set of DMUs in all groups through all time is denoted PPS^G . When $PPS = PPS^G$ in model (6.4), the output distance $1/\phi$ of (x, y) is denoted by $D^G(x, y)$.

The metafrontier Malmquist-Luenberger productivity index (MMLPI) is decomposed into three individual measures: within-group efficiency change (the catching-up effect), best-practice gap change (the innovation effect), and technology leadership change (the technology leading effect) as follows.

$$\begin{aligned}
& MMLPI(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t, x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) \\
&= \frac{D^{t+1}(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)} \times \frac{D^t(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) / D^{t+1}(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t) / D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)} \\
&\quad \times \frac{D^G(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) / D^I(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^G(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t) / D^I(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)} \quad (6.5) \\
&= \frac{TE^{t+1}}{TE^t} \times \frac{BPG^{t+1}}{BPG^t} \times \frac{TGR^{t+1}}{TGR^t} \\
&= EC \times BPC \times TGC
\end{aligned}$$

where TE^t , BPG^t , and TGR^t are respectively the level of technical efficiency of a DMU (such as a provincial transportation sector) within Group R , the best practice gap of the observation within Group R , and the technology gap of the observations for the DMU in Group R to the global technology, all at time t (Battese et al. 2004; Oh and Lee 2010).

(i) The within-group efficiency change is $EC = \frac{D^{t+1}(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)}$.

$EC > 1$ ($EC < 1$) represents the efficiency improvement (deterioration) of the transportation sector from time t to time $t+1$.

(ii) The best-practice gap change

$$BPC = \frac{BPG^{t+1}}{BPG^t} = \frac{D^I(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) / D^{t+1}(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^I(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t) / D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)}.$$

BPC provides a measure of technical change within a group from time t to time $t+1$, which reflects the within-group technical change (Pastor and Lovell 2005). $BPC > 1$ ($BPC < 1$) represents the technical progress (regress) of the transportation sector.

(iii) The technology gap change

$$TGC = \frac{TGR^{t+1}}{TGR^t} = \frac{D^G(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) / D^I(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^G(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t) / D^I(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)}.$$

$TGC > 1$ ($TGC < 1$) represents the change of a group becoming more (less) of a technical leader in the transportation sector. This concept is also called technology leadership change.

(iv) The metafrontier Malmquist-Luenberger productivity index

$MMLPI(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t, x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) > 1$ represents the increase of the productivity of the transportation sector from time t to time $t+1$.

6.3 Application to the environmental efficiency evaluation of China's transportation sector considering regional heterogeneity

In this section, we will present the transportation database and descriptive statistics in Section 6.3.1. In Section 6.3.2 we will evaluate the performance of transportation and discuss the main features of the China's transportation in each region.

6.3.1 Data and variables

The data used in this study comes from the National Bureau of Statistics of the People's Republic of China. It includes databases from the China Statistical Yearbook for Regional Economy 2008-2014, China Statistical Yearbook 2008-2014, China Energy Statistical Yearbook 2008-2014, China City Statistical Yearbook 2008-2014, and Yearbook of China Transportation and Communications 2008-2014. Since much data is unavailable for Tibet, only the 30 regions which are shown in Table 6.4 were used in this analysis.

Based on Figure 6.1, we explain the input and output selection in detail as follows. With respect to inputs, the individual inputs of the four subsystems are the number of employed persons in each of the four modes of transportation. Energy consumption and capital stock of the transportation sector are the shared inputs. In this chapter, the total fixed assets in the transportation sector are used for estimating the capital stock. Regarding the outputs, the gross product, CO₂ emission, the number of passengers and amount of freight are selected. Among them, the gross product made by the transportation sector is the desirable output, and CO₂ emission of the transportation sector is the undesirable output. We assume that these two outputs are shared outputs since they can be split out in the subsystems exactly and the real values of them for each subsystem are not available from the statistical yearbooks, which is similar to the assumption on banks in the work of Chen et al. (2010). In addition, the individual desirable outputs for the four subsystems are the number of passengers and amount of freight for each of the four subsystems. Except for the data of energy consumption by the transportation sector and CO₂ emissions of the transportation sector, all the other data can be obtained from the China City Statistical Yearbook, China Statistical Yearbook, and some reports of the transportation sector.

The data for provincial CO₂ emissions from the transportation sector and the data for provincial energy consumption by the transportation sector are not available for China. Following Chang et al. (2013), we thus use the fuel-based carbon calculation model based on the conversion factor to estimate provincial transportation CO₂ emissions. Based on the Intergovernmental Panel on Climate Change guidelines for National Greenhouse Gas Inventories (IPCC, 2006), CO₂ emissions can be estimated using the following equation.

$$CO_2 = \sum_{i=1}^n A \times CCF_i \times HE_i \times COF_i \times \frac{44}{12} \quad (6.6)$$

Through formula (6.6), CO₂ emissions are related to the amount of all carbonaceous fuel combusted (A), the carbon content factor (CCF), the heat equivalent (HE), and the carbon oxidation factor (COF) of carbonaceous fuel. The constant (44/12) represents the ratio of the molecular weight of CO₂ (44) to the molecular weight of carbon (12). Thus, $CCF_i \times HE_i \times COF_i \times \frac{44}{12}$ is the CO₂ emission factor of a fuel. Following the method of Chang et al. (2013), we use the domestic report from the Energy Research Institute (ERI) of the National Development and Reform Commission (NDRC) (2007) in China to represent the true carbon emission factors. The CO₂ emission factors shown in Table 6.2 reflect several major types of carbonaceous fuels in China.

Table 6.2 CO₂ emission factors by major carbonaceous fuel types in China

Fuel	Coal	Petrol	Kerosene	Diesel	Fuel Oil	Natural gas
CCF	27.28	18.9	19.6	20.17	21.09	15.32
HE	192.14	448	447.5	433.3	401.9	0.384
COF(%)	92.3	98	98.6	98.2	98.5	99

Besides, the energy consumption of transportation in the form of standard coal cannot be obtained from statistics directly, so we use the consumption of types of fuels to estimate the total energy consumption of transportation. The transformation coefficient of each fuel to the standard coal is given in Table 6.3.

Table 6.3 Transformation coefficient to standard coal

Fuel	Coal	Coke	Petrol	Kerosene	Diesel	Fuel Oil	Natural gas	Electricity
Rate	0.7143	0.9714	1.4714	1.4714	1.4571	1.4286	12.143	1.229

There are significant differences among the different regions of China. By adopting geographical closeness as the criteria to decide the groups and using Chinese regional classifications, the regions were classified into three areas: Eastern China, Western China, and Central China. The classification of the 30 administrative regions (i.e., provinces, autonomous regions, and municipalities) is shown in Table 6.4.

Table 6.4 Distribution of 30 administrative regions in three areas of China

Area	Administrative regions
Eastern China	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central China	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
Western China	Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia

The three areas are characterized as follows: (1) the Eastern area is well developed in transportation and it has larger gross domestic products (GDP) than the other two areas; (2) the Central area is an underdeveloped area in transportation but has achieved rapid development in recent years; and (3) the Western area has the largest land area with comparatively low population density and is the least developed area in terms of the transportation density. The administrative regions in the same area are similar (homogenous) but in the different areas are largely different (heterogeneous).

6.3.2 Results Analysis

(1) Average Metafrontier Malmquist-Luenberger index and its decompositions

Through our approach, the MMLPI and its decomposition across the different areas' transportation sectors during 2007-2013 are calculated. To assess changes in China's transportation sector performance incorporating regional heterogeneity, the average MMLPI and the parts in its decomposition during the period 2007 to 2013 are calculated for each region.

Table 6.5 The average metafrontier Malmquist-Luenberger index and its decompositions for each region 2007-2013

	EC	BPC	TGC	MMLPI
Beijing(E)	0.9840	0.8964	1.0443	0.9211
Tianjin(E)	1.2496	1.1604	0.9843	1.4272
Hebei(E)	1.0623	1.1521	1.0050	1.2300
Liaoning(E)	1.4145	1.0779	1.0008	1.5260
Shanghai(E)	1.0036	0.8924	1.0497	0.9402
Jiangsu(E)	1.3125	1.1791	0.9949	1.5396
Zhejiang(E)	1.1464	0.9188	1.0049	1.0585
Fujian(E)	0.9991	1.0455	0.9969	1.0413
Shandong(E)	1.5063	1.2533	0.9692	1.8296
Guangdong(E)	1.0338	0.8352	1.0241	0.8842
Hainan(E)	0.9587	0.8037	0.9943	0.7661
Shanxi(C)	1.0060	0.8522	1.2343	1.0582
Jilin(C)	1.0200	1.0026	1.1286	1.1540
Heilongjiang(C)	1.1068	1.0744	1.1240	1.3365
Anhui(C)	1.0021	1.1054	1.0247	1.1351
Jiangxi(C)	1.0470	0.9850	1.1017	1.1362
Henan(C)	1.0534	0.9561	1.0770	1.0847
Hubei(C)	0.9675	0.8731	1.3248	1.1191
Hunan(C)	1.0000	0.9106	1.4583	1.3280
Guangxi(W)	1.0331	1.0280	1.0311	1.0951
Chongqing(W)	1.0499	0.9677	1.0117	1.0279
Sichuan(W)	1.0492	0.9642	0.9996	1.0112
Guizhou(W)	1.0540	1.1693	0.9970	1.2287
Yunnan(W)	1.0255	1.2486	0.9062	1.1603
Shaanxi(W)	1.0352	1.0864	1.0140	1.1404
Gansu(W)	0.9765	0.9805	1.0071	0.9643
Qinghai(W)	0.9463	1.2816	0.9861	1.1960
Ningxia(W)	1.1872	1.0624	1.1349	1.4314
Xinjiang(W)	1.0272	0.9998	0.9659	0.9920
Inner Mongolia(W)	1.2423	1.0615	0.9640	1.2712

Note: E, C, and W in parentheses refer to the Eastern, Central, and Western areas respectively.

It should be noted that the average MMLPI of each region is not obtained by the product of the region's average EC, BPC, TGC in column 2, 3 and 4, i.e., $\text{average(MMLPI)} = \text{average(EC)} * \text{average(BPC)} * \text{average(TGC)}$, but by the mean of the MMLPIs of the regions during 2007-2013, i.e., $\text{average(MMLPI)} = \text{average(EC} * \text{BPC} * \text{TGC)}$. We think this way is more reasonable because it is the average of the real MMLPI of a region during 2007-2013.

With the results shown in Table 6.5, among the 30 regions, only 6 regions showed a downward trend in the MMLPI. Considering specific regions, Shandong showed the largest increase in the average MMLPI, while Hainan showed the largest decrease. For the EC index, 6 regions lagged further behind from the frontiers, one region kept unchanged, and the other regions showed increases in the average EC. Considering the three different areas, in Eastern China, Shandong had the highest EC (1.5063), while Hainan had the lowest (0.9587). In Central China, Heilongjiang had the highest EC (1.1068) and Hubei had the lowest (0.9675). In Western China, Inner Mongolia had the highest EC (1.2423) and Qinghai had the lowest (0.9463). This indicates that Shandong, Heilongjiang, and Inner Mongolia had a high catching-up effect in the transportation sector during 2007-2013, which may have been caused by the Chinese government strongly stimulating infrastructure development and the steel industry for purposes of economic recovery. Note that higher EC does not mean the higher performance but means high-efficiency improvement during these years. These results clearly point out which regions can be used as benchmarks within the same group because their experience may benefit other regions to improve performance or to avoid transportation sector setbacks. Analogously, BPC and TGC can help sector managers determine the effect of innovation and technology leading in the productivity increase of each region's transportation sector. To save space, this paper does not give further details about these indexes.

(2) Metafrontier Malmquist-Luenberger index and its decompositions for each area

In order to analyze the transportation development trends of regions from a larger scale viewpoint, we use the group classification of the 30 regions in Table 6.4 and determine the MMLPI and its decompositions for Eastern China, Central China, Western China, and all of China.

As Figure 6.3 shows, the MMLPI of China's transportation sector presents a positive trend over the 2007-2013 period. The MMLPI increased by 0.0744 units on

average from 2007 to 2013, which means the productivity of China's transportation sector increased 7.44%. Western China and Central China showed the highest transportation productivity growth value over the period, with 0.1576 and 0.1104, respectively, while Eastern China showed an average decrease of 0.0350. In the longitudinal aspect, the average MMLPI changed greatly in 2007-2008 and 2008-2009 in China and then maintained a stable level with minor changes thereafter. The average MMLPI of the Central China decreased in 2008-2009 while that of Eastern and Western China increased in 2008-2009.

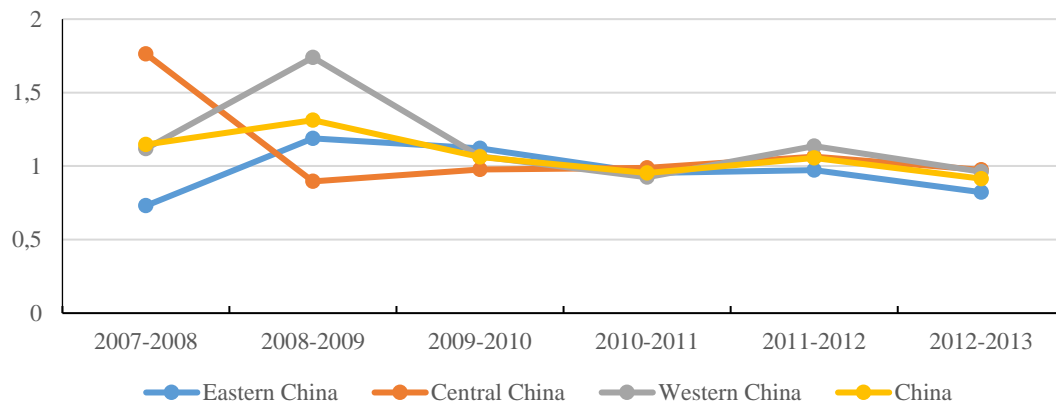


Figure 6.3 Metafrontier Malmquist-Luenberger index change of China and its three areas

In order to investigate the sources of these changes in China's transportation performance, the MMLPI is decomposed into three individual measures: within-group efficiency change (EC), best-practice gap change (BPC) and technology gap change (TGC). From Table 6.6, we can find the increase of China's transportation MMLPI mainly came from BPC and TGC, but different areas performed differently.

Table 6.6 Changes in MMPI and its decompositions of China's transportation sector 2007-2013

Year	Eastern China				Central China			
	EC	BPC	TGC	MMLPI	EC	BPC	TGC	MMLPI
2007-2008	0.5538	1.6147	0.9612	0.7303	0.8775	1.5444	1.2657	1.7631
2008-2009	2.3527	0.6114	1.0231	1.1887	1.2500	0.6687	0.9547	0.8961
2009-2010	0.9845	1.1202	1.0191	1.1214	1.0110	0.9797	0.9687	0.9764
2010-2011	1.0524	0.9390	0.9748	0.9540	0.9567	0.5998	1.9292	0.9880
2011-2012	0.9662	1.0173	0.9962	0.9724	0.9980	1.0808	0.9912	1.0640
2012-2013	1.0017	0.8146	1.0627	0.8232	1.0590	0.9462	0.9956	0.9746

Mean	1.1519	1.0195	1.0062	0.9650	1.0254	0.9699	1.1842	1.1104
-------------	--------	--------	--------	--------	--------	--------	--------	--------

Table 6.6 (*Continued*)

Year	Western China				China			
	EC	BPC	TGC	MMLPI	EC	BPC	TGC	MMLPI
2007-2008	0.7432	1.2888	1.0667	1.1183	0.7096	1.4764	1.0811	1.1480
2008-2009	1.4137	0.9783	1.0544	1.7396	1.7143	0.7612	1.0164	1.3127
2009-2010	1.1447	0.9813	1.0060	1.0655	1.0503	1.0318	1.0008	1.0622
2010-2011	1.0501	1.0469	0.8302	0.9243	1.0260	0.8881	1.1763	0.9521
2011-2012	0.8525	1.3888	0.9880	1.1354	0.9330	1.1705	0.9919	1.0566
2012-2013	1.1376	0.7795	1.0642	0.9625	1.0668	0.8368	1.0454	0.9146
Mean	1.0570	1.0773	1.0016	1.1576	1.0833	1.0275	1.0520	1.0744

The average efficiency change (EC) measure of transportation performance from 2007 to 2013 under the MMLPI framework was 1.0833, which indicates that the transportation sector moved toward the technology frontier over the study period, which can be regarded as a catching-up effect. Considering the three geographic areas, the average efficiency change of Eastern China fluctuated largely from 2007 to 2010, then remained at a similar level around 1 from 2010 to 2013. Central China and Western China performances had the same trend as Eastern China. This phenomenon can be clearly seen in Figure 6.4, and was probably caused by the global financial crisis which occurred in 2008. China began the “4 Trillion Plan” in the second half of 2008 to stimulate the development of the economy, including infrastructure development, energy saving, and emission reduction. In particular, investments in the highway system and high-speed railways accounted for more than half of the total capital. Thus, the MMLPI saw a large increase in 2008-2009. After 2009, however, the effect became weak and the average efficiency changes were approximately 1 which means there was almost no change in the efficiency.

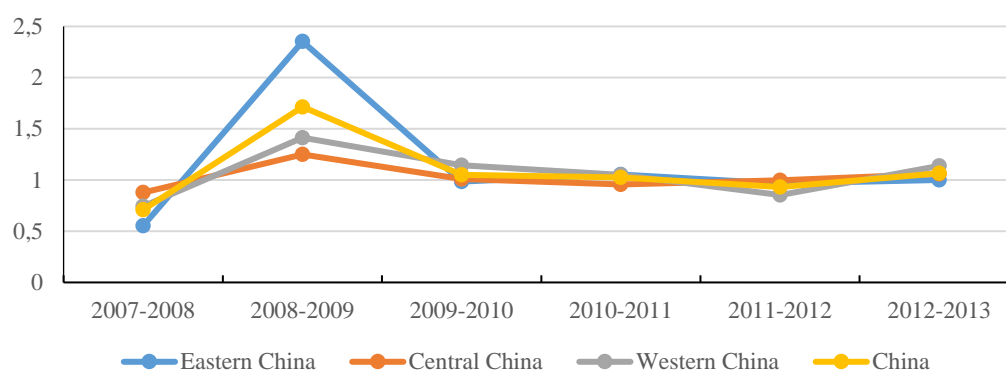


Figure 6.4 Efficiency change of China and its three areas

The BPC is the best-practice gap change, it indicates the innovation effect within a group. The average BPC measure of China's transportation performance was 1.0275 during 2007-2013 which meant slight technical progress was observed for the study period. Considering the different areas, as Figure 6.5 shows, the average BPC measure of the three areas fluctuated greatly from 2007 to 2009 but later increased on average. BPC provides a measure of technical change within a group during a period. From the results in Table 6.6, we can find that the technical progress (regress) of the transportation sector in all areas during 2007-2008 was larger than 1. Then, the technical progress decreased greatly during 2008-2009 because of the global financial crisis. During 2009-2010, the technical progress increased which may be caused by the structural adjustment of Chinese transportation to face the financial crisis of 2008. The strong policy support for the development of high-speed railway which requires many high technologies undoubtedly increased the technical process of the entire transportation system. This effect decreased during 2010-2011 in Eastern and Central China. The Central China increased the most in 2011-2012 which probably is because of the large investments in the transportation infrastructure in Central China based on the "Planning implementation opinions for promoting the rise of the central area" published by the National Development and Reform Commission (NDRC). It can be seen from Table 6.6 and Figure 6.5 that in of all these areas, BPC decreased from 2012 to 2013 at a similar rate. This indicates that the deviation of technical process between the three Chinese areas decreased, which was probably caused by the new technology adoption and diffusion of transportation in China such as high-speed railway, highway, and aviation transportation.

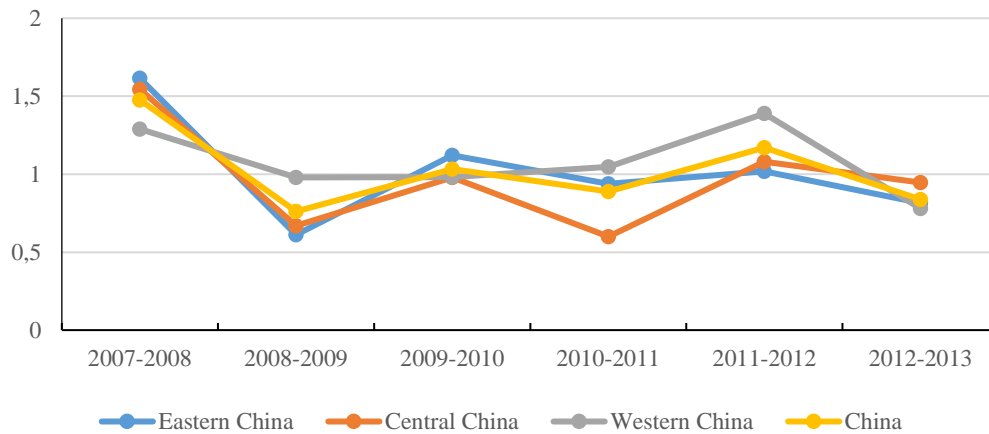


Figure 6.5 Best-practice gap change of China and its three areas

The TGC represents the change in technology gap, measuring the gap between the global production possibility frontier and the intertemporal production frontier. As observed in Table 6.6, the average TGC of China's transportation performance was 1.0520, which means that that the gap between the global frontier and intertemporal frontier was reduced. This suggests that the average Chinese region had a technical leadership effect during the sample period.

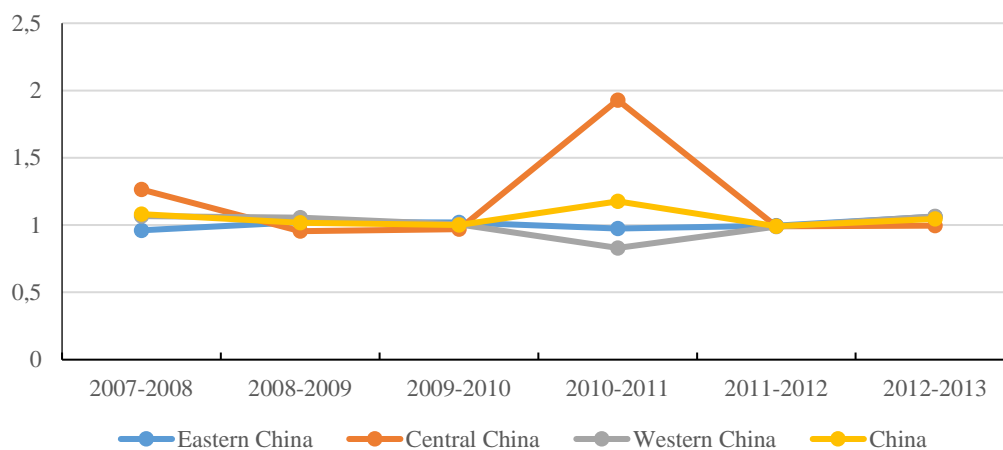


Figure 6.6 Technology gap change of China and its three areas

From Figure 6.6, we can find the TGC of China's transportation stayed smooth around 1 in 2007-2013, as did the Eastern and Western China areas. From 2007 to 2013, the TGC of the three areas stayed almost the same, except for 2010-2011. During 2010-2011, Western China decreased its TGC value and Eastern China kept its TGC value almost the same, while Central China increased its TGC value by a large amount. Central China had the largest global frontier technology gap change in that year, which

indicates that Central China had an evident technical leadership effect during 2010-2011.

6.4 Conclusions

China's transportation sector has developed greatly in recent years. In this chapter, we go inside the transportation sector and divide it into four parallel subsystems: railway, highway, waterway, and civil aviation. Firstly, a new network DEA model is built for measuring the performance of transportation sectors with four subsystems in consideration of the "green" factor of CO₂ emission. Since the regions in different areas of China have large differences, a metafrontier Malmquist-Luenberger productivity index is used to investigate the productivity growth of provincial transportation sectors so as to consider the heterogeneity of transportation sectors in different regions of China. This approach is then applied to analyze the transportation sector of 30 Chinese regions in the period 2007-2013.

Using the decompositions of the metafrontier Malmquist-Luenberger productivity index, we found that Eastern China had the largest within-group efficiency change, Western China had the largest best-practice gap change, and Central China had the largest technology leadership change. By calculating these three factors for driving productivity growth, each region can find its weakness directly and arrange its resources for its transportation sector accordingly. Specifically, MMLPI can be improved by the following measures.

Firstly, adjust the energy structure of the transportation industry and encourage the use of new energy transportation vehicles. It can be seen from Table 6.2 that the corresponding carbon dioxide emission coefficients of crude oil, diesel oil, fuel oil, gasoline, etc. are very high, while the emission factors of natural gas and electric energy are very low. Therefore, in order to reduce the undesirable output-carbon dioxide emissions in the transportation industry to increase MMLPI, the Chinese government should optimize the energy structure of the transportation sector.

Secondly, rational planning and strengthening cooperation between regions. It can be seen from the analysis results of 6.3.3 that the development of China's transportation sector is regional. Among them, the catch-up effect (EC) is the largest in the eastern China, the innovation effect (BPC) is the largest in the western China, and the

technology leading effect (TGC) is the largest in the central China. Therefore, cooperation and exchanges between regions should be strengthened to gradually narrow the gap in the regional transportation sector.

CHAPTER 7

Conclusions and perspectives

Contents

7.1 Conclusions	111
7.2 Perspectives	113

In this chapter, we conclude the works of this thesis and give some directions for further study.

7.1 Conclusions

In recent years, environmental problems have seriously blocked sustainable development of many countries, especially in developing countries. The contradiction between environment protection and economic development is becoming more and more obvious. In order to realize the sustainable development of environment and economy, China has formulated a series of development plans, environmental protection policies and so on. Among them, scientific environmental efficiency evaluation is particularly important, which is a comprehensive assessment of the economic outputs and environmental outputs. It not only provides a macroscopic understanding of the environmental efficiency of the system, but also provides detailed benchmarking information for the environmental efficiency improvement. Therefore, environmental efficiency evaluation is one of important keys to solve environmental issues. So far, this topic has attracted extensive attention from scholars. Among the related research, data envelopment analysis (DEA) is one of the most popular methods. Based on the DEA method, the main works of this paper are summarized as follows:

(1) This thesis studies the environmental efficiency evaluation of a single-stage system considering fuzzy numbers and its application. Even though environmental efficiency has already extensively applied in many areas, it is rarely seen in the fuzzy

circumstance. In this thesis, we propose an enhanced Russell measure DEA model to analyze the environmental performance of thermal power firms with fuzzy undesirable outputs. The result shows that six of the 30 thermal power firms are efficient, and the inefficient thermal power firms should focus on the consumption of inputs to improve environmental performance.

(2) We study environmental efficiency evaluation of a single-stage system considering the performance improvement path and its application to Xiangjiang River. Since the target (benchmark) set by the previous environmental performance studies is usually the furthest one for a DMU to be efficient, it may be hardly accepted by the DMUs. In order to make the evaluated DMU achieve the environmental efficient with the least effort (cost), this paper proposes a closest target DEA model based on range adjusted measure to evaluate the water environmental efficiency of 15 monitoring areas in seven cities in Xiangjiang River basin of China. The results show that the average closest target environmental efficiencies of Xiangjiang River basin in 2008-2014 are steady around 0.93. Comparing the efficiencies of the 15 areas, we find the Trunk area of Changsha, the Mishui area of Hengyang, the Trunk area of Hengyang, and the Chuling area of Hengyang perform well, and the efficiencies are all higher than 0.99. The results indicate that Hunan Province has made some achievements in the control of water quality pollution in Xiangjiang River.

(3) This thesis studies the environmental efficiency evaluation of a two-stage system. With the rapid development of the industry, the problems of energy consumption and environmental pollution have attracted more and more attention from government and scholars, while improving the industrial environmental efficiency and identifying the key factors affecting efficiency are of great significance for achieving coordinated development of industry and environmental protection. However, almost all previous works considered the internal structure as a “black box” when they measured the environmental efficiency of industrial system, which probably resulted in ignorance of some deficiencies in the system. To solve this problem, we divide the process of China’s industry into two stages: the industrial energy utilization stage and the industrial pollution treatment stage. Accordingly, the industrial overall environmental efficiency is decomposed into two parts, i.e., industrial energy utilization efficiency and industrial pollution treatment efficiency. The results show that all the four kinds of efficiencies of the six areas had an increasing trend. North China, East

China, and South Central China had relatively better performance than the other areas. This indicates that the efficiency in China has the regional characteristics. Compared with the areas of Northeast, Southwest, and Northwest China, the areas of North China, East China, and South Central China are more attractive for skilled laborers and qualified enterprises. Many skilled laborers in Northwest China migrate to other places such as Beijing in North China, Shanghai in East China, and Guangzhou in South Central China for seeking better job opportunity. Besides, through the China Energy Statistical Yearbook 2007-2011, the natural resources in the Northeast and Southwest were relatively fewer. Therefore, the Chinese government should pay attention to the differences among areas so as to balance the development of Chinese industry.

(4) This thesis studies the environmental efficiency evaluation of a parallel network system considering heterogeneity, and further applies to China's transportation sector. Firstly, based on the parallel network structure, we establish a parallel network DEA model considering undesirable output. Second, according to the difference of transportation development in different areas of China, we use the Metafrontier Malmquist-Luenberger productivity index (MMLPI) based on the proposed DEA model to dynamically analyze the environmental efficiency of China's transportation sector. Finally, we analyze the transportation sector of 30 administrative regions in China from 2007 to 2013 based on the network DEA model and MMLPI. we found that Eastern China had the largest within-group efficiency change, Western China had the largest best-practice gap change, and Central China had the largest technology leadership change. By calculating these three factors for driving productivity growth, each region can find its weakness directly and arrange its resources for its transportation sector accordingly.

7.2 Perspectives

Several environmental efficiency evaluation models have been proposed and studied for the environmental efficiency evaluation for the single-stage system and the network system. However, there are still some future directions that can further extend our works.

(1) The first direction is to consider the stochastic data in the environmental efficiency evaluation. In addition to the existence of fuzzy numbers in the environmental efficiency evaluation of the single-stage system in Chapter 3, the multi-

input and multi-output data may have a certain degree of uncertainty, such as just the distribution function, which commonly exists in the environmental issues. Therefore, we will study the environmental performance evaluation with stochastic data by stochastic DEA method and its applications to some real problems.

(2) With the development of internet technology, artificial intelligence, high precision sensors and other technologies, the amount of data in the field of environment greatly increases. These fast-updated, massive environmental big data will bring the new challenge and opportunity to the environmental efficiency evaluation. Currently, the research of environmental management under big data has been widely concerned by scholars. However, in the field of environmental efficiency evaluation, the theoretical research on environmental management under the background of big data is rare. Big data in the field of environmental management provides important information for in-depth analysis of the interaction within the network system, which can be used to solve complex environmental problems. Meanwhile, the internal relationship of the system revealed by the environmental big data puts forward new requirements for the existing performance evaluation methods, thus it is necessary to construct the corresponding interactive network system environment evaluation model. Environmental big data will also greatly increase the complexity of dealing with the corresponding problems. The traditional performance evaluation methods are often inefficient in solving these environmental efficiency evaluation problems because of the large number of DMUs. The future research will study the environmental efficiency evaluation under the circumstance of big data and establish the adaptive environmental efficiency evaluation method in order to solve the more complicated environmental efficiency evaluation problem

(2) The second direction is to consider the stochastic data in the environmental efficiency evaluation. In addition to the existence of fuzzy numbers in the environmental efficiency evaluation of the single-stage system in Chapter 3, the multi-input and multi-output data may have a certain degree of uncertainty, such as just the distribution function, which commonly exists in the environmental issues. Therefore, we will study the environmental performance evaluation with stochastic data by stochastic DEA method and its applications to some real problems.

Appendix of French Abstract

Contents

A.1 Introduction	115
A.2 Théorie DEA de base	118
A.3 Evaluation de l'efficacité environnementale d'un système à une seule étape avec paramètres flous	121
A.4 Évaluation de l'efficacité environnementale d'un système à une seule étape tenant compte de l'amélioration des performances	126
A.5 Evaluation de l'efficacité environnementale d'un système à deux étapes via l'efficacité énergétique de facteur total.....	130
A.6 Evaluation de l'efficacité environnementale d'un système de réseau parallèle prenant en compte l'hétérogénéité régionale	135
A.7 Conclusions et perspectives.....	139

A.1 Introduction

1.1 Contexte pour l'évaluation de l'efficacité environnementale

Ces dernières années, les problèmes environnementaux persistants, tels que la pollution de l'eau et la pollution de l'air, ont gravement nui le développement durable des économies de la plupart des pays, en particulier de certains pays en développement, tels que l'Inde et la Chine. Par conséquent, l'équilibre dynamique entre l'environnement et l'économie est devenu un problème social important (Wu et al., 2014). Après l'analyse des pratiques à long terme, on reconnaît que le développement durable de l'économie et de l'environnement est la principale méthode pour résoudre ce problème, ce qui indique que le développement doit répondre aux besoins de la génération présente sans compromettre le développement des générations futures. Afin de parvenir à un

développement économique durable, la protection de l'environnement est devenue un consensus mondial. En tant que membre important, la Chine joue un rôle essentiel dans l'amélioration de l'environnement mondial. Par conséquent, cette thèse se concentre principalement sur les problèmes environnementaux en Chine.

Après la recherche intensive sur les problèmes environnementaux, nous réalisons progressivement que la réalisation du développement durable ne peut être réalisée sans une gestion efficace de l'environnement, laquelle dépend d'une évaluation scientifique et objective de l'efficacité environnementale (Wu et al., 2014; Song et al., 2012). L'évaluation de l'efficacité environnementale est une évaluation complète des performances d'une organisation dans tous les aspects de la consommation de ressources, des résultats économiques et des résultats environnementaux. Elle ne peut pas seulement montrer l'efficacité environnementale d'un système évalué au niveau macroscopique, mais doit fournir également des informations de référence détaillées pour l'élaboration et la mise en œuvre de politiques de gestion environnementale (Song et al., 2012). Par conséquent, l'évaluation de l'efficacité environnementale est un facteur clé dans la résolution des problèmes environnementaux (Halkos et Tzeremes, 2013).

1.2 Revue de la littérature: évaluation de l'efficacité environnementale basée sur la DEA

L'évaluation de l'efficacité environnementale a attiré une attention soutenue de la part des chercheurs et a été profondément explorée et appliquée dans la vie réelle (Sueyoshi et al., 2017). Parmi les différentes méthodes d'évaluation de l'efficacité environnementale, l'analyse par enveloppement de données (DEA) est l'une des méthodes les plus populaires. La recherche d'évaluation de l'efficacité environnementale basée sur la DEA a retenu l'attention des chercheurs (Färe et al., 1989; Seiford and Zhu 2005; Kao and Hwang, 2008; Halkos and Tzeremes, 2013; Sueyoshi and Goto, 2017). Selon les méthodes utilisées pour traiter les extrants indésirables, les études d'évaluation de l'efficacité environnementale peuvent être classées en deux catégories: approches directes (Färe et al., 1989; Seiford and Zhu, 2005; Zhou et al., 2013; Wang et al., 2016) et approches indirectes (Liu and Sharp, 1999; Wu et al., 2013; Yang et al., 2015).

La plupart des travaux sur l'efficacité environnementale réalisés par la DEA étaient axés sur un système à une étape ou considéraient un système évalué comme une «boîte noire» sans tenir compte de sa structure interne. Cependant, nous ne pouvons pas

trouver l'inefficacité dans le processus de production interne d'un système de cette manière et il est donc difficile d'améliorer les performances du système. Avec la concurrence croissante et les relations entre les entités économiques, les systèmes deviennent de plus en plus complexes, il est important de proposer des méthodes pour l'évaluation de l'efficacité environnementale d'un système de réseau. Au cours des dernières années, la méthode DEA en réseau est devenue une méthode efficace pour mesurer la performance de systèmes multi-étapes. Elle fournit de nouvelles idées et de nouvelles percées pour l'étude de problèmes complexes d'évaluation de l'efficacité environnementale. (Song and Wang, 2013; Lin and Liu, 2015; An et al., 2017; Kao and Hwang, 2008).

1.3 Sujets de recherche

La littérature citée ci-dessus montre que l'évaluation de l'efficacité environnementale a été largement prise en compte par les spécialistes, mais il reste quelques lacunes à combler. Par exemple, comment évaluer l'efficacité environnementale des systèmes flous avec des nombres flous? Comment mesurer l'efficacité environnementale afin de définir l'objectif le plus proche pour un système inefficace en matière d'environnement en utilisant le moins d'effort possible pour atteindre l'efficacité environnementale? Comment mesurer l'efficacité environnementale globale et l'efficacité énergétique de facteur totale d'un système complexe à deux étages? Et comment évaluer l'évolution dynamique de l'efficacité environnementale d'un système de réseau parallèle? Cette thèse vise à étudier ces problèmes théoriques et à appliquer les résultats théoriques à des problèmes environnementaux dans la vie réelle.

1.4 Structure de la thèse

Cette thèse porte sur l'évaluation de l'efficacité environnementale par l'analyse d'enveloppement de données et ses applications.

Cette thèse sera divisée en deux parties selon la structure du système évalué. La première partie concerne les méthodes d'évaluation de l'efficacité environnementale pour les systèmes à une étape et leurs applications, qui comprend deux chapitres. La deuxième partie concerne les méthodes d'évaluation de l'efficacité environnementale pour les systèmes en réseau et leurs applications, qui contient deux chapitres.

A.2 Théorie DEA de base

2.1 Analyse d'enveloppement des données

L'analyse d'enveloppement des données est une méthode de programmation non paramétrique permettant d'évaluer l'efficacité d'un ensemble d'entités appelées unités de prise de décision (DMU) qui convertissent plusieurs entrées en plusieurs sorties. Il s'agit d'un domaine de recherche mixte entre la recherche opérationnelle, les sciences de la gestion et l'économie mathématique. Le modèle séminal DEA a été proposé par Charnes, Cooper et Rhodes en 1978. Jusqu'à présent, il a été largement développé et appliqué dans de nombreux domaines, tels que les entreprises, les hôpitaux, les banques, les centrales thermiques et autres.

(1) Unité de prise de décision

Dans les activités réelles de production et de services, nous rencontrons souvent un problème de gestion qui nous oblige à évaluer la performance de certains départements homogènes au cours d'une période dans laquelle chaque département est appelé unité de prise de décision. On peut voir que DMU désigne toute entité qui convertit des intrants en extrants, tels que des universités, des entreprises, des hôpitaux, des banques, etc.

(2) Évaluation des performances

L'évaluation des performances d'une unité DMU avec une entrée et une sortie est généralement basée sur le rapport entre la sortie et l'entrée. Pour l'évaluation des performances d'une unité DMU à entrées multiples et à sorties multiples, elle est définie comme le rapport entre la valeur pondérée des sorties et la valeur pondérée des entrées. Il convient de noter que, sans perte de généralité, les performances dans cette thèse se réfèrent à l'efficacité relative de la DMU, c'est-à-dire que l'efficacité relative de la DMU évaluée est obtenue en comparant avec les entrées et sorties multiples des autres DMU.

(3) L'ensemble de possibilités de production

Considérons un ensemble de n DMU, avec chacun, $DMU_j (j = 1, \dots, n)$, en utilisant m entrées $X_j = (x_{1j}, \dots, x_{mj})^T$ pour produire s sorties $Y_j = (y_{1j}, \dots, y_{sj})^T$, où

T en exposant indique une transposition. Pendant ce temps, $X_j \geq 0$, $Y_j \geq 0$, $j = 1, \dots, n$, c'est-à-dire que la valeur de chaque entrée et sortie est supérieure ou égale à sur 0, et au moins la valeur d'un indicateur d'entrée et d'un indicateur de sortie est positive. De plus, x_{ij} indique la i ème entrée de DMU_j , et y_{rj} indique la i ème sortie de DMU_j .

L'ensemble de possibilités de production est ensuite défini comme un ensemble de tous les points de production réalisables, à savoir:

$$T = \{(X, Y) | X \text{ peuvent produire } Y\} \quad (\text{A.2.1})$$

De manière équivalente, la technologie T peut être représentée de manière équivalente par ses ensembles de sortie $P(X) = \{Y | (X, Y) \in T\}$ ou ses ensembles d'entrée $P(Y) = \{X | (X, Y) \in T\}$.

(4) Frontière de production

La frontière de production est une surface incurvée constituée de tous les points efficaces du PPS. Il représente la limite à laquelle la production peut être définie pour obtenir le rendement maximal des intrants existants ou pour obtenir les intrants minimums des produits existants. Selon Wei (2004), la frontière de production est définie comme suit:

Définition 2.1. En supposant que $\omega \geq 0$, $\mu \geq 0$, $L = \{(X, Y) | \omega^T X - \mu^T Y = 0\}$, $T \subset \{(X, Y) | \omega^T X - \mu^T Y \geq 0\}$ et $L \cap T \neq \emptyset$, le jeu de possibilités de production faiblement efficace défini sur T est L, et la frontière de production faible correspondante est $L \cap T$. En particulier, si $\omega \geq 0$, $\mu \geq 0$, alors L est appelée la surface efficace de T, $L \cap T$ est la frontière de production de l'ensemble de possibilités de production T.

2.2 Modèles DEA de base

Dans cette section, deux modèles DEA de base, à savoir le modèle CCR et le modèle BCC, sont introduits.

En supposant qu'il y ait n DMU évaluées, chaque DMU utilise les mêmes entrées pour produire les mêmes sorties. $X_j = (x_{1j}, \dots, x_{mj})^T$ et $Y_j = (y_{1j}, \dots, y_{sj})^T$ sont le vecteur d'entrée et le vecteur de sortie de DMU_j , respectivement, où T dans le superscript indique Transpos L'efficacité de chaque DMU est le rapport des sorties

pondérées aux entrées pondérées, la DMU évaluée est notée DMU_0 . Le modèle CCR peut être formulé comme suit.

$$\begin{aligned}
 & \min \quad \theta \\
 & s. t. \quad \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{i0}, i = 1, \dots, m, \\
 & \quad \quad \sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, \dots, s, \\
 & \quad \quad \lambda_j \geq 0, j = 1, \dots, n.
 \end{aligned} \tag{A.2.2}$$

On peut voir que le modèle CCR repose sur l'hypothèse de rendements d'échelle constants. Banker, Charnes et Cooper (1984) ont étendu le modèle DEA en utilisant l'hypothèse de rendements d'échelle variables, qui est abrégée en modèle BCC. Le modèle BCC multiplicateur peut être formulé comme suit.

$$\begin{aligned}
 & \min \quad \theta \\
 & s. t. \quad \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{i0}, i = 1, \dots, m, \\
 & \quad \quad \sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, \dots, s, \\
 & \quad \quad \sum_{j=1}^n \lambda_j = 1, \\
 & \quad \quad \lambda_j \geq 0, j = 1, \dots, n.
 \end{aligned} \tag{A.2.3}$$

2.3 Concepts de base de l'évaluation de l'efficacité environnementale

(1) Efficacité environnementale

Selon la théorie de la production en commun, les rendements souhaitables sont toujours accompagnés de certains rendements qui devraient être moins importants en cours de production, tels que le dioxyde de carbone, le dioxyde de soufre, les eaux usées et les déchets solides. Si des résultats indésirables sont pris en compte dans le cadre

technologique DEA, la technologie correspondante peut être appelée technologie DEA environnementale. Ensuite, l'efficacité obtenue à partir de la technologie environnementale DEA est définie par l'efficacité environnementale (Zhou et al., 2008; Sueyoshi et al., 2017).

(2) Ensemble de possibilités de production environnementale

Supposons que les résultats souhaités et indésirables soient produits dans le processus de production, notons $X_j = (x_{1j}, \dots, x_{mj})$, $U_j = (u_{1j}, \dots, u_{bj})$, $Y_j = (y_{1j}, \dots, y_{sj})$ comme entrées, sorties indésirables et sorties souhaitables de $DMU_j (j = 1, \dots, n)$, respectivement. L'ensemble de possibilités de production associé est exprimé comme suit.

$$T = \{(X, Y, U): X \text{ peuvent produire } (Y, U)\} \quad (\text{A.2.4})$$

Sur la base des définitions de jetabilité faible et forte, pour les systèmes tenant compte de facteurs environnementaux, si $(X, Y, U) \in T$, $Y' \leq Y$, $U' \geq U$ et $(X, Y', U') \in T$, alors les sorties sont fortement jetables. Si $(X, Y, U) \in T$, $\mu \in [0, 1]$ et $(X, \mu Y, \mu U) \in T$, les sorties sont faiblement disponibles.

A.3 Evaluation de l'efficacité environnementale d'un système à une seule étape avec paramètres flous

3.1 Introduction

Ces dernières années, avec le développement rapide de l'économie chinoise, la Chine est confrontée à une consommation d'énergie énorme et à de graves problèmes de pollution de l'environnement. Parmi tous les types d'énergie, l'électricité est la principale source d'énergie en Chine depuis de nombreuses années.

En outre, parmi les divers modes de production d'électricité, la Chine s'appuie fortement sur l'énergie thermique, l'énergie hydraulique et la thermoélectricité. En particulier, l'énergie thermique représentait environ 74,4% de toute l'électricité en 2016. Cette situation sera maintenue pendant longtemps. Étant donné que la production d'énergie thermique génère généralement un grand nombre de pollutions (rendements indésirables), mais avec moins de traitement, elle est devenue la principale source de problèmes environnementaux en Chine. Il est donc essentiel pour nous de mesurer l'efficacité des entreprises thermiques afin d'accroître leur productivité et de réduire leurs émissions.

Jusqu'à présent, de nombreux modèles DEA ont été proposés pour traiter les résultats indésirables et finalement obtenir l'efficacité environnementale (Färe et al., 1989; Seiford et Zhu, 2002; Zhou et al., 2008). Dans ce chapitre, une nouvelle approche utilisant la mesure Russell prenant en compte les extrants indésirables est proposée pour mesurer l'efficacité environnementale d'une entreprise de production d'énergie thermique.

3.2 Examen de Russell Measure, de DEA floue et de résultats indésirables

(1) Mesure Russell

La mesure Russell a été introduite pour la première fois par Färe et Lovell (1978). Il a été nommé «Russell» parce que le spécialiste R.R. Russell a par la suite contribué à son développement ultérieur. En raison de sa propriété non radiale, il a de nombreuses applications (Lozano et al., 2011; Hsiao et al., 2011).

(2) Fuzzy DEA models

Comme nous le savons, les modèles DEA traditionnels supposent que toutes les données pour les entrées et les sorties sont précises, ils ne peuvent donc pas traiter de données imprécises. Pour résoudre cette situation incertaine, la théorie des nombres flous est introduite dans la zone DEA. Le concept d'ensemble flou a été proposé par Zadeh (1965) pour traiter des estimations imprécises dans des circonstances incertaines. Ces dernières années, de nombreux modèles DEA ont été développés dans les environnements flous (Kao et Liu 2000a; Kao et Liu 2000b; Leon et al., 2003; Lertworasirikul et al., 2001; Wang et Li 2014).

(3) Sorties indésirables et efficacité environnementale

La littérature dans ce domaine peut être classée en deux catégories: les approches directes et les approches indirectes. Les approches directes sont principalement basées sur Färe et al. (1989), qui a remplacé l'hypothèse forte des résultats en termes de disponibilité par des hypothèses faiblement disponibles. Ce travail a été largement développé (Färe et al., 1993; Seiford et Zhu, 2005; Färe et al., 2005; Zhou et al., 2007; Zhou et al., 2008; Tone, 2004). Les approches indirectes sont basées sur une hypothèse de résultats forte et jetable (Liu et Sharp, 1999; Dyckhoff et Allen, 2001; Seiford et Zhu, 2002; Tone, 2004). L'efficacité environnementale désigne l'efficacité des UDM qui tiennent compte à la fois des résultats souhaitables et des résultats indésirables. Jusqu'à présent, de nombreuses analyses d'efficacité environnementale par approche DEA ont été effectuées (Korhonen et Luptacik, 2004; Bi et al., 2012; Huang et al., 2014).

Bien que l'efficacité environnementale ait déjà été largement appliquée dans de nombreux domaines, elle n'est que rarement visible dans les circonstances floues, y compris les travaux théoriques et pratiques. Dans ce chapitre, un modèle de mesure Russell amélioré intégré est proposé pour évaluer l'efficacité environnementale avec la présence de sorties indésirables dans des circonstances floues. Il est ensuite appliqué aux entreprises thermiques en Chine.

3.3 Modélisation d'un système à une étape avec des sorties indésirables et des nombres flous

Supposons qu'il y a n DMU dans l'ensemble N à évaluer. Pour $DMU_j (j = 1, 2, \dots, n)$, il applique les entrées $x_{ij} (i = 1, \dots, m) \geq 0$, pour produire les sorties

souhaitables $y_{rj}(r = 1, \dots, s) \geq 0$ et sorties indésirables $u_{kj}(k = 1, \dots, g) \geq 0$.

Notons \tilde{x}_{ij} , \tilde{y}_{rj} et \tilde{u}_{kj} sont les équivalents flous de x_{ij} , y_{rj} et u_{kj} , respectivement. Le modèle ERM flou permettant de mesurer l'efficacité de DMU_0 avec des sorties indésirables est le suivant:

$$\begin{aligned}
 \min R_e &= \frac{\frac{1}{m} \sum_{i=1}^m \theta_i}{\frac{1}{s+g} \left(\sum_{r=1}^s \varphi_r + \sum_{k=1}^g \phi_k \right)} \\
 s.t. \quad &\sum_{j=1}^n \lambda_j \tilde{x}_{ij} \leq \theta_i \tilde{x}_{i0}; i = 1, \dots, m, \\
 &\sum_{j=1}^n \lambda_j \tilde{y}_{rj} \geq \varphi_r \tilde{y}_{r0}; r = 1, \dots, s, \\
 &\sum_{j=1}^n \lambda_j \tilde{u}_{kj} \geq \phi_k \tilde{u}_{k0}; k = 1, \dots, g, \\
 &\theta_i \leq 1, \forall i, \\
 &\varphi_r, \phi_k \geq 1, \forall r, k, \\
 &\phi_k \leq \frac{w}{\tilde{u}_{kj}}, \forall k, \\
 &\lambda_j \geq 0, j = 1, \dots, n.
 \end{aligned} \tag{A.3.1}$$

Le modèle est clairement une programmation non linéaire avec une fonction d'objectif à structure fractionnaire. Par la transformation de Charnes-Cooper, le modèle non linéaire (A.3.1) peut être converti en une formulation de programmation linéaire.

$$\begin{aligned}
 \min \tilde{R}_e &= \frac{\sum_{i=1}^m b_i}{m} \\
 \text{s.t.} \quad &\sum_{r=1}^s a_r + \sum_{k=1}^g c_k = s + g \\
 &\sum_{j=1}^n t_j \tilde{x}_{ij} \leq b_i \tilde{x}_{i0}; i = 1, \dots, m, \\
 &\sum_{j=1}^n t_j \tilde{y}_{rj} \geq a_r \tilde{y}_{r0}; r = 1, \dots, s, \\
 &\sum_{j=1}^n t_j \tilde{u}_{kj} \geq c_k \tilde{u}_{k0}; k = 1, \dots, g, \\
 &b_i \leq \beta, \forall i, \\
 &\beta \leq a_r, \forall r, \\
 &\beta \leq c_k, \forall k, \\
 &c_k \leq \tilde{\ell} \beta, \forall k, \\
 &t_j \geq 0, j = 1, \dots, n, \\
 &0 \leq \beta \leq 1.
 \end{aligned} \tag{A.3.2}$$

Sur la base du modèle (A.3.2), nous pouvons utiliser la méthode α -cut pour calculer les efficacités environnementales des bornes supérieure et inférieure des DMU_0 .

3.4 Application à l'évaluation de l'efficacité environnementale des entreprises thermiques

Dans cette section, nous appliquons notre approche pour évaluer l'efficacité environnementale de 30 entreprises d'énergie thermique en Chine en 2010, laquelle contient un nombre flou et une production indésirable.

Sur la base du modèle proposé, les limites supérieures et inférieures de l'efficacité floue coupée en α des DMU sous-évaluées sont obtenues. Nous pouvons constater que 6 des 30 entreprises d'énergie thermique étaient pleinement efficaces et que leurs bornes supérieure et inférieure étaient toutes égales à 1 pour tout α et que les 24 entreprises restantes devenaient inefficaces lorsque la valeur de α variait de 0 à 1. De plus, lorsque α augmente, l'efficacité de la borne supérieure de la DMU évaluée diminue et celle de la borne inférieure augmente. De plus, notre approche peut fournir des points de repère aux entreprises évaluées pour améliorer leur efficacité. Nous trouvons que la plupart des améliorations devraient être prises sur les intrants. La valeur totale de la

production industrielle et les déchets solides n'ont besoin que d'augmenter une petite valeur au niveau actuel. Cela indique que si l'entreprise veut être écologiquement efficace, elle doit se concentrer sur l'utilisation d'intrants.

A.4 Évaluation de l'efficacité environnementale d'un système à une seule étape tenant compte de l'amélioration de performances

4.1 Introduction

La rivière Xiangjiang, la plus grande rivière de la province du Hunan en Chine, est la «rivière mère» de la province du Hunan. Le bassin de la rivière Xiangjiang est la région la plus densément peuplée avec le plus haut niveau d'urbanisation et l'économie la plus développée de la province du Hunan. Cependant, la population nombreuse et le développement économique rapide ont entraîné la plus grande pression sur les ressources et l'environnement. Toutefois, en raison du manque d'évaluation de l'efficacité environnementale par les professionnels et d'objectifs scientifiques d'amélioration de l'efficacité, le bassin de la rivière Xiangjiang est toujours confronté à une pénurie de ressources en eau, à la pollution de l'eau et de la pollution atmosphérique et aux métaux lourds. Par conséquent, il est urgent de mesurer l'efficacité environnementale de l'eau et de définir les critères de référence pour le bassin de la rivière Xiangjiang. Dans ce chapitre, une approche d'analyse d'enveloppement de données (DEA) avec la cible la plus proche est appliquée pour mesurer l'efficacité environnementale et définir les cibles les plus proches pour le bassin de la rivière Xiangjiang.

La DEA, en tant que technique de programmation non paramétrique, est de plus en plus utilisée pour évaluer les performances d'un ensemble d'unités de prise de décision homogènes (Li and Lin, 2016). Jusqu'à présent, il a été largement appliqué dans l'évaluation de l'efficacité environnementale ou de l'efficacité écologique (Färe et al., 1989; Leleu, 2013). Cependant, les études précédentes fixaient presque l'objectif "le plus éloigné" qu'une unité de gestion soit à même d'atteindre l'efficacité tout en mesurant l'efficacité environnementale. Ainsi, la référence (cible) peut ne pas être facilement acceptable par la DMU. Récemment, certains développements se concentrent sur la recherche de la cible «la plus proche», de sorte que la DMU en cours d'évaluation puisse être efficace avec le «moindre» effort. L'idée sous-jacente de la cible la plus proche est que la cible la plus proche suggère des axes d'amélioration pour les entrées et les sorties de l'unité inefficace qui amènera la DMU à être efficace avec moins d'effort (Aparicio and Pastor 2014a).

Pour mesurer l'efficacité environnementale du système d'alimentation en eau dans le bassin de la rivière Xiangjiang et définir la cible d'efficacité la plus proche pour la DMU évaluée, nous proposons dans ce chapitre un nouveau modèle de cible la plus proche basé sur la mesure de distance ajustée (RAM). La RAM est choisie comme modèle de base, car il ne s'agit pas uniquement d'un modèle DEA non radial, elle peut également traiter des données non positives dans les indicateurs d'entrée et de sortie (Ding et al., 2018).

4.2 Modèle de RAM cible le plus proche prenant en compte les sorties indésirables

Supposons que n DMU soient évalués. $DMU_j (j = 1, \dots, n)$ utilisent chacun m entrées pour produire s sorties souhaitables tout en générant q sorties indésirables. Les notations sont données comme suit. $x_{ij} (i = 1, \dots, m)$ est la i ème entrée de DMU_j , $y_{rj} (r = 1, \dots, s)$ est la troisième sortie souhaitable de DMU_j et $z_{pj} (p = 1, \dots, q)$ est la p th sortie indésirable de DMU_j . Sur la base du modèle RAM, nous construisons le modèle cible suivant le plus proche pour mesurer l'efficacité environnementale de la DMU_o évaluée.

$$\begin{aligned}
 \text{Max} \quad & 1 - \frac{1}{m+p+s} \left(\sum_{i=1}^m \frac{s_{i0}^-}{R_i^-} + \sum_{p=1}^q \frac{s_{p0}^{--}}{R_p^{--}} + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^+}{R_r^+} \right) \\
 \text{s.t.} \quad & \sum_{j \in H} \lambda_j x_{ij} + s_{i0}^- = x_{i0}, i = 1, \dots, m, \\
 & \sum_{j \in H} \lambda_j y_{rj} - s_{r0}^+ = y_{r0}, r = 1, \dots, s, \\
 & \sum_{j \in H} \lambda_j z_{pj} + s_{p0}^{--} = z_{p0}, p = 1, \dots, q, \\
 & - \sum_{i=1}^m v_i x_{ij} - \sum_{p=1}^q \pi_p z_{ij} + \sum_{r=1}^s w_r y_{rj} + d_j = 0, j \in H, \\
 & v_i \geq \frac{1}{(m+q+s)R_i^-}, i = 1, \dots, m, \\
 & \pi_p \geq \frac{1}{(m+q+s)R_p^{--}}, p = 1, \dots, q, \\
 & w_r \geq \frac{1}{(m+q+s)R_r^+}, r = 1, \dots, s, \\
 & d_j \leq M b_j, j \in H, \\
 & \lambda_j \leq M(1-b_j), j \in H, \\
 & b_j \in \{0,1\}, d_j \geq 0, \lambda_j \geq 0, j \in H, \\
 & s_{i0}^-, s_{r0}^+, s_{p0}^{--} \geq 0, i = 1, \dots, m; r = 1, \dots, s; p = 1, \dots, q.
 \end{aligned} \tag{A.4.1}$$

Supposer que $(\lambda_j^*, s_{i0}^{-*}, s_{r0}^{+*}, s_{p0}^{--*}, v_i^*, \pi_p^*, w_r^*, d_j^*, b_j^*)$ est une solution optimale du modèle cible le plus proche (A.4.1). Ensuite, la cible la plus proche pour le DMU_o évalué peut être exprimée par:

$$(\hat{x}_{i0} = x_{i0} - s_{i0}^{-*}, \hat{y}_{r0} = y_{r0} + s_{r0}^{+*}, \hat{z}_{p0} = z_{p0} - s_{p0}^{--*}) \tag{A.4.2}$$

L'efficacité environnementale pour la DMU_o évaluée basée sur la cible la plus proche peut être obtenue en calculant la formule suivante.

$$\rho_{env} = 1 - \frac{1}{m+p+s} \left(\sum_{i=1}^m \frac{s_{i0}^{-*}}{R_i^-} + \sum_{p=1}^q \frac{s_{p0}^{--*}}{R_p^{--}} + \frac{1}{s} \sum_{r=1}^s \frac{s_{r0}^{+*}}{R_r^+} \right) \tag{A.4.3}$$

4.3 Application à l'évaluation de l'efficacité environnementale de l'eau du bassin de la rivière Xiangjiang

Nous appliquons le modèle proposé pour évaluer l'efficacité environnementale du système d'alimentation en eau dans le bassin de la rivière Xiangjiang en Chine. Les

résultats montrent que l'efficacité environnementale moyenne de l'eau est très élevée pendant cette période. Comparé à l'efficacité classique de l'environnement aquatique, nous constatons que l'efficacité de l'environnement aquatique est plus stable et que la différence entre les villes est beaucoup plus petite. Les résultats montrent que la cible la plus proche de chaque ville inefficace est stable et plus facilement atteinte. En outre, nous constatons que la plupart des zones économiquement rationnelles en eau sont des villes développées sur le plan économique, telles que Changsha et Zhuzhou. Par conséquent, les autres zones inefficaces peuvent apprendre de ces zones efficaces et formuler les politiques correspondantes en fonction de leur niveau économique et des conditions environnementales afin d'améliorer l'efficacité environnementale.

A.5 Evaluation de l'efficacité environnementale d'un système à deux étapes via l'efficacité énergétique de facteur total

5.1 Introduction

Alors que la Chine connaît un succès considérable en matière de développement économique au cours des dernières décennies, le gouvernement fait face aux défis internes actuels de la pénurie d'énergie et de la dégradation de l'environnement. Afin de réaliser les objectifs du douzième plan quinquennal chinois, il est nécessaire d'analyser la situation de mise en œuvre du onzième plan quinquennal chinois pour la période 2006-2010 afin analyse des rendements énergétiques et environnementaux antérieurs.

En raison des avantages de la méthode DEA, la DEA est choisie comme méthode de base pour évaluer l'efficacité énergétique et l'efficacité environnementale. Récemment, un nombre croissant d'études ont utilisé des modèles DEA conventionnels (Hu and Wang, 2006), des modèles DEA non radiaux (Fukuyama and Weber, 2009; Zhou et al., 2012; Zhang and Choi, 2013), mesure ajustée en fonction de la plage. modèles basés sur la DEA (RAM-DEA) (Wang et al., 2013) et modèles de fonction de distance directionnelle (DDF) (Wang et al., 2013; Zhou et al., 2012) pour évaluer l'efficacité énergétique et environnementale, bien que rarement axé sur l'efficacité énergétique industrielle totale et l'efficacité environnementale industrielle en Chine. L'industrie joue un rôle essentiel dans le développement de l'économie en Chine, comme en témoigne le fait que la valeur de la production industrielle brute représentait environ 38,5% du produit intérieur brut (GDP) de la Chine en 2012. Plus important encore, le secteur industriel est un secteur à forte intensité énergétique qui représentait 70% de la consommation totale d'énergie finale en 2012 (NBSC, 2013, 2014). La pollution industrielle est également la principale source de pollution en Chine. Il est donc urgent et utile d'étudier l'efficacité énergétique industrielle totale et industrielle en Chine.

Au meilleur de nos connaissances, presque tous les ouvrages publiés antérieurement considéraient le système industriel comme une «boîte noire» lorsqu'ils mesuraient l'efficacité environnementale du système industriel, ce qui a probablement conduit à la méconnaissance de certaines défaillances du système. Dans ce chapitre, nous divisons le processus de consommation et d'utilisation de l'énergie dans

l'industrie chinoise en deux phases: la phase d'utilisation industrielle de l'énergie et la phase de traitement de la pollution industrielle. En analysant la structure en deux étapes du processus de consommation d'énergie de l'industrie chinoise, nous pouvons étudier efficacement les inefficacités de la structure interne du système et fournir des indications précieuses pour la gestion lors de l'évaluation du double impact des stratégies opérationnelles et commerciales du secteur industriel chinois.

5.2 Modélisation de l'évaluation de l'efficacité environnementale du système industriel chinois

Pour notre étude de l'évaluation de l'efficacité environnementale industrielle en Chine, nous divisons le processus de production industrielle en deux sous-processus: le processus d'utilisation de l'énergie et le processus de traitement de la pollution. Le premier sous-processus est axé sur l'utilisation d'intrants énergétiques et non énergétiques pour produire les extrants souhaitables et indésirables, tandis que le dernier sous-processus est axé sur le recyclage et l'élimination de la pollution et des déchets produits dans le premier. La structure est visible à la figure 5.1.

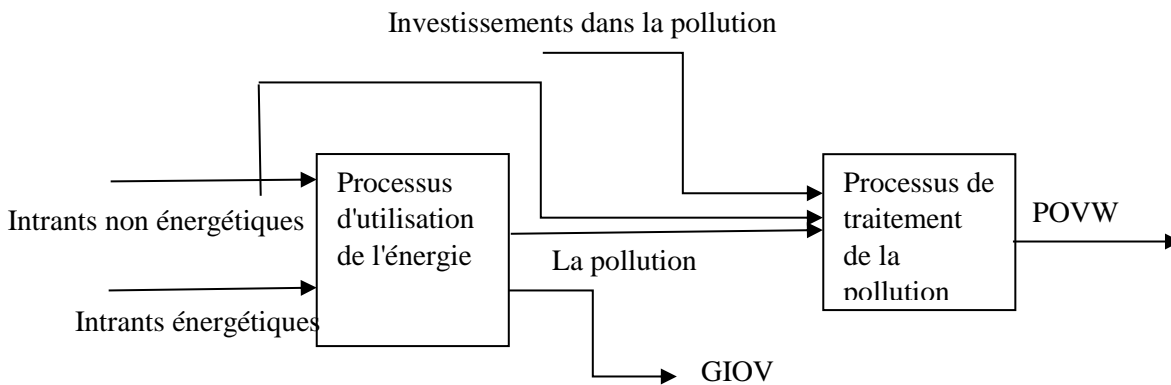


Figure 5.1 Système de structure en deux étapes de l'industrie chinoise

Supposons qu'il y a n DMU, chacun représentant l'industrie d'une région administrative de la Chine ($DMU_j, j = 1, \dots, n$). Indiquez les entrées partagées par $X_j = (x_{1j}, \dots, x_{Mj})$ et les entrées d'énergie par $Z_j = (z_{1j}, \dots, z_{Kj})$ au premier stade. Les sorties souhaitables du premier étage sont notées $D_j = (d_{1j}, \dots, d_{Sj})$ et les sorties indésirables du premier étage par $U_j = (u_{1j}, \dots, u_{Fj})$, qui sont également les entrées du deuxième étage. Notons les nouvelles entrées du deuxième étage par $I_j = (i_{1j}, \dots, i_{Gj})$

et les sorties du deuxième étage par $Y_j = (y_{1j}, \dots, y_{Hj})$. Indique la DMU en cours d'évaluation par DMU_0 .

Nous construisons le modèle centralisé suivant, qui intègre les deux étapes sous le contrôle d'un décideur centralisé, pour mesurer l'efficacité environnementale globale du système à deux étapes.

$$\min e_0 = \frac{1}{2} \left[\frac{1}{M + K + F} \left[\sum_{m=1}^M \beta_m + \sum_{k=1}^K \delta_k + \sum_{f=1}^F \theta_f \right] + \frac{1}{F + G + M} \left[\sum_{f=1}^F \theta_f + \sum_{g=1}^G \phi_g + \sum_{m=1}^M \varphi_m \right] \right]$$

s.t.

Stage 1 constraints:

$$\sum_{j=1}^n (\rho^j + \mu^j) \alpha^j x_m^j \leq \beta_m \alpha^0 x_m^0, \quad m = 1, \dots, M$$

$$\sum_{j=1}^n (\rho^j + \mu^j) z_k^j \leq \delta_k z_k^0, \quad k = 1, \dots, K$$

$$\sum_{j=1}^n \rho^j d_s^j \geq d_s^0, \quad s = 1, \dots, S$$

$$\sum_{j=1}^n \rho^j u_f^j = \theta_f u_f^0, \quad f = 1, \dots, F$$

Stage 2 constraints:

$$\sum_{j=1}^n \rho^j u_f^j = \theta_f u_f^0, \quad f = 1, \dots, F$$

$$\sum_{j=1}^n (\rho^j + \mu^j) i_g^j \leq \phi_g i_g^0, \quad g = 1, \dots, G$$

$$\sum_{j=1}^n (\rho^j + \mu^j) (1 - \alpha^j) x_m^j \leq \varphi_m (1 - \alpha^0) x_m^0, \quad m = 1, \dots, M$$

$$\sum_{j=1}^n (\rho^j + \mu^j) y_h^j \geq y_h^0, \quad h = 1, \dots, H$$

generic constraints:

$$\sum_{j=1}^n (\rho^j + \mu^j) = 1$$

$$LW^j \leq \alpha^j \leq UP^j \quad j = 1, \dots, n$$

$$\rho^j, \mu^j \geq 0, \quad j = 1, \dots, n$$

$$0 \leq \beta_m, \delta_k, \theta_f, \phi_g, \varphi_m \leq 1, \quad \text{for all } m, k, f, g, m.$$

(A.5.1)

En résolvant le modèle (A.5.1), l'efficacité environnementale globale du système e_0^* et l'efficacité de la première étape de e_{10}^* et de la deuxième étape by e_{20}^* sont obtenues. De plus, selon Hu et Wang (2006), l'indice TFEE de DMU_0 du modèle proposé peut être obtenu.

5.3 Application à l'évaluation de l'efficacité environnementale de l'industrie chinoise

Nous utilisons le modèle DEA en deux étapes proposé pour évaluer l'efficacité énergétique industrielle, l'efficacité environnementale globale, l'efficacité d'utilisation de l'énergie industrielle et l'efficacité du traitement de la pollution industrielle de 30 provinces en Chine.

Les résultats ont montré que l'efficacité énergétique moyenne totale de l'industrie était passée de 0,674 en 2006 à 0,850 en 2010. Les provinces du Guangdong et de Hainan étaient éconergétiques au cours de cette période. Outre ces régions d'efficacité énergétique totale des facteurs, la ville de Beijing et la province de Jiangsu affichaient une efficacité énergétique totale élevée. Cela indique que les performances en termes d'utilisation de l'énergie dans ces régions ont été relativement bonnes. En outre, les résultats montrent que l'efficacité environnementale globale ainsi que l'efficacité de la phase 1 et l'efficacité de la phase 2 se sont considérablement améliorées de 2006 à 2010 pour la plupart des provinces. La valeur moyenne de l'efficacité environnementale globale de toutes les régions a augmenté d'année en année, passant de 0,499 en 2006 à 0,770 en 2010. En comparant l'efficacité de deux étapes, nous avons constaté que l'efficacité de la première étape était supérieure à celle de la deuxième étape, mais que l'écart a été réduit.

Afin d'analyser les tendances d'efficacité des provinces d'un point de vue plus large, nous avons classé ces 30 régions en six zones administratives: la Chine du Nord, la Chine du Nord-Est, la Chine de l'Est, la Chine du Centre-Sud, la Chine du Sud-Ouest et la Chine du Nord-Ouest division de la Chine. On peut constater que les quatre types d'efficacité des six domaines ont tous eu une tendance à la hausse. La Chine du Nord, la Chine de l'Est et la Chine du Centre-Sud ont eu des performances relativement meilleures que les autres régions. Comparées aux régions du nord-est, du sud-ouest et du nord-ouest de la Chine, les régions du nord, de l'est et du sud de la Chine sont plus attractives pour les travailleurs qualifiés et les entreprises qualifiées. De plus, les ressources naturelles du Nord-Est et du Sud-Ouest étaient limitées, comme le montre

l'Annuaire statistique de l'énergie de Chine 2007-2011. Avec le développement du système de transport intérieur de la Chine, les inconvénients de l'emplacement pour les zones du nord-est et du sud-ouest s'atténuent, puisqu'elles peuvent obtenir plus facilement des ressources d'ailleurs. Sur la base de ces résultats, nous suggérons au gouvernement chinois de prêter attention aux différences entre les zones afin d'équilibrer le développement de l'industrie chinoise. De plus, grâce à nos modèles, nous pouvons également obtenir des points de repère permettant à l'une quelconque de ces industries de devenir écologiquement efficace.

A.6 Evaluation de l'efficacité environnementale d'un système de réseau parallèle prenant en compte l'hétérogénéité régionale

6.1 Introduction

En tant que partie importante des activités sociales et économiques humaines, le transport consiste à réaliser le déplacement physique des personnes et des biens en organisant diverses ressources telles que des outils, du personnel, des fonds, etc. Selon les moyens de transport, les services de transport comprennent principalement le transport ferroviaire, transport routier, voie navigable et transport de l'aviation civile. Bien que le secteur des transports en Chine se soit développé rapidement, ces progrès se sont accompagnés de problèmes. a) En Chine, le secteur des transports représentait 8% de la consommation totale d'énergie et 10% des émissions totales de carbone en 2013, selon le China Statistical Yearbook 2015. b) La structure globale des infrastructures de transport de la Chine est importante à présent, mais la construction s'intéresse principalement à la Chine orientale et la disparité entre la Chine orientale, la Chine centrale et la Chine occidentale s'élargit. La réduction de la consommation d'énergie et des émissions de carbone du secteur des transports dans ces trois domaines est donc cruciale pour le développement durable à long terme des transports, des ressources et de l'environnement.

Dans ce chapitre, nous construirons un nouveau cadre de mesure de l'évolution de la performance des secteurs du transport sur la base d'une analyse de l'enveloppement des données prenant en compte la structure interne. En outre, compte tenu de l'hétérogénéité des secteurs de transport des provinces chinoises, un nouvel indice de productivité métafrontier Malmquist-Luenberger (MMLPI) basé sur notre modèle de réseau DEA est dérivé pour étudier la croissance de la productivité.

6.2 Evaluation de l'efficacité environnementale d'un réseau de transport parallèle

Dans cette section, nous examinons d'abord le modèle DEA classique, puis développons un nouveau modèle DEA en réseau pour un secteur des transports. En outre, nous définissons l'indice de productivité du méta-frontalier Malmquist-Luenberger pour le secteur des transports. Le secteur des transports en Chine étant principalement composé de quatre sous-systèmes: le transport ferroviaire, le transport routier, le transport fluvial et le transport aérien, nous formulons le système à l'aide d'un

modèle DEA à réseau parallèle. La structure correspondante pour le secteur des transports est donnée à la figure 6.1 comme suit.

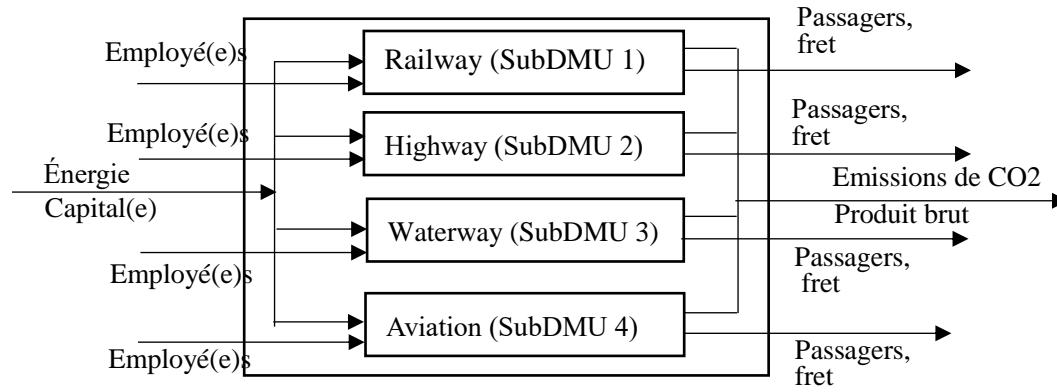


Figure 6.1 La structure du réseau du secteur des transports en Chine

Sur la base de la structure du secteur des transports illustrée à la figure 6.1, nous avons proposé un nouveau modèle d' DEA de réseau qui partage non seulement les intrants, les extrants souhaitables partagés et les extrants indésirables, mais également les intrants individuels et les extrants individuels. Le modèle est le suivant:

$$\begin{aligned}
 \phi &= \min \sum_{i=1}^m \omega_i x_{i0} + \sum_{l=1}^d (\mathcal{G}_l \sum_{p=1}^q \tilde{x}_{l0}^p) + \sum_{h=1}^k v_h z_{h0} \\
 s.t. \quad & \sum_{r=1}^b \mu_r \tilde{y}_{r0} + \sum_{g=1}^f \xi_g y_{g0} = 1, \\
 & \sum_{r=1}^b (\mu_r (\sum_{p=1}^q \tilde{y}_{rj}^p)) + \sum_{g=1}^f \xi_g y_{gj} - \sum_{i=1}^m \omega_i x_{ij} - \sum_{l=1}^d (\mathcal{G}_l (\sum_{p=1}^q \tilde{x}_{lj}^p)) - \sum_{h=1}^k v_h z_{hj} \leq 0, j \in PPS, \\
 & \sum_{r=1}^b \mu_r \tilde{y}_{rj}^p + \sum_{g=1}^f \xi_g \gamma_g^p y_{gj} - \sum_{i=1}^m \omega_i \alpha_i^p x_{ij} - \sum_{l=1}^d \mathcal{G}_l \tilde{x}_{lj}^p - \sum_{h=1}^k v_h \beta_h^p z_{hj} \leq 0, p = 1, \dots, q, j \in PPS, \\
 & \sum_{p=1}^q \alpha_i^p = 1, i = 1, \dots, m, \\
 & \sum_{p=1}^q \beta_h^p = 1, h = 1, \dots, k, \\
 & \sum_{p=1}^q \gamma_g^p = 1, g = 1, \dots, f, \\
 & \omega_i, \mu_r, v_h, \mathcal{G}_l, \xi_g, \alpha_i^p, \beta_h^p, \gamma_g^p \geq 0, \\
 & i = 1, 2, \dots, m; r = 1, \dots, b; h = 1, \dots, k; l = 1, \dots, d; g = 1, \dots, f; p = 1, \dots, q.
 \end{aligned} \tag{A.6.1}$$

De plus, compte tenu de l'hétérogénéité des secteurs des transports dans différentes régions de la Chine, un nouvel indice de productivité métafrontier Malmquist-

Luenberger est proposé, basé sur le modèle de réseau DEA. L'indice de productivité du métafrontier Malmquist-Luenberger (MMLPI) est décomposé en trois mesures individuelles: le changement d'efficacité au sein du groupe (l'effet de rattrapage), le changement de meilleure pratique (l'effet d'innovation) et le changement de leadership technologique) comme suit.

$$\begin{aligned}
 & MMLPI(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t, x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) \\
 &= \frac{D^{t+1}(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)} \times \frac{D^t(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) / D^{t+1}(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t) / D^t(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)} \\
 &\quad \times \frac{D^G(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1}) / D^I(x^{t+1}, \tilde{x}^{t+1}, y^{t+1}, \tilde{y}^{t+1}, z^{t+1})}{D^G(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t) / D^I(x^t, \tilde{x}^t, y^t, \tilde{y}^t, z^t)} \\
 &= \frac{TE^{t+1}}{TE^t} \times \frac{BPG^{t+1}}{BPG^t} \times \frac{TGR^{t+1}}{TGR^t} \\
 &= EC \times BPC \times TGC
 \end{aligned}
 \tag{A.6.2}$$

TE^t , BPG^t , et TGR^t sont respectivement le niveau d'efficacité technique d'un DMU (comme un secteur de transport provincial) dans le groupe R, le fossé des meilleures pratiques en matière d'observation au sein du groupe R et le fossé technologique des observations pour le DMU du groupe R par rapport à la technologie globale, le tout à l'heure t (Battese et al. 2004; Oh et Lee 2010).

6.3 Application à l'évaluation de l'efficacité environnementale du secteur des transports

(1) Indice Metafrontier Malmquist-Luenberger moyen et ses décompositions

Parmi les 30 régions, seules 6 régions ont affiché une tendance à la baisse du MMLPI. Shangdong a enregistré la plus forte augmentation du MMLPI moyen, tandis que Hainan a enregistré la plus forte baisse. En ce qui concerne l'indice CE, six régions sont plus éloignées des frontières, une région est restée inchangée et les autres régions ont enregistré une augmentation de la CE moyenne. Notez qu'une CE plus élevée ne signifie pas une performance supérieure, mais une amélioration à haut rendement au cours de ces années. Ces résultats indiquent clairement quelles régions peuvent être utilisées comme références dans le même groupe, car leur expérience peut être bénéfique à d'autres régions pour améliorer leurs performances ou éviter les revers du secteur des transports. De manière analogue, BPC et TGC peuvent aider les

gestionnaires de secteur à déterminer l'effet de l'innovation et de la technologie en vue d'accroître la productivité du secteur des transports de chaque région.

(2) Indice Metafrontier Malmquist-Luenberger et ses décompositions pour chaque zone

Afin d'analyser les tendances du développement des transports des régions d'un point de vue plus large, les régions ont été classées en trois zones: la Chine orientale, la Chine occidentale et la Chine centrale. Les résultats montrent que la Chine occidentale et la Chine centrale ont affiché la plus forte croissance en termes de croissance de la productivité des transports au cours de la période, avec 0,1576 et 0,1104, respectivement, tandis que l'est de la Chine a enregistré une baisse moyenne de 0,0350. Afin d'enquêter sur les sources de ces changements dans les performances du secteur des transports en Chine, le MMLPI est décomposé en trois mesures distinctes: le changement d'efficacité au sein du groupe, le changement de meilleure pratique (BPC) et le changement de déficit technologique (TGC). Nous pouvons constater que l'augmentation du MMLPI des transports en Chine provient principalement de BPC et de TGC, mais les résultats ont été différents selon les régions.

A.7 Conclusions et perspectives

Dans cette thèse, plusieurs modèles d'évaluation de l'efficacité environnementale sont proposés et étudiés pour l'évaluation de l'efficacité environnementale du système à une étape et du système de réseau. Les principaux travaux de cette thèse se résument comme suit:

Tout d'abord, un modèle de mesure de Russell amélioré est proposé sur la base d'une analyse d'enveloppement de données pour évaluer la performance des unités de prise de décision en présence de sorties indésirables dans des circonstances floues. Ensuite, le nouveau modèle est appliqué pour analyser l'efficacité environnementale et fournir des repères aux entreprises d'énergie thermique en Chine, ce qui peut guider les décideurs dans l'élaboration de plans de production appropriés pour améliorer leurs performances. Ensuite, en prenant en compte les résultats indésirables, un nouveau modèle DEA cible plus proche basé sur une mesure de distance ajustée (RAM) est établi pour mesurer la performance environnementale d'un système à une étape. Le modèle proposé est utilisé pour mesurer l'efficacité environnementale des régions du bassin de la rivière Xiangjiang en Chine, et l'objectif le plus proche est défini pour ces régions inefficaces afin qu'elles puissent faire le minimum d'efforts pour atteindre l'efficacité.

En outre, nous construisons un nouveau modèle d'analyse de l'enveloppement des données en deux étapes avec des entrées partagées pour analyser l'industrie chinoise, communément considérée comme une «boîte noire» dans les méthodes traditionnelles d'efficacité environnementale. Sur la base de l'analyse théorique du modèle, certaines suggestions de politiques sont données à cette industrie. Enfin, nous examinons le secteur des transports en Chine en le divisant en quatre sous-systèmes principaux: les chemins de fer, les autoroutes, les voies navigables et l'aviation civile, puis nous construisons un modèle d'analyse de l'enveloppement des données de réseau permettant de mesurer les performances du secteur en tenant compte des émissions indésirables de CO₂. En outre, compte tenu de l'hétérogénéité des secteurs des transports dans différentes régions de Chine, un nouvel indice de productivité métafrontier Malmquist-Luenberger est proposé, fondé sur le modèle de réseau DEA, qui permet d'enquêter sur la croissance de la productivité des secteurs des transports de 30 régions en 2007-2013. Enfin, quelques suggestions sont données pour guider le

développement du secteur des transports en Chine.

Bien que des résultats de recherche intéressants aient été obtenus, certaines directions intéressantes pour cette thèse peuvent être approfondies à l'avenir. Avec le développement de la technologie Internet, de l'intelligence artificielle, des capteurs de haute précision et d'autres technologies, la quantité de données dans le domaine de l'environnement augmente considérablement. Ces données massives sur l'environnement, volumineuses, imprécises et de grande valeur, apporteront une nouvelle dimension à l'évaluation de l'efficacité environnementale. Il est urgent de mettre au point la méthode d'évaluation de l'efficacité environnementale du système de réseau interactif dans le cas des données volumineuses liées à l'environnement.

References

- Adler, N., Martini, G., & Volta, N. (2013). Measuring the environmental efficiency of the global aviation fleet. *Transportation Research Part B: Methodological*, 53, 82-100.
- Amirteimoori, A., & Kordrostami, S. (2010). A Euclidean distance-based measure of efficiency in data envelopment analysis. *Optimization*, 59(7), 985-996.
- An, Q., Chen, H., Xiong, B., Wu, J., & Liang, L. (2017). Target intermediate products setting in a two-stage system with fairness concern. *Omega*, 73, 49-59.
- An, Q., Pang, Z., Chen, H., & Liang, L. (2015). Closest targets in environmental efficiency evaluation based on enhanced Russell measure. *Ecological Indicators*, 51, 59-66.
- An, Q., Wen, Y., Xiong, B., Yang, M., & Chen, X. (2017). Allocation of carbon dioxide emission permits with the minimum cost for Chinese provinces in big data environment. *Journal of Cleaner Production*, 142, 886-893.
- An, Q., Chen, X., Yu Y., & Chu, J. (2017). Fair setting for intermediate products in two-stage system based on DEA. *Journal of Management Sciences in China*, 20(01), 32-40. (in Chinese)
- Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39(10), 1261-1264.
- Ando, K., Kai, A., Maeda, Y., & Sekitani, K. (2012). Least distance based inefficiency measures on the Pareto-efficient frontier in DEA. *Journal of the Operations Research Society of Japan*, 55(1), 73-91.
- Aparicio, J., Ruiz, J. L., & Sirvent, I. (2007). Closest targets and minimum distance to the Pareto-efficient frontier in DEA. *Journal of Productivity Analysis*, 28(3), 209-218.
- Aparicio, J., & Pastor, J. T. (2013). A well-defined efficiency measure for dealing with closest targets in DEA. *Applied Mathematics and Computation*, 219(17), 9142-9154.
- Aparicio, J., & Pastor, J. T. (2014a). On how to properly calculate the Euclidean distance-based measure in DEA. *Optimization*, 63(3), 421-432.
- Aparicio, J., & Pastor, J. T. (2014b). Closest targets and strong monotonicity on the

- strongly efficient frontier in DEA. *Omega*, 44, 51-57.
- Arabi, B., Munisamy, S., Emrouznejad, A., & Shadman, F. (2014). Power industry restructuring and eco-efficiency changes: A new slacks-based model in Malmquist–Luenberger Index measurement. *Energy Policy*, 68, 132-145.
- Ashrafi, A., Jaafar, A. B., & Lee, L. S. (2012). An enhanced Russell measure of efficiency in the presence of non-discretionary factors in data envelopment analysis. *Proceedings of the Romanian Academy Series A-Mathematics Physics Technical Sciences Information Science*, 13(2), 91-96.
- Baek, C., & Lee, J. D. (2009). The relevance of DEA benchmarking information and the least-distance measure. *Mathematical and Computer Modelling*, 49(1-2), 265-275.
- Bai, Y., Niu, J., & Hao, Y. (2012). Research of Regional Energy Efficiency Based on Undesirable Outputs and Its Influential Factors: A Case of Western China. *Energy Procedia*, 16, 802-809.
- Bai-Chen, X., Ying, F., & Qian-Qian, Q. (2012). Does generation form influence environmental efficiency performance? An analysis of China's power system. *Applied Energy*, 96, 261-271.
- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092.
- Barba-Gutiérrez, Y., Adenso-Díaz, B., & Lozano, S. (2009). Eco-efficiency of electric and electronic appliances: a data envelopment analysis (DEA). *Environmental Modeling & Assessment*, 14(4), 439-447.
- Battese, G. E., Rao, D. P., & O'donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, 21(1), 91-103.
- Beasley, J. E. (1995). Determining teaching and research efficiencies. *Journal of the Operational Research Society*, 46, 441-452.
- Bi, G., Luo, Y., Ding, J., & Liang, L. (2015). Environmental performance analysis of Chinese industry from a slacks-based perspective. *Annals of Operations Research*, 228(1), 65-80.
- Bi, G. B., Song, W., Zhou, P., & Liang, L. (2014). Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from

- a slacks-based DEA model. *Energy Policy*, 66, 537-546.
- Bi, G., Feng, C., & Ding, J. (2011). DEA Model for Parallel Production System with Environmental Constraint. *Chinese Journal of Management Science*, 19(06), 79-86. (in Chinese)
- Bian, Y., & Yang, F. (2010). Resource and environment efficiency analysis of provinces in China: A DEA approach based on Shannon's entropy. *Energy Policy*, 38(4), 1909-1917.
- Bian, Y., Yan, S., & Xu, H. (2014). Efficiency evaluation for regional urban water use and wastewater decontamination systems in China: A DEA approach. *Resources, Conservation and Recycling*, 83, 15-23.
- Bian, Y., Liang, N., & Xu, H. (2015). Efficiency evaluation of Chinese regional industrial systems with undesirable factors using a two-stage slacks-based measure approach. *Journal of Cleaner Production*, 87, 348-356.
- Boyd, G. A., Tolley, G., & Pang, J. (2002). Plant level productivity, efficiency, and environmental performance of the container glass industry. *Environmental and Resource Economics*, 23(1), 29-43.
- Boyd, G. A. (2005). A method for measuring the efficiency gap between average and best practice energy use: the Energy Star industrial energy performance indicator. *Journal of Industrial Ecology*, 9(3), 51-65.
- Boyd, G., Dutrow, E., & Tunnessen, W. (2008). The evolution of the Energy Star: energy performance indicator for benchmarking industrial plant manufacturing energy use. *Journal of Cleaner Production*, 16(6), 709-715.
- Boudreau, J. W. (2004). 50th Anniversary Article: Organizational behavior, strategy, performance, and design in management science. *Management Science*, 50(11), 1463-1476.
- Briec, W., & Leleu, H. (2003). Dual representations of non-parametric technologies and measurement of technical efficiency. *Journal of Productivity Analysis*, 20(1), 71-96.
- Briec, W., & Lemaire, B. (1999). Technical efficiency and distance to a reverse convex set. *European Journal of Operational Research*, 114(1), 178-187.
- Brockett, P. L., Rousseau, J. J., Wang, Y., & Zhou, L. (1997). Implementation of DEA models using GAMS. *Research Report 765*.
- Castelli, L., Pesenti, R., & Ukovich, W. (2010). A classification of DEA models when

- the internal structure of the Decision Making Units is considered. *Annals of Operations Research*, 173(1), 207-235.
- Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica: Journal of the Econometric Society*, 1393-1414.
- Central Committee of the Communist Party of China. (2015). Recommendations for the 13th Five-year Plan for Economic and Social Development. *Central Compilation & Translation Press*.
- Chang, Y. T., Zhang, N., Danao, D., & Zhang, N. (2013). Environmental efficiency analysis of transportation system in China: A non-radial DEA approach. *Energy Policy*, 58, 277-283.
- Charnes, A., & Cooper, W. W. (1962). Programming with linear fractional functionals. *Naval Research Logistics Quarterly*, 9(3 - 4), 181-186.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444.
- Chen, C. C. (2017). Measuring departmental and overall regional performance: applying the multi-activity DEA model to Taiwan' s cities/counties. *Omega*, 67, 60-80.
- Chen, Y., Cook, W. D., Li, N., & Zhu, J. (2009). Additive efficiency decomposition in two-stage DEA. *European Journal of Operational Research*, 196(3), 1170-1176.
- Chen, Y., Du, J., Sherman, H. D., & Zhu, J. (2010). DEA model with shared resources and efficiency decomposition. *European Journal of Operational Research*, 207(1), 339-349.
- Chen, L., Wang, Y., & Wang, L. (2016). Eco-efficiency measurement and decomposition in the two-stage DEA analysis framework. *Systems Engineering-Theory & Practice*, 36(3), 642-649. (in Chinese)
- Chen, L., & Jia, G. (2017). Environmental efficiency analysis of China's regional industry: a data envelopment analysis (DEA) based approach. *Journal of Cleaner Production*, 142, 846-853.
- Chen, P. C., & Yu, M. M. (2014). Total factor productivity growth and directions of technical change bias: evidence from 99 OECD and non-OECD countries. *Annals of Operations Research*, 214(1), 143-165.
- Chen, K., & Zhu, J. (2019). Scale efficiency in two-stage network DEA. *Journal of the*

- Operational Research Society*, 70(1), 101-110.
- Chen, C., Zhu, J., Yu, J. Y., & Noori, H. (2012). A new methodology for evaluating sustainable product design performance with two-stage network data envelopment analysis. *European Journal of Operational Research*, 221(2), 348-359.
- Chen, L., Wang, Y. M., & Wang, L. (2016). Congestion measurement under different policy objectives: an analysis of Chinese industry. *Journal of Cleaner Production*, 112, 2943-2952.
- Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *Journal of Environmental Management*, 51(3), 229-240.
- Chung, W., Zhou, G., & Yeung, I. M. (2013). A study of energy efficiency of transport sector in China from 2003 to 2009. *Applied Energy*, 112, 1066-1077.
- Chu, J., Wu, J., Zhu, Q., An, Q., & Xiong, B. (2016). Analysis of China's regional eco-efficiency: a DEA two-stage network approach with equitable efficiency decomposition. *Computational Economics*, <https://doi.org/10.1007/s10614-015-9558-8>.
- Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An Introduction to Efficiency and Productivity Analysis*. Springer Science & Business Media.
- Cook, W. D., & Hababou, M. (2001). Sales performance measurement in bank branches. *Omega*, 29(4), 299-307.
- Cook, W. D., Hababou, M., & Tuenter, H. J. (2000). Multicomponent efficiency measurement and shared inputs in data envelopment analysis: an application to sales and service performance in bank branches. *Journal of Productivity Analysis*, 14(3), 209-224.
- Cook, W. D., Liang, L., & Zhu, J. (2010). Measuring performance of two-stage network structures by DEA: a review and future perspective. *Omega*, 38(6), 423-430.
- Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA)—Thirty years on. *European Journal of Operational Research*, 192(1), 1-17.
- Cook, W. D., Harrison, J., Imanirad, R., Rouse, P., & Zhu, J. (2013). Data envelopment analysis with nonhomogeneous DMUs. *Operations Research*, 61(3), 666-676.
- Cooper, W. W., Huang, Z., Li, S. X., Parker, B. R., & Pastor, J. T. (2007). Efficiency aggregation with enhanced Russell measures in data envelopment analysis. *Socio-Economic Planning Sciences*, 41(1), 1-21.

- Cooper, W. W., Park, K. S., & Pastor, J. T. (1999). RAM: a range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. *Journal of Productivity Analysis*, 11(1), 5-42.
- Cooper, W. W., Seiford, L. M., & Zhu, J. (Eds.). (2011). *Handbook on Data Envelopment Analysis* (Vol. 164). Springer Science & Business Media.
- De Nicola, A., Gitto, S., & Mancuso, P. (2013). Airport quality and productivity changes: A Malmquist index decomposition assessment. *Transportation Research Part E: Logistics and Transportation Review*, 58, 67-75.
- Ding, L., Zheng, H., & Liu, X. (2018). Production efficiency, environmental governance efficiency and comprehensive efficiency of Marine Economy in China. *Forum on Science and Technology in China*, (3), 48-57. (in Chinese)
- Du, J., & Huo, J. (2014). DEA-based Evaluation on City Innovation in China. *Chinese Journal of Management Science*, 22(6), 85-93. (in Chinese)
- Dyckhoff, H., & Allen, K. (2001). Measuring ecological efficiency with data envelopment analysis (DEA). *European Journal of Operational Research*, 132(2), 312-325.
- Esmacili, M. (2012). An enhanced Russell measure in DEA with interval data. *Applied Mathematics and Computation*, 219(4), 1589-1593.
- Fang, K., Hong, X., Li, S., Song, M., & Zhang, J. (2013). Choosing competitive industries in manufacturing of China under low-carbon economy: A three-stage DEA analysis. *International Journal of Climate Change Strategies and Management*, 5(4), 431-444.
- Färe, R., & Grosskopf, S. (1992). Malmquist productivity indexes and Fisher ideal indexes. *The Economic Journal*, 102(410), 158-160.
- Färe, R., Grosskopf, S., & Whittaker, G. (2007). Network dea. In *Modeling data Irregularities and Structural Complexities in Data Envelopment Analysis* (pp. 209-240). Springer, Boston, MA.
- Färe, R., & Grosskopf, S. (2004). *New Directions: Efficiency and Productivity*. Kluwer Academic Publishers, Boston.
- Färe, R., Grosskopf, S., & Brännlund, R. (1996). Intertemporal production frontiers: with dynamic DEA. *Boston: Kluwer Academic*.
- Färe, R., Grabowski, R., Grosskopf, S., & Kraft, S. (1997). Efficiency of a fixed but allocatable input: A non-parametric approach. *Economics Letters*, 56(2), 187-193.

- Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1994). Productivity developments in Swedish hospitals: a Malmquist output index approach. In *Data Envelopment Analysis: Theory, Methodology, and Applications* (pp. 253-272). Springer, Dordrecht.
- Färe, R., Grosskopf, S., Lovell, C. K., & Pasurka, C. (1989). Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *The Review of Economics and Statistics*, 90-98.
- Färe, R., Grosskopf, S., Lovell, C. K., & Yaisawarng, S. (1993). Derivation of shadow prices for undesirable outputs: a distance function approach. *The Review of Economics and Statistics*, 374-380.
- Frei, F. X., & Harker, P. T. (1999). Projections onto efficient frontiers: theoretical and computational extensions to DEA. *Journal of Productivity Analysis*, 11(3), 275-300.
- Fukuyama, H., Maeda, Y., Sekitani, K., & Shi, J. (2014). Input-output substitutability and strongly monotonic p-norm least distance DEA measures. *European Journal of Operational Research*, 237(3), 997-1007.
- Fukuyama, H., & Weber, W. L. (2009). A directional slacks-based measure of technical efficiency. *Socio-economic Planning Sciences*, 43(4), 274-287.
- Gitto, S., & Mancuso, P. (2012). Bootstrapping the Malmquist indexes for Italian airports. *International Journal of Production Economics*, 135(1), 403-411.
- González, E., & Álvarez, A. (2001). From efficiency measurement to efficiency improvement: The choice of a relevant benchmark. *European Journal of Operational Research*, 133(3), 512-520.
- Gong, Y., Zhu, J., Chen, Y., & Cook, W. D. (2018). DEA as a tool for auditing: Application to Chinese manufacturing industry with parallel network structures. *Annals of Operations Research*, 263(1-2), 247-269.
- Glucker, A. N., Driessen, P. P., Kolhoff, A., & Runhaar, H. A. (2013). Public participation in environmental impact assessment: why, who and how?. *Environmental Impact Assessment Review*, 43, 104-111.
- Grubeshic, T. H., & Wei, F. (2012). Evaluating the efficiency of the Essential Air Service program in the United States. *Transportation Research Part A: Policy and Practice*, 46(10), 1562-1573.
- Hailu, A., & Veeman, T. S. (2001). Non-parametric productivity analysis with

- undesirable outputs: an application to the Canadian pulp and paper industry. *American Journal of Agricultural Economics*, 83(3), 605-616.
- Halkos, G. E., & Tzeremes, N. G. (2009). Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. *Ecological Economics*, 68(7), 2168-2176.
- Halkos, G. E., & Tzeremes, N. G. (2013). A conditional directional distance function approach for measuring regional environmental efficiency: Evidence from UK regions. *European Journal of Operational Research*, 227(1), 182-189.
- Halkos, G. E., Tzeremes, N. G., & Kourtzidis, S. A. (2014). A unified classification of two-stage DEA models. *Surveys in Operations Research and Management Science*, 19(1), 1-16.
- Halkos, G. E., Tzeremes, N. G., & Kourtzidis, S. A. (2015). Regional sustainability efficiency index in Europe: an additive two-stage DEA approach. *Operational Research*, 15(1), 1-23.
- Hampf, B. (2014). Separating environmental efficiency into production and abatement efficiency: a nonparametric model with application to US power plants. *Journal of Productivity Analysis*, 41(3), 457-473.
- Han, Z. Y., Fan, Y., Jiao, J. L., Yan, J. S., & Wei, Y. M. (2007). Energy structure, marginal efficiency and substitution rate: An empirical study of China. *Energy*, 32(6), 935-942.
- Herrera-Restrepo, O., Triantis, K., Trainor, J., Murray-Tuite, P., & Edara, P., 2016. A multi-perspective dynamic network performance efficiency measurement of an evacuation: A dynamic network-DEA approach. *Omega*, 60, 45-59.
- Hsiao, B., Chern, C. C., & Chiu, C. R. (2011). Performance evaluation with the entropy-based weighted Russell measure in data envelopment analysis. *Expert Systems with Applications*, 38(8), 9965-9972.
- Hsiao, B., Chern, C. C., Chiu, Y. H., & Chiu, C. R. (2011). Using fuzzy super-efficiency slack-based measure data envelopment analysis to evaluate Taiwan's commercial bank efficiency. *Expert Systems with Applications*, 38(8), 9147-9156.
- Hu, Y. (2012). Energy conservation assessment of fixed-asset investment projects: An attempt to improve energy efficiency in China. *Energy Policy*, 43, 327-334.
- Hu, J. L., & Wang, S. C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy*, 34(17), 3206-3217.

- Huang, J., Yang, X., Cheng, G., & Wang, S. (2014). A comprehensive eco-efficiency model and dynamics of regional eco-efficiency in China. *Journal of Cleaner Production*, 67, 228-238.
- Huang, C. W., Chiu, Y. H., Fang, W. T., & Shen, N. (2014). Assessing the performance of Taiwan's environmental protection system with a non-radial network DEA approach. *Energy Policy*, 74, 547-556.
- Imanirad, R., Cook, W. D., Aviles-Sacoto, S. V., & Zhu, J. (2015). Partial input to output impacts in DEA: The case of DMU-specific impacts. *European Journal of Operational Research*, 244(3), 837-844.
- IPCC. 2006. *IPCC Guidelines for National Greenhouse Gas Inventories*. <<http://www.ipcc-nggip.iges.or.jp/public/2006gl/vol2.html>>.
- Institutes of Science and Development, Chinese Academy of Sciences, The National Science Library, Chinese Academy of Sciences, Clarivate Analytics (2016). *Research Fronts 2016*.
- Jahanshahloo, G. R., Vakili, J., & Mirdehghan, S. M. (2012). Using the minimum distance of DMUs from the frontier of the PPS for evaluating group performance of DMUs in DEA. *Asia-Pacific Journal of Operational Research*, 29(02), 1250010.
- Johnson, A. L., & Ruggiero, J. (2014). Nonparametric measurement of productivity and efficiency in education. *Annals of Operations Research*, 221(1), 197-210.
- Kao, C. (2010). Malmquist productivity index based on common-weights DEA: The case of Taiwan forests after reorganization. *Omega*, 38(6), 484-491.
- Kao, C. (2017). Measurement and decomposition of the Malmquist productivity index for parallel production systems. *Omega*, 67, 54-59.
- Kao, C., & Liu, S. T. (2000a). Fuzzy efficiency measures in data envelopment analysis. *Fuzzy Sets and Systems*, 113(3), 427-437.
- Kao, C., & Liu, S. T. (2000b). Data envelopment analysis with missing data: an application to university libraries in Taiwan. *Journal of the Operational Research Society*, 51(8), 897-905.
- Kao, C., & Hwang, S. N. (2008). Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *European Journal of Operational Research*, 185(1), 418-429.
- Koopmans, T. C. (1951). An analysis of production as an efficient combination of

- activities. *Activity Analysis of Production and Allocation*.
- Korhonen, P. J., & Luptacik, M. (2004). Eco-efficiency analysis of power plants: An extension of data envelopment analysis. *European Journal of Operational Research*, 154(2), 437-446.
- Kuosmanen, T. (2005). Weak disposability in nonparametric production analysis with undesirable outputs. *American Journal of Agricultural Economics*, 87(4), 1077-1082.
- Lee, C. C. (2005). Energy consumption and GDP in developing countries: a cointegrated panel analysis. *Energy Economics*, 27(3), 415-427.
- Leleu, H. (2013). Shadow pricing of undesirable outputs in nonparametric analysis. *European Journal of Operational Research*, 231(2), 474-480.
- León, T., Liern, V., Ruiz, J. L., & Sirvent, I. (2003). A fuzzy mathematical programming approach to the assessment of efficiency with DEA models. *Fuzzy Sets and Systems*, 139(2), 407-419.
- Lertworasirikul, S., 2001. Fuzzy data envelopment analysis for supply chain modeling and analysis, dissertation proposal in industrial engineering. North Carolina State University.
- Lertworasirikul, S., Fang, S. C., Nuttle, H. L., & Joines, J. A. (2003). Fuzzy BCC model for data envelopment analysis. *Fuzzy Optimization and Decision Making*, 2(4), 337-358.
- Levkoff, S. B., Russell, R. R., & Schworm, W. (2012). Boundary problems with the “Russell” graph measure of technical efficiency: a refinement. *Journal of Productivity Analysis*, 37(3), 239-248.
- Li, K., & Lin, B. (2016). Heterogeneity analysis of the effects of technology progress on carbon intensity in China. *International Journal of Climate Change Strategies and Management*, 8(1), 129-152.
- Li, H., & Shi, J. F. (2014). Energy efficiency analysis on Chinese industrial sectors: an improved Super-SBM model with undesirable outputs. *Journal of Cleaner Production*, 65, 97-107.
- Li, Y., Shi, X., Emrouznejad, A., & Liang, L. (2018). Environmental performance evaluation of Chinese industrial systems: a network SBM approach. *Journal of the Operational Research Society*, 69(6), 825-839.
- Li, F., Zhu, Q., & Zhuang, J. (2018). Analysis of fire protection efficiency in the United

- States: a two-stage DEA-based approach. *OR Spectrum*, 40(1), 23-68.
- Liang, L., Cook, W. D., & Zhu, J. (2008). DEA models for two-stage processes: Game approach and efficiency decomposition. *Naval Research Logistics*, 55(7), 643-653.
- Lin, B., & Wang, X. (2014). Exploring energy efficiency in China's iron and steel industry: A stochastic frontier approach. *Energy Policy*, 72, 87-96.
- Lin, B., & Liu, H. (2015). Do energy and environmental efficiency benefit from foreign trade? — The case of China's industrial sectors. *Economic Research Journal*, 9, 127-141. (in Chinese)
- Liu, W. B., Meng, W., Li, X. X., & Zhang, D. Q. (2010). DEA models with undesirable inputs and outputs. *Annals of Operations Research*, 173(1), 177-194.
- Liu, W., & Sharp, J. (1999). DEA models via goal programming. In *Data Envelopment Analysis in the Service Sector* (pp.79-101). Deutscher Universitätsverlag, Wiesbaden.
- Liu, H., Zhang, Y., Zhu, Q., & Chu, J. (2017). Environmental efficiency of land transportation in China: A parallel slack-based measure for regional and temporal analysis. *Journal of Cleaner Production*, 142, 867-876.
- Liu, X., & Wu, J. (2017). Energy and environmental efficiency analysis of China's regional transportation sectors: a slack-based DEA approach. *Energy Systems*, 8(4), 747-759.
- Lozano, S., Adenso-Díaz, B., & Barba-Gutiérrez, Y. (2011). Russell non-radial eco-efficiency measure and scale elasticity of a sample of electric/electronic products. *Journal of the Franklin Institute*, 348(7), 1605-1614.
- Lozano, S. (2017). Technical and environmental efficiency of a two-stage production and abatement system. *Annals of Operations Research*, 255(1-2), 199-219.
- Lu, W. M., Wang, W. K., Hung, S. W., & Lu, E. T. (2012). The effects of corporate governance on airline performance: Production and marketing efficiency perspectives. *Transportation Research Part E: Logistics and Transportation Review*, 48(2), 529-544.
- Lv, W., Hong, X., & Fang, K. (2015). Chinese regional energy efficiency change and its determinants analysis: Malmquist index and Tobit model. *Annals of Operations Research*, 228(1), 9-22.
- Ma, Z. (2010). Data envelopment analysis model and method. *Beijing: China Science Publishing*. (in Chinese)

- Maghbouli, M., Amirteimoori, A., & Kordrostami, S. (2014). Two-stage network structures with undesirable outputs: A DEA based approach. *Measurement*, 48, 109-118.
- Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Estadística y de Investigación Operativa*, 4(2), 209-242.
- Miao, Z., Geng, Y., & Sheng, J. (2016). Efficient allocation of CO₂ emissions in China: a zero sum gains data envelopment model. *Journal of Cleaner Production*, 112, 4144-4150.
- Ministry of Transport of the People's Republic of China (MTPRC), 2017. "Statistics and Development Bulletin of the Transport Industry in 2016.
- Mirhedayatian, S. M., Azadi, M., & Saen, R. F. (2014). A novel network data envelopment analysis model for evaluating green supply chain management. *International Journal of Production Economics*, 147, 544-554.
- Paradi, J. C., Rouatt, S., & and Zhu, H. (2011). Two-stage evaluation of bank branch efficiency using data envelopment analysis. *Omega*, 39(1), 99-109.
- Oh, D. H., & Lee, J. D. (2010). A metafrontier approach for measuring Malmquist productivity index. *Empirical Economics*, 38(1), 47-64.
- Oikonomou, V., Becchis, F., Steg, L., & Russolillo, D. (2009). Energy saving and energy efficiency concepts for policy making. *Energy Policy*, 37(11), 4787-4796.
- Oggioni, G., Riccardi, R., & Toninelli, R. (2011). Eco-efficiency of the world cement industry: a data envelopment analysis. *Energy Policy*, 39(5), 2842-2854.
- Pastor, J. T., & Lovell, C. K. (2005). A global Malmquist productivity index. *Economics Letters*, 88(2), 266-271.
- Pastor, J. T., Ruiz, J. L., & Sirvent, I. (1999). An enhanced DEA Russell graph efficiency measure. *European Journal of Operational Research*, 115(3), 596-607.
- Portela, M. S., Thanassoulis, E., & Simpson, G. (2004). Negative data in DEA: A directional distance approach applied to bank branches. *Journal of the Operational Research Society*, 55(10), 1111-1121.
- Portela, M. C. A. S., Borges, P. C., & Thanassoulis, E. (2003). Finding closest targets in non-oriented DEA models: the case of convex and non-convex technologies. *Journal of Productivity Analysis*, 19(2-3), 251-269.
- Pérez-Calderón, E., Milanés-Montero, P., Meseguer-Santamaría, M. L., & Mondéjar-Jiménez, J. (2011). Eco-efficiency: Effects on economic and financial performance.

- Evidences from Dow Jones Sustainability Europe Index. *Environmental Engineering & Management Journal (EEMJ)*, 10(12).
- Picazo-Tadeo, A. J., Beltrán-Esteve, M., & Gómez-Limón, J. A. (2012). Assessing eco-efficiency with directional distance functions. *European Journal of Operational Research*, 220(3), 798-809.
- Rivas, J., & Magadán, M. (2010). Less green taxes and more control over pollutant industries: a theoretical proposal. *Environmental Engineering & Management Journal (EEMJ)*, 9(9).
- Ruiz, J. L., Segura, J. V., & Sirvent, I. (2015). Benchmarking and target setting with expert preferences: An application to the evaluation of educational performance of Spanish universities. *European Journal of Operational Research*, 242(2), 594-605.
- Scheel, H. (2001). Undesirable outputs in efficiency valuations. *European Journal of Operational Research*, 132(2), 400-410.
- Scotti, D., & Volta, N. (2015). An empirical assessment of the CO₂-sensitive productivity of European airlines from 2000 to 2010. *Transportation Research Part D: Transport and Environment*, 37, 137-149.
- Seiford, L. M., & Zhu, J. (1999). Profitability and marketability of the top 55 U.S. commercial banks. *Management Science*, 45(9), 1270-1288.
- Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 142(1), 16-20.
- Seiford, L. M., & Zhu, J. (2005). A response to comments on modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 2(161), 579-581.
- Sengupta, J. K. (1992). A fuzzy systems approach in data envelopment analysis. *Computers & Mathematics with Applications*, 24(8-9), 259-266.
- Shi, X. (2016). Environmental efficiency analysis based on relational two-stage DEA model. *RAIRO-Operations Research*, 50(4-5), 965-977.
- Shi, G. M., Bi, J., & Wang, J. N. (2010). Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. *Energy Policy*, 3(10), 6172-6179.
- Song, M., An, Q., Zhang, W., Wang, Z., & Wu, J. (2012). Environmental efficiency evaluation based on data envelopment analysis: A review. *Renewable and Sustainable Energy Reviews*, 16(7), 4465-4469.

- Song, M., & Wang, S. (2013). Analysis of environmental regulation, technological progression and economic growth from the perspective of statistical tests. *Economic Research Journal*, 3, 122-134. (in Chinese)
- Song, X., Hao, Y., & Zhu, X. (2015). Analysis of the environmental efficiency of the Chinese transportation sector using an undesirable output slacks-based measure data envelopment analysis model. *Sustainability*, 7(7), 9187-9206.
- Song, M., & Guan, Y. (2014). The environmental efficiency of Wanjiang demonstration area: A Bayesian estimation approach. *Ecological Indicators*, 36, 59-67.
- Song, M., Peng, J., & Wu, Q. (2014). An undesirable-output-considered super-efficiency DEA model and its illustration in evaluation of thermoelectric enterprises. *Journal of Intelligent & Fuzzy Systems*, 27(3), 1507-1517.
- Song, M., Zhang, L., An, Q., Wang, Z., & Li, Z. (2013). Statistical analysis and combination forecasting of environmental efficiency and its influential factors since China entered the WTO: 2002–2010–2012. *Journal of Cleaner Production*, 42, 42-51.
- Song, M., Zhang, G., Zeng, W., Liu, J., & Fang, K. (2016). Railway transportation and environmental efficiency in China. *Transportation Research Part D: Transport and Environment*, 48, 488-498.
- Song, M., Wang, S., & Liu, W. (2014). A two-stage DEA approach for environmental efficiency measurement. *Environmental Monitoring and Assessment*, 186(5), 3041-3051.
- Song, M., Zhang, J., & Wang, S. (2015). Review of the network environmental efficiencies of listed petroleum enterprises in China. *Renewable and Sustainable Energy Reviews*, 43, 65-71.
- Song, M., Peng, J., Wang, J., & Zhao, J. (2018). Environmental efficiency and economic growth of China: a Ray slack-based model analysis. *European Journal of Operational Research*, 269(1), 51-63.
- Sueyoshi, T., & Goto, M. (2018). *Environmental Assessment on Energy and Sustainability by Data Envelopment Analysis*. John Wiley & Sons.
- Sueyoshi, T., & Sekitani, K. (2007). Measurement of returns to scale using a non-radial DEA model: A range-adjusted measure approach. *European Journal of Operational Research*, 176(3), 1918-1946.
- Sueyoshi, T., Yuan, Y., & Goto, M. (2017). A literature study for DEA applied to energy

- and environment. *Energy Economics*, 62, 104-124.
- Sueyoshi, T., Yuan, Y., Li, A., & Wang, D. (2017). Methodological comparison among radial, non-radial and intermediate approaches for DEA environmental assessment. *Energy Economics*, 67, 439-453.
- Tavassoli, M., Badizadeh, T., & Saen, R. F. (2016). Performance assessment of airlines using range-adjusted measure, strong complementary slackness condition, and discriminant analysis. *Journal of Air Transport Management*, 54, 42-46.
- Tavassoli, M., Faramarzi, G. R., & Saen, R. F. (2014). Efficiency and effectiveness in airline performance using a SBM-NDEA model in the presence of shared input. *Journal of Air Transport Management*, 34, 146-153.
- The National People's Congress Standing Committee of China, 2014. Environmental Protection Law of People's Republic of China. Beijing, China, http://news.xinhuanet.com/politics/2014-04/25/c_126431703.htm.
- Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130(3), 498-509.
- Tone, K. (2003). Dealing with undesirable outputs in DEA: A slacks-based measure (SBM) approach. *GRIPS Research Report Series*, 2003.
- Viton, P. A. (1997). Technical efficiency in multi-mode bus transit: A production frontier analysis. *Transportation Research Part B: Methodological*, 31(1), 23-39.
- Wang, Z., & Feng, C. (2015). Sources of production inefficiency and productivity growth in China: a global data envelopment analysis. *Energy Economics*, 49, 380-389.
- Wang, M., & Li, Y. (2010). Enhanced Russell measure in fuzzy DEA. *International Journal of Data Analysis Techniques and Strategies*, 2(2), 140-154.
- Wang, C. H., Gopal, R. D., & Zionts, S. (1997). Use of data envelopment analysis in assessing information technology impact on firm performance. *Annals of Operations Research*, 73, 191-213.
- Wang, K., Lu, B., & Wei, Y. M. (2013). China's regional energy and environmental efficiency: A Range-Adjusted Measure based analysis. *Applied Energy*, 112, 1403-1415.
- Wang, Q., Su, B., Zhou, P., & Chiu, C. R. (2016). Measuring total-factor CO₂ emission performance and technology gaps using a non-radial directional distance function: A modified approach. *Energy Economics*, 56, 475-482.

- Wang, K., & Wei, Y. M. (2014). China's regional industrial energy efficiency and carbon emissions abatement costs. *Applied Energy*, 130, 617-631.
- Wang, K., Wei, Y. M., & Huang, Z. (2016). Potential gains from carbon emissions trading in China: A DEA based estimation on abatement cost savings. *Omega*, 63, 48-59.
- Wang, H., Xu, J., Zhang, M., Yang, Y., Shen, X., Wang, Y., Chen, D., & Guo, J. (2014). A study of the meteorological causes of a prolonged and severe haze episode in January 2013 over central-eastern China. *Atmospheric Environment*, 98, 146-157.
- Wang, W. W., Zhang, M., & Zhou, M. (2011). Using LMDI method to analyze transport sector CO₂ emissions in China. *Energy*, 36(10), 5909-5915.
- Wang, K., Yu, S., & Zhang, W. (2013). China's regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation. *Mathematical and Computer Modelling*, 58(5-6), 1117-1127.
- Wang, H., Zhou, P., & Zhou, D. Q. (2013). Scenario-based energy efficiency and productivity in China: A non-radial directional distance function analysis. *Energy Economics*, 40, 795-803.
- Wanke, P. F. (2013). Physical infrastructure and shipment consolidation efficiency drivers in Brazilian ports: A two-stage network-DEA approach. *Transport Policy*, 29, 145-153.
- Wen, M., & Li, H. (2009). Fuzzy data envelopment analysis (DEA): Model and ranking method. *Journal of Computational and Applied Mathematics*, 223(2), 872-878.
- Wu, J., An, Q., Xiong, B., & Chen, Y. (2013). Congestion measurement for regional industries in China: A data envelopment analysis approach with undesirable outputs. *Energy Policy*, 57, 7-13.
- Wu, J., An, Q., Yao, X., & Wang, B. (2014). Environmental efficiency evaluation of industry in China based on a new fixed sum undesirable output data envelopment analysis. *Journal of Cleaner Production*, 74, 96-104.
- Wu, J., Yu, Y., Zhu, Q., An, Q., & Liang, L. (2018). Closest target for the orientation-free context-dependent DEA under variable returns to scale. *Journal of the Operational Research Society*, 69(11), 1819-1833.
- Wu, J., Zhu, Q., Chu, J., Liu, H., & Liang, L. (2016). Measuring energy and environmental efficiency of transportation systems in China based on a parallel DEA approach. *Transportation Research Part D: Transport and Environment*, 48,

- 460-472.
- Wu, H. Q., Shi, Y., Xia, Q., & Zhu, W. D. (2014). Effectiveness of the policy of circular economy in China: A DEA-based analysis for the period of 11th five-year-plan. *Resources, Conservation and Recycling*, 83, 163-175.
- Xi, J. (2017). Secure a Decisive Victory in Building a Moderately Prosperous Society in All Respects and Strive for the Great Success of Socialism with Chinese Characteristics for a New Era. The 19th National Congress of the Communist Party of China. http://www.xinhuanet.com/english/download/Xi_Jinping's_report_at_19th_CPC_National_Congress.pdf.
- Yang, G., Liu, W., & Zheng, H. (2013). Review of data envelopment analysis. *Journal of Systems Engineering*, 28(6), 840-860. (in Chinese)
- Yang, L., Ouyang, H., Fang, K., Ye, L., & Zhang, J. (2015). Evaluation of regional environmental efficiencies in China based on super-efficiency-DEA. *Ecological Indicators*, 51, 13-19.
- Yang, F., Wu, D. X., Liang, L., Bi, G., & Wu, D. D. (2011). Supply chain DEA: production possibility set and performance evaluation method. *Annals of Operations Research*, 185, 195-211.
- Yu, M. M., & Lin, E. T. (2008). Efficiency and effectiveness in railway performance using a multi-activity network DEA model. *Omega*, 36(6), 1005-1017.
- Yu, M. M., Chen, L. H., & Hsiao, B. (2016). Dynamic performance assessment of bus transit with the multi-activity network structure. *Omega*, 60, 15-25.
- Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, 8(3), 338-353.
- Zha, Y., & Liang, L. (2010). Two-stage cooperation model with input freely distributed among the stages. *European Journal of Operational Research*, 205(2), 332-338.
- Zhang, N., & Choi, Y. (2013). Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. *The Social Science Journal*, 50(2), 225-234.
- Zhang, X. P., Cheng, X. M., Yuan, J. H., & Gao, X. J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy*, 39(2), 644-650.
- Zhang, N., & Wei, X. (2015). Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. *Applied energy*, 146, 409-420.
- Zhang, N., Zhou, P., & Kung, C. C. (2015). Total-factor carbon emission performance

- of the Chinese transportation industry: A bootstrapped non-radial Malmquist index analysis. *Renewable and Sustainable Energy Reviews*, 41, 584-593.
- Zhao, X. L., Yang, R., & Ma, Q. (2014). China's total factor energy efficiency of provincial industrial sectors. *Energy*, 65, 52-61
- Zhou, P., & Ang, B. W. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy*, 36(8), 2911-2916.
- Zhou, P., Ang, B. W., & Poh, K. L. (2006). Slacks-based efficiency measures for modeling environmental performance. *Ecological Economics*, 60(1), 111-118.
- Zhou, P., Ang, B. W., & Poh, K. L., (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, 189(1), 1-18.
- Zhou, P., Ang, B.W., Poh, K.L., 2008. Measuring environmental performance under different environmental DEA technologies. *Energy Economics*. 30 (1), 1-14.
- Zhou, P., Ang, B. W., & Wang, H. (2012). Energy and CO₂ emission performance in electricity generation: a non-radial directional distance function approach. *European Journal of Operational Research*, 221(3), 625-635.
- Zhou, G., Chung, W., & Zhang, X. (2013). A study of carbon dioxide emissions performance of China's transport sector. *Energy*, 50, 302-314.
- Zhou, G., Chung, W., & Zhang, Y. (2014). Measuring energy efficiency performance of China's transport sector: A data envelopment analysis approach. *Expert Systems with Applications*, 41(2), 709-722.
- Zhou, P. Poh, K.L. Ang, B.W., 2007. A non-radial DEA approach to measuring environmental performance. *European Journal of Operational Research*, 178, 1-9.
- Zhou, X., Xu, Z., Yao, L., Tu, Y., Lev, B., & Pedrycz, W. (2018). A novel Data Envelopment Analysis model for evaluating industrial production and environmental management system. *Journal of Cleaner Production*, 170, 773-788.
- Wang, M., & Li, Y. (2014). Full rank of fuzzy decision making units based on enhanced Russell measure. *Chinese Journal of Management Science*, 22(03), 115-120. (in Chinese)
- Wu, J., An, Q., Xiong, B., & Chen, Y. (2013). Congestion measurement for regional industries in China: A data envelopment analysis approach with undesirable outputs. *Energy Policy*, 57, 7-13.

- Wu, J., Yin, P., Sun, J., Chu, J., & Liang, L. (2016). Evaluating the environmental efficiency of a two-stage system with undesired outputs by a DEA approach: An interest preference perspective. *European Journal of Operational Research*, 254(3), 1047-1062.
- Wu, J., Zhu, Q., Chu, J., & Liang, L. (2015). Two-stage network structures with undesirable intermediate outputs reused: A DEA based approach. *Computational Economics*, 46(3), 455-477.
- Wu, J., Zhu, Q., Chu, J., Liu, H., & Liang, L. (2016a). Measuring energy and environmental efficiency of transportation systems in China based on a parallel DEA approach. *Transportation Research Part D: Transport and Environment*, 48, 460-472.

Beibei XIONG

Doctorat : Optimisation et Sûreté des Systèmes

Année 2019

Évaluation de l'efficacité environnementale par l'analyse d'enveloppement de données et ses applications

Avec le développement de l'économie, la pollution de l'environnement est devenue de plus en plus grave, en particulier dans les pays en voie de développement tels que la Chine et l'Inde. Pour réaliser le développement durable de l'environnement et de l'économie, l'évaluation scientifique de l'efficacité environnementale est très importante.

Cette thèse examine l'évaluation de l'efficacité environnementale basée sur l'analyse d'enveloppement de données (DEA). Quatre problèmes d'évaluation de l'efficacité environnementale sont étudiés. Tout d'abord, un modèle de mesure Russell renforcé est proposé pour évaluer l'efficacité environnementale des entreprises de production d'énergie thermique en Chine. Ensuite, compte tenu de la production indésirable, un nouveau modèle DEA plus proche d'un cible basé sur un intervalle de mesure ajusté est établi pour mesurer l'efficacité environnementale du bassin de la rivière Xiangjiang en Chine. De plus, un nouveau modèle DEA en deux étapes avec entrées partagées est construit pour évaluer l'efficacité énergétique du facteur total et l'efficacité environnementale globale du secteur industriel de la Chine. Enfin, le modèle d'évaluation de l'efficacité environnementale d'un réseau parallèle prenant en compte l'hétérogénéité est proposé pour analyser le secteur de transport en Chine. Tous ces modèles sont appliqués à des exemples réels et utilisés pour mesurer leur efficacité environnementale et donner une référence pour l'amélioration de leur performance.

Mots clés : DEA, méthode – homme, effets de l'environnement – programmation linéaire – efficience (gestion) – référencement.

Environmental Efficiency Evaluation by Data Envelopment Analysis and its Applications

With the development of economy, environmental pollution has become increasingly serious, especially in developing countries such as China and India. To realize the sustainable development of environment and economy, the scientific evaluation of environmental efficiency is very important.

This thesis investigates the environmental efficiency evaluation based on data envelopment analysis (DEA). Four environmental efficiency evaluation problems are studied. Firstly, an integrated Enhanced Russell measure model is proposed for evaluating the environmental efficiency with the presence of undesirable outputs. It is then applied to thermal power firms in China. Then, by considering undesirable outputs, a new closest target DEA model based on Range Adjusted Measure is established to measure the water environmental efficiency of the Xiangjiang River Basin in China. In addition, a new two-stage DEA model with shared inputs is built to evaluate the total-factor energy efficiency and the overall environmental efficiency of China's industrial sector. Finally, the dynamic environmental efficiency evaluation of a parallel network considering heterogeneity is considered. The Metafrontier Malmquist-Luenberger productivity index based on a network DEA model is built and then applied to analyze China's transportation sector. All these models are applied to real-life examples and used to measure their environmental efficiency and set the benchmark for their performance improvement.

Keywords: data envelopment analysis – human beings, effect of environment on – linear programming – industrial efficiency – benchmarking (management).

Thèse réalisée en partenariat entre :

