The Hong Kong Polytechnic University
Institute of Textiles and Clothing

Development of a Green Index for the Textile Industry: An Application in China

By

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requirements for the degree of Doctor of Philosophy

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CERTIFICATE OF ORIGINALITY

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Dedicated to my Family and Husband
for their Love and Support

ABSTRACT

The textile manufacturing activities have been seriously criticised for the amount of pollutants they produce. It is imperative for the textile industry to compromise a balance between achieving the goal of environmental protection and sustaining economic growth. Environmental performance indicator (EPI), which helps in regulating the negative impact brought to the environment, is one effective measure to assist in pursuing optimal balance. However, the existing environmental performance indicators for the textile industry suffer deficiencies from inconsistent framework, lack of comprehensive view and a biased weighting. To fill the present research gap, a Green Index is developed to cater for the textile industry in monitoring environmental performance. The present study is divided into two stages.

Stage One is the introduction of a new model in assessing the environmental performance. In developing the Green Index, Data Envelopment Analysis (DEA), a methodology which has been widely used to measure the efficiency of organisations (also called a decision making unit, DMU) is employed. With increasing public attention in the environment, researchers have started to include undesirable output into the study of DEA which is termed as eco-DEA. There are numerous aspects in incorporating undesirable output in the literature. However, the economic implication and the suitability for the DEA research background of the undesirable output are yet to be seriously investigated and discussed. By comparing the various existing eco-DEA approaches, the findings offer several implications for theoretical development. When an undesirable output is accommodated into the calculation of eco-DEA, it gives higher, instead of lower efficiency scores. This is an anomaly that needs to be ascertained and the undesirable output needs to be properly addressed so that the impact of the undesirable output is quantified in the overall efficiency score. Thus, a new eco-DEA termed as the Ratio Model is developed from the present study to incorporate both the desirable and undesirable outputs from a new perspective.

Stage Two is about the establishment of the Green Index which is derived from the newly developed Ratio Model. There are three sub-indices which represent the three undesirable outputs discharged from the textile industry: polluted air, wastewater and solid waste. They are summed up to give the Green Index in the end. With four different scenarios, the Green Index monitors the environmental performance of China's textile industry at national and provincial (Jiangsu) levels and the textile products studied are yarn, cloth and chemical fibre. China is adopted since it plays a significant role as the world's exporter of textile products. It would be of interest to examine how the Chinese textile industry is performing from an environmental point of view. To validate the Ratio Model, the Green Index is also compared with the four existing eco-DEA approaches. The results from the four case studies further confirm the two main findings and show that the newly developed Ratio Model is able to characterise undesirable output better than other approaches, thus giving a more accurate performance assessment. The environmental performance of China's textile industry has been fluctuating since 1991 but has been improving for the last seven years. For Jiangsu textile industry, the Green Index shows that it has a stable annual progression in its environmental performance. Suggestions of improvement for the least efficient DMUs are also provided. To conclude, the study shows the possibility of

applying the Green Index as a new approach in assessing environmental performance. The Green Index can be a complementary tool to the existing environmental management systems and provide guidelines to profitably manage the textile industry, as well as the production of environmental friendly products.

LIST OF PUBLICATIONS

Refereed Journal

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Conference Proceedings

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Yan, H., Gujar, G., and You, S., DEA-Efficiency of Dry Ports and Service Quality, The Internationl Forum on Shipping Ports and Airports 2010, Chengdu, China, 15-18 October,2010.

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CHAPTER 1 INTRODUCTION

1.1 Research Background

With an increasing emphasis on the environment, there is no doubt that being ecologically conscious is a necessary agenda in all kinds of businesses. The textile industry, which is reported to have a significant impact on the environment, is no exception to this statement (Achwal, 1998; Bide, 2001; Chavan, 2001; Chen & Burns, 2006; Deo & Wasif, 1998, 1999; Joshi, 2001; Nieminen et al., 2007; Shroff, 2001; USA Environmental Protection Agency, 1997; Visvanathan et al., 2000a; Visvanathan et al., 2000b; Zu et al., 2005). Typical textile production processes, regardless of whether cotton or manmade materials are used, inevitably impose an adverse effect on the environment. From the earliest stage such as yarn formation to the later stage namely wet processing, the negative environmental consequences induced are air, water and land pollution. For instance, the chemical auxiliaries used in spinning and weaving or the wet processing of fabric cause serious water pollution. Full details of the environmental impact of the textile industry are provided in Section 2.2 of Chapter 2.

There is a considerable amount of practices to restrict and minimize the environmental impact induced by the textile industry. For example, the use of physico-chemical treatment for wastewater (Pathe et al., 2005), the enhancement of the bonding between dye and fibre (Hauser, 2000), the introduction of eco-labels (Amstel et al., 2008; Gallastegui Galarraga, 2002; International Trade Centre UNCTAD/GATT, 1994; Kalliala & Nousiainen, 1999; McCarthy &

Burdett, 1998; Nieminen et al., 2007) as well as the adoption of life cycle assessment (LCA) (Curran & James, 2003; Rebitzer et al., 2004; Zygouras et al., 2005). Indeed, these approaches are less effective if green management systems are ignored. Appropriate management tools help companies to regulate their eco-policy effectively (International Organization for Standardization, 2004). Therefore, environmental performance indicators (EPIs) is developed to review, monitor and evaluate the environmental performance from a broader spectrum of the manufacturing process (Alanya et al., 2006). It is applied to monitor the ongoing process by collecting and assessing data and information for evaluation process. EPI focuses on the comprehensive performance of the whole company rather than a single procedure. This is compatible to the nature of textile industry as it takes a chain of processes to produce one product. Details of EPI are covered in Section 2.3, Chapter 2.

1.1.1 Problems of the existing environmental performance indicators in the textile industry

Although several studies attempted to develop EPIs for various industries (Alanya et al., 2006; Cao, 2007; Mirata, 2001; Nieminen et al., 2007; Olsthoorn et al., 2001; Ren, 2000; Tyteca & Carlens, 2002; Young et al., 1996), there are three common problems encountered by the existing approaches and they are shown in Figure 1-1.

Firstly, the framework to develop the prior EPIs are not consistent and standardised (Young et al., 1996). The drawback of this problem is a less effective communication between the stakeholders as they adopt different approaches of EPIs (Olsthoorn et al., 2001).

Secondly, some EPIs are developed specifically for the textile industry, but they focus on the environmental performance of wet processing only (Alanya et al., 2006; Mirata, 2001; Ren, 2000). These EPIs have overlooked the whole production process and do not present a comprehensive view of textile manufacturing.

Thirdly, it is the problem of weight subjectivity. The previous research is not based on a scientific approach in determining the relative rating of the variables (Hui et al., 2002; Zhang et al., 2008; Zhao et al., 2006).

As the EPI for the textile industry is underdeveloped, there is a need to develop an industry specific assessment method to manage green issues. A more in-depth discussion on the research gap of this issue is covered in Section 2.4 of Chapter 2.

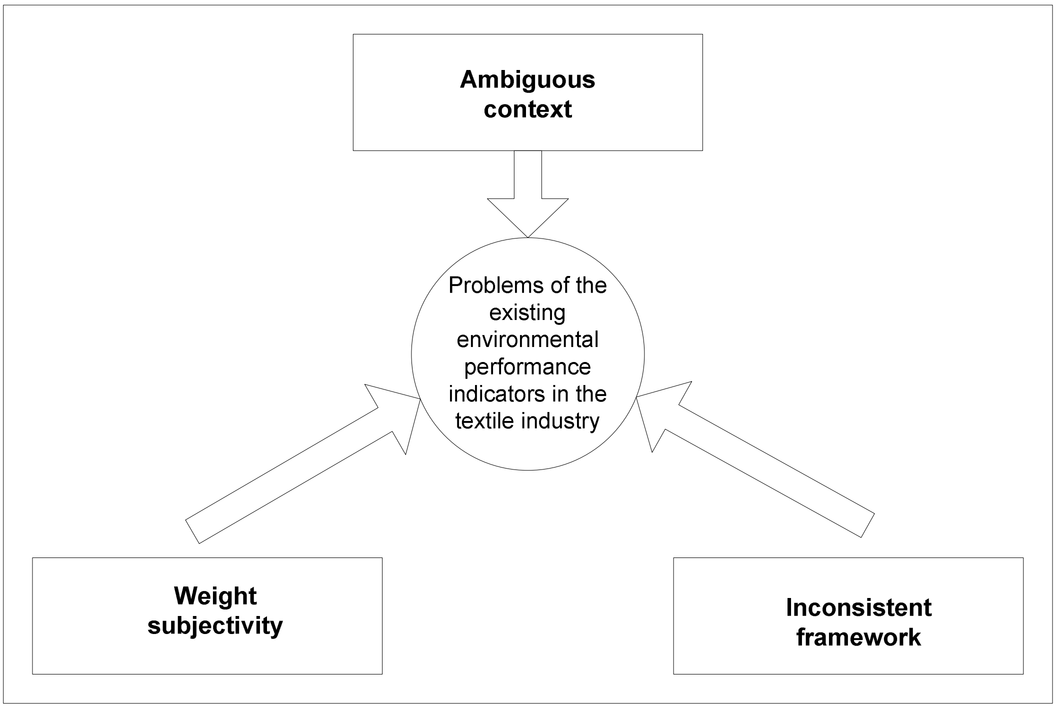


Figure 1-1 Problems of the existing environmental performance indicators in the textile industry

1.1.2 Problems of the existing eco-DEA

With regard to the mentioned research gap of the prior research on EPI, Data Envelopment Analysis (DEA) is introduced in this study to measure the environmental performance of the textile industry. DEA is a common and well established method to assess the efficiency of organisations, known as decision making units (DMU), with the same set of inputs and outputs (Zhou et al., 2008b). One of the strengths of DEA is its ability to administer multiple output and input scenarios and convert the large amount of available data into information that is useful to both government and managers (Shimshak et al., 2009), and corresponds to the complex nature of the textile industry.

However, the conventional DEA does not incorporate pollutants which are termed as undesirable outputs. The increasing attention on the environment motivates researchers to include undesirable outputs into their study of DEA. There exists a wide choice of DEA which focus on including environmental factors into calculation and they are termed as eco-DEA (Chung et al., 1997; Färe et al., 2004; Jahanshahloo et al., 2005; Kuosmanen & Kortelainen, 2005, 2007; Lozano & Gutiérrez, 2008; Yörük & Zaim, 2008; Zhang et al., 2008). Yet, there are two major problems associated with the present eco-DEA which are shown in Figure 1-2.

First, some researchers (Hua & Bian, 2007; Lu & Lo, 2007a, 2007b; Nakashima et al., 2006) ignore the presence of pollutants of the DMU which pollutants are unavoidable during production. If pollutants are ignored in the calculation, the results fail to indicate the environmental performance of the DMU. Therefore, pollutants should be distinguished and incorporated into calculation. Second, some researchers (Dyckhoff & Allen, 2001; Golany & Roll, 1989; Seiford & Zhu, 2002) fail to properly describe the characteristics of pollutants. They manipulate the pollutants with approaches that the result is distorted and the presence of the pollutants solely favours the efficiency score. Therefore, a new DEA is necessary to incorporate pollutants in an alternative way that the prior knowledge on the relevant knowledge is questioned. A detailed discussion on the research gap is discussed in Section 2.6 of Chapter 2.

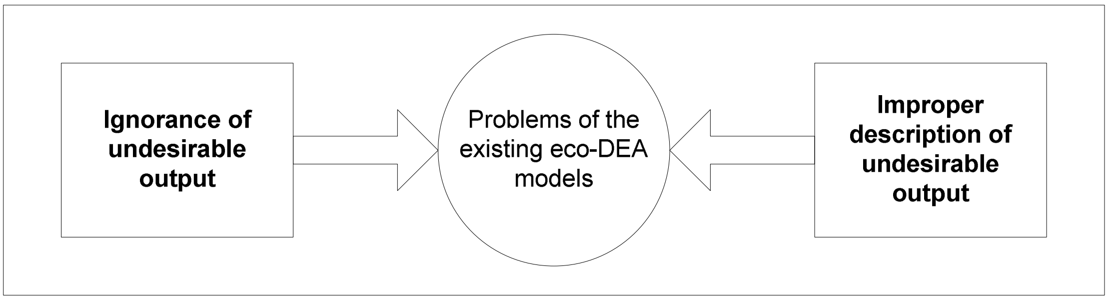


Figure 1-2 Problems of the existing eco-DEA

1.1.3 Development of a new approach in monitoring the environmental performance

In light of the research problems mentioned previously, the present investigation focuses on employing the primal eco-DEA as a tool to construct a “Green Index” to measure the environmental performance of the textile industry. It is named as “Green Index” because “Green” refers to the environmental perspective of viewing the problem and “Index” stands for a consistent and systematic method in evaluating the issue.

The objective of this research is to develop a Green Index to assess the environmental performance of China’s textile industry. According to the World Trade Organization (WTO) trade statistics, China is now the world’s largest exporter of textile products. From 1990 to 2008 (the latest year that data are available), the value of Chinese textile exports has increased significantly, from over USD7.21 billion to USD65.26 billion. This is a more than nine-fold increase in less than two decades (The World Trade Organization). Even though China's economic development is benefited by the textile industry, it puts the country's environment under pressure at the same time (Chai, 2002; Cheng & Shen, 2004; Cheung, 1998; Duan & Gao, 2008; Fang, 2001; Jahiel, 2007; Kahn & Yardley, 26 August 2007; Murray & Cook, 2002; Smil, 1996; The World Bank, 2001, 2008; Visvanathan et al., 2000a). Therefore, with the significant position of China in the textile industry, it is of interest to evaluate whether the negative impact of the environment can be offset by the economy benefit of the sector.

Given that the importance of environmental management to the China's textile industry, this study aims to develop a Green Index in an attempt to evaluate the environmental performance of the sector with a more scientific and structured approach. The Green Index provides a scientific, objective weighting of variables and a consistent framework which is constructed for the manufacturing process of various textile products. When an appropriate green management tool such as the Green Index gets complement with a green technology, not only the environment is improved, other industries are also motivated to follow this approach.

1.2 Research Aim and Objectives

The aim of the present research is to provide a consistent and structured framework, defined as a Green Index, that allows the textile industry to monitor the products and their production process in terms of environmental factors. For this purpose, Data Envelopment Analysis (DEA) is firstly introduced in the textile field to construct an environmental performance index (EPI). The Green Index explores new perspectives related to eco-efficiency, and uses a scientific approach to measure the environmental performance of China’s textile industry at the national and provincial levels. Based on the China Statistical Yearbook, yarn, cloth and chemical fibres are the textile products studied together with the pollutants which are polluted air, wastewater and solid waste in the Green Index. The following objectives are to be achieved:

(1) To review the impact of the textile industry on the environment;

(2) To investigate the existing tools in measuring environmental performance;

(3) To develop a new eco-DEA for assessing environmental performance; and

(4) To apply the newly developed Green Index to evaluate the environmental performance of China’s textile industry.

1.3 Scope of Study

The proposed Green Index aims to evaluate the environmental performance of the textile industry in China and Jiangsu Province across the period 1991-2007 and 1997-2007 respectively. The setting of the research is confined to China for her representative position in the worldwide textile industry and Jiangsu for her significant role in the nationwide textile industry (The World Trade Organization). Annual comparative study is conducted as this gives a more comprehensive way to examine the environmental problem in China on a continuous basis. Detailed discussion on these subjects is covered in Section 3.3.3.3 of Chapter 3.

In this study, “textile industry” is referred to as the processes involved in the manufacturing of textile products: yarn, cloth and chemical fibres. It does not include the performance of apparel and footwear production.

Yarn, cloth and chemical fibres are chosen as the desirable outputs studied because the China Statistical Yearbook, which is an official database authorized by the National Bureau of Statistics, indicates that these three textile products are China’s major industrial products. In addition, the present work based on the data mainly collected from this source to study the model developed in the later stage of the research. The details on these three textile products are provided Section 5.3.3 of Chapter 5.

According to the China Statistical Yearbook, “yarn” comprises of pure and blended cotton yarn, and pure chemical fibre yarn, but excludes cotton thread, substitute fibre yarn and hand-made yarn.

“Cloth” includes pure and blended cotton cloth, pure chemical-fibre cloth and canvas, but excludes substitute fibre cloth, hand-woven cloth and cord cloth.

“Chemical fibre” comprehends of synthetic fibre such as polyester fibre, acrylic fibre, polyvinyl fibre and manmade or cellulose fibre.

1.4 Research Significance

The current study aims at developing a Green Index to evaluate the environmental performance of China's textile industry. The research outcomes are expected to contribute to knowledge and managerial practice as well as provide insights to the country environmental policy makers. With this attempt, the significance of the study are illustrated as follows:

For academia, the newly established eco-DEA provides a new perspective in incorporating the undesirable output into the eco-DEA with an improved and comprehensive view;

For managerial practice, the textile mill's reputation is enhanced as a recognized green plant when the Green Index is applied. Also, the Green Index provides a consistent framework for the textile industry to evaluate the environmental performance of the manufacturing processes with an unbiased approach with the adoption of DEA; and

For country policy maker, the annual performance of the country's textile industry is assessed so the policy makers can formulate appropriate regulations to sustain the development of the environment.

1.5 Research Originality

This research project concentrates on the development of a framework called the Green Index to evaluate the environmental performance of the textile industry in China by the methodology of DEA. This study is related to the textile industry and DEA respectively and its originality is illustrated in two aspects: the methodological approach and the study focus.

For the methodological approach, the undesirable output is incorporated into the eco-DEA in an entire different way under this new attempt. Each undesirable output is proportionately related to the total amount of the desirable output and therefore, the impact of the undesirable output is directly associated with the amount of the desirable output and thus the performance of the DMU. This new perspective provides a more sensitive approach in incorporating undesirable output into the eco-DEA and the efficiency score for each DMU gives a more subjective and reasonable results.

For the study focus, it is for the first time ever the concept of eco-efficiency is applied in the textile industry by using DEA on the environmental related topic. This new perspective is regarded as an association between economic output and pollution of the production activities (Bidoki et al., 2006) and looks into the eco-problems encountered by the management level. As revealed by the research background in Section 1.1, pollutants such as polluted air, wastewater and solid wastes are unavoidable during the manufacturing process. Under the inevitable presence of the undesirable outputs, the environmental performance of the manufacturing processes is evaluated in the light of eco-efficiency. It combines the monetary value and sustainable development together as an assessment to achieve the optimum operation condition. Therefore, the present study evaluates the undesirable outputs in an unprecedented way in order to properly describe the pollution problems of the textile industry. Also, DEA is also a new approach to solve the weighting problem in monitoring the environmental performance of the textile industry.

1.6 Definition of Terms

To further clarify and strengthen the idea of the present study, the following provides the definition of the important and commonly used terms which are shown in alphabetic order.

Data Envelopment Analysis (DEA): It is a methodology adopted in this study. It is a non-parametric method in which multiple inputs and outputs could be used to measure firm’s performance (Düzakın & Düzakın, 2007).

Decision Making Unit (DMU): It is defined as the entity responsible for converting inputs into outputs and whose performances are to be evaluated under DEA (Düzakın & Düzakın, 2007).

Desirable output: It is referred to as the preferred product of the DMU (Lu & Lo, 2007a).

Eco-DEA: It is referred to as the one DEA approach which is applied to measure the environmental performance of a DMU with the presence of undesirable output(s).

Environmental Performance Evaluation (EPE): It is the process to facilitate management decisions regarding an organisation’s environmental performance by selecting indicators, collecting and analysing data, assessing information against environmental performance criteria, reporting and communication, and periodically reviewing and improving this process (International Organization for Standardization, 1999).

Environmental Performance Indicator (EPI): It is defined as the specific expression that provides information about an organisation’s environmental performance (International Organization for Standardization, 1999).

Green Index: It is the EPI developed from the present study to evaluate the China’s textile industry. A new eco-DEA approach is applied in the Green Index for measure the environmental performance.

Textile Industry: It is defined as the processes involved in the manufacturing of textile products yarn, cloth and chemical fibres. It does not include the performance of apparel and footwear production.

Undesirable Output: It indicates the ecologically unfavoured output produced along with the desirable output (Scheel, 2001).

1.7 Thesis Organisation

There are six chapters in this thesis. The outline for each chapter is as follows:

Chapter 1 gives an overview of the research on the present study and covers the sections that illustrate the research aim and objectives, scope of study, research significance, research originality, definition of terms and thesis organisation.

Chapter 2 examines the literature relevant to the research background and model adopted in the present study. Firstly, it discusses the environmental impact on the manufacturing process of yarn, cloth and chemical fibre. Followed by is the illustration of the environmental management tool employed in this study – environmental performance indicator (EPI). Data envelopment analysis (DEA) is introduced as it is the adopted tool to evaluate the eco-performance of textile industry. Based on the previous studies of EPI and DEA, research gaps are identified.

Chapter 3 provides the details of the research methodology of the present study. There are two stages identified in this study. The chapter firstly discusses the steps involved in Stage One then in Stage Two. In-depth examination on the data source, software, preliminary study, selection of DMU, input and output variables are also presented.

Chapter 4 discusses the various existing eco-DEA in the literature and develops as new eco-DEA that accommodates the undesirable outputs in a proper perspective. A considerable number of detailed comparative studies are executed amongst the various approaches of eco-DEA to illustrate the anomaly in the efficiency score obtained. Thus, an improved and new approach, as called the Ratio Model, is developed.

Chapter 5 demonstrates the adoption of the Ratio Model developed as the Green Index for China’s textile industry. This chapter covers the preliminary study that is conducted in the very early stage of research. Then it describes the design of the Green Index in details and shows how it is applied as an environmental management tool for decision makers. Four case studies are carried out in order to analyse the annual environmental performance of China’s textile industry at national and provincial level. The result of the Green Index is also compared with the existing four eco-DEA approaches in order to further validate the findings.

Chapter 6 concludes the present study and firstly illustrates the summary of the whole research. Then, the major findings are presented. The implication and significance, limitation and recommendation for future work of the present study are also discussed.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

In the present chapter, the literature examined is relevant to the research background presented in Chapter 1. The purpose of this review is to provide an understanding of the previous research in this area, as well as providing a rationale for the choice of research questions in the present study. This chapter consists of three main parts. The first part discusses the environmental and health impact of textile manufacturing which is specifically relates to the production of yarn, cloth and chemical fibre (Section 2.2). These three textile products are examined because they would be the subject of the model developed in the later stage. In addition to the environmental impact of the textile product, the health impact induced from the manufacturing process is also discussed. Followed by the next section is the introduction of management tool which evaluates the environmental performance of a product or manufacturing process (Section 2.3). The review focuses on the environmental performance indicator (EPI) which is used to assess the environmental performance of a product or production process. Research gaps are pointed out based on the discussion of the prior EPI studies (Section 2.4). In the next section, details of the theory behind DEA and the measurement of efficiency with DEA are outlined (Section 2.5). Based on the previous studies of DEA in the application of environmental performance, research gaps are identified for further improvement (Section 2.6).

2.2 Environmental Impact on Textile Manufacturing

All industrial activities unavoidably cause pollution and the textile industry is of no exception. Although the textile industry has been flourishing and brings enormous economic advantage to China, the sector is damaging the environment of the historic land at the same time. There is a profusion of studies illustrating the environmental problems induced by the textile industry in China (Chai, 2002; Cheng & Shen, 2004; Cheung, 1998; Duan & Gao, 2008; Fang, 2001; Jahiel, 2007; Jhala et al., 1981; Kahn & Yardley, 26 August 2007; Klyszejko, 1980; Murray & Cook, 2002; Noweir & Jamil, 2003; Smil, 1996; Talukdar, 2001; The World Bank, 2001, 2008; Visvanathan et al., 2000a). To further illustrate the negative impact, the following section discusses how a typical manufacturing process of yarn, cloth and chemical fibre can impose an adverse effect on the environment.

2.2.1 Yarn

As defined in Section 1.3, the “yarn” products discussed in the present study comprise of yarn made from cotton and chemical fibre. Therefore, the following paragraphs examine the environmental impact of the production of the two yarn types.

For chemical fibre yarn, there are three production techniques for the production of filament namely dry (solvent) spinning, melt spinning and wet spinning. These spinning methods would cause various levels of pollution. During the production of synthetic fibre yarn, nitrous oxide which depletes the Earth’s ozone layer is emitted, causing an undesirable load on the environment. Wet spinning is a common way in regenerated fibre yarn production. However, the use of chemicals such as acids and alkali during the process poses a threat to the environment (Slater, 2003).

For cotton yarn, spinning is the process in yarn production to assemble the cotton fibres by inserting twists onto the yarn. However, noise and a large amount of dust is produced during spinning. The dust generated is a mixture of traces of fibres as well as organic and inorganic particles such as leaf, husk fragments and sand (Kane, 2001). As an air pollutant, cotton dust would induce an occupational lung disease named as byssinosis. Details are shown in Section 2.2.4. Another source of pollution is the use of lubricating oils which are applied to the spinning machines to prevent fibre loss and allow high speed processing (Walters et al., 2005). This creates polluted effluent. Energy consumption is also an environmental issue in the spinning mills. Owing to machinery operation and air conditioning (a stable indoor condition is critical for spinning to ensure a reduction in yarn breakages and an increase in productivity), more than 90% of the energy used in a spinning mill is electricity power (Cooper, 1978).

2.2.2 Cloth

Knitting and weaving are the two traditional fabric production methods. A large amount of energy is consumed due to machine size and complexity. To prevent the breakage of yarn, sizing is applied to the warp yarn which makes it more slippery, supple and stronger (Walters et al., 2005). However, the sizing agent, which is made up of either natural or chemical materials, is washed in the subsequent steps causing water pollution. Therefore, 70% of the COD (chemical oxygen demand) load of a mill finishing woven fabric comes from desizing liquor (Walters et al., 2005).

The wet processing stage, which gives the final product some desired properties, is further divided into 3 phases: pretreatment, colouring and finishing. Some of these steps may be optional depending on the type of fabric being manufactured (USA Environmental Protection Agency, 1997). The consequence of each process could be of “varying severity” (Fang, 2001; Mirata, 2001; Tobler-Rohr, 2000). Water is a necessary means for the wet processing treatment. The amount of water consumption per operation varies with the type of fibre being processed as well as the chemicals being used (Deo & Wasif, 1998).

Air pollutants generated from other textile finishing processes are originated mainly from the pathways such as singeing, thermofixing, thermosoling and impregnating (Lacasse & Baumann, 2004). Figure 2-1 shows that the total energy consumption in weaving and wet processing accounted for over 50% in the textile processing. High energy consumption is equivalent to a higher emission of greenhouse gas during the electricity generation (Visvanathan et al., 2000a).

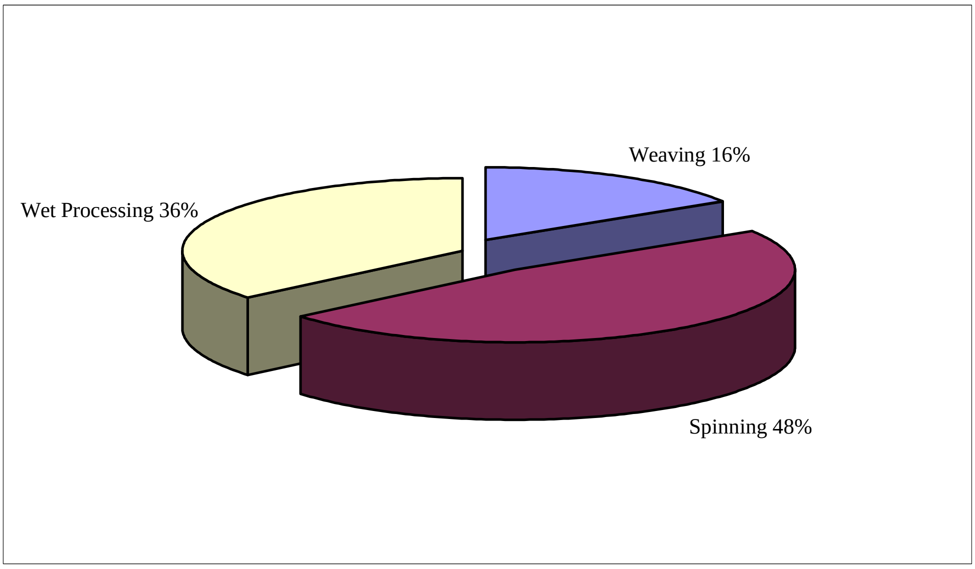


Figure 2-1 Energy consumption in textile processing (Visvanathan et al., 2000a)

According to the Environmental Protection Agency (USA Environmental Protection Agency, 1996), high-temperature drying and curing ovens are the most common source of polluted air emissions in a textile operation. All these high temperature operations are needed to process coating of textile materials. Heat-setting and thermofixation, with typical operation temperature ranging from 250^{o}F to 400^{o}F, emit certain level of air particles and waste detergent which can cause air and water pollution (Slater, 2003). Apart from the production stages mentioned previously, transportation of goods between production sites also emits air pollutants such as sulphur dioxide, carbon monoxide and carbon dioxide. Therefore, the environmental problems created by transportation should not be neglected. Moreover, the overall textile production produces miscellaneous solid wastes such as selvedge trimmings, fly ash, aluminium cans and wooden pallets. This makes textile manufacturing a source of the waste stream (USA Environmental Protection Agency, 1996).

2.2.3 Chemical fibre

Chemical fibres are classified into two groups which include synthetic fibre and regenerated fibre. Synthetic fibre is made from the extraction of petroleum which is a non-renewable and non-biodegradable resource (Chen & Burns, 2006; Fang, 2001). The environmental cost is high due to the non-renewable source to produce the synthetic fibre (Slater, 2003). For regenerated fibre such as rayon, it is made from wood pulp which comes from mature forests and the processing of wood pulp would use up a large quantities of chemicals that induces both water and air pollution (Chen & Burns, 2006).

2.2.4 Health impact induced from pollution

The desirable characteristics obtained from finishing are created with the consumption of many chemicals and auxillaries which not only affect the environment but also human health (Lacasse & Baumann, 2004; Mirata, 2001). A case was reported that excessive formaldehyde which was found on some easy-care garments irritated human skin (Sewekow, 1996). Therefore, the potential harm that textile products impart to our health cannot be ignored. Some textile materials emit formaldehyde and amine odours which irritate the human respiratory system (USA Environmental Protection Agency, 1996). Additionally, the exposure of industrial wastes such as waste effluent or dyes may led to negative health impact. The health impact ranges from headaches, nausea to serious illness such as congenital malfunction or mutagenicity (Mathur et al., 2005; Walters et al., 2005).

Cotton dust, which is a form of air pollution, generated from the cotton yarn formation would induce respiratory health problem named as byssinosis. It is a classic form of occupational lung disease commonly found among the cotton mill workers (Khan & Nanchal, 2007; Wang & Christiani, 2003). Byssinosis is characterised by the symptoms of chest tightness and breathing difficulty (Niven & Pickering, 1996). As cotton dust is considered as the core cause of byssinosis (Hughson, 1999), each stage of the cotton yarn formation process would contribute to the exposure of byssinosis. Opening of bales and removing impurities and short fibres in the blowing room are regarded as the incredibly dusty processes where higher concentration of cotton dust was found (Levenstein et al., 2002; Newman Taylor & Pickering, 1994). Workers are also exposed to cotton dust during the process of carding, drawing, combing, roving, spinning and weaving where cotton fibres are turned into yarn. Additionally, workers who are responsible for the cleaning of various machines parts, for example strippers and grinders for the carding machine, are at a particular high risk for the development of byssinosis due to the dusty nature of the machineries (Levenstein et al., 2002; Tanoue, 2002). From the research of Lane et al. (2004), it is evident that the blowing room measured the most concentrated amount of endotoxin, which is the causative agent for byssinosis.

2.3 Environmental Performance Indicator (EPI) Approach

From the literature covered in the previous section, the environmental impact of textile manufacturing process is acknowledged. This section discusses the environmental performance indicator (EPI) approach which is applicable to the textile industry on green management.

Although green consumerism is a perennial issue in the modern world (Butler & Francis, 1997; Chan, 1999; Clothing Industry Training Authority, 2007; Kim & Damhorst, 1998) and the textile industry endeavours to promote eco-textile through the use of environmentally benign materials (Phipps & Park, 2002), the results will be less effective if green manufacturing and management systems are ignored. Indeed, the necessary step for policy makers is to put forward recommendations and encourage companies to be actively involved in environmental management, and choose the plan best suited for their situation (Crowe & Brennan, 2007). It is believed that in order to follow both local and international policies persistently and effectively, the only solution is to incorporate environmental issues into a corporation's routine management practices (Epstein & Roy, 1998). Consequently, a strong environmental management system is a driving force for companies to understand their roles and responsibilities in protecting the environment. Tools and guidelines are then introduced for textile industry to identify their opportunities for continuous improvement in their own green policy. The environmental management systems can help companies incorporate both the global perspective and local view in a balanced way (Epstein & Roy, 1998). Among the significant number of approaches, environmental performance indicator is one of them.

2.3.1 Description and justification of EPI

The present study aims to develop a Green Index to evaluate the environmental performance of the textile industry. In fact, the Green Index is one example of

EPI. EPI is a form of environmental management system introduced by the International Organization for Standardization (ISO) under the ISO 14000 series.

ISO has established a number of non- compulsory international standards for industrial activities such as manufacturing, communication, trade and administration (Sonnemann et al., 2004). In 1996, the ISO 14000 was introduced as a guideline for implementing “an effective environmental management system (EMS) that can be integrated with other management requirements and help organisations to achieve environmental and economic goals” (International Organization for Standardization, 2004). The ISO calls for an absolute commitment to the environmental management system at all levels of an organisation for continuous improvement (International Organization for Standardization, 2004; Jasch, 2000). The ISO 14000 series helps upgrading a company’s environmental profile by implementing a more comprehensive management framework (Tsikos & Mariolakos, 2003). Table 2-1 outlines the types of guidelines offered by the ISO 14000 series. Under the ISO 14000 series, several management tools are introduced for efficient implementation of the environmental management system. Among them, EPI is one of the tools that are popular in the textile industry as well as recommend by the ISO.

Table 2-1 ISO 14000 series

ISO series no.	Title
14001-04	Environmental management systems
14010-15	Guidelines for environmental auditing
14020-24	Environmental labelling
14031	**Environmental performance evaluation**
14040-49	Life-cycle assessment

The present study focuses on developing an EPI for performance evaluation. In fact, under the environmental performance evaluation (EPE), there are three components and EPI is one of them (Kolk & Mauser, 2002). The branches of environmental performance evaluation are shown in Figure 2-2.

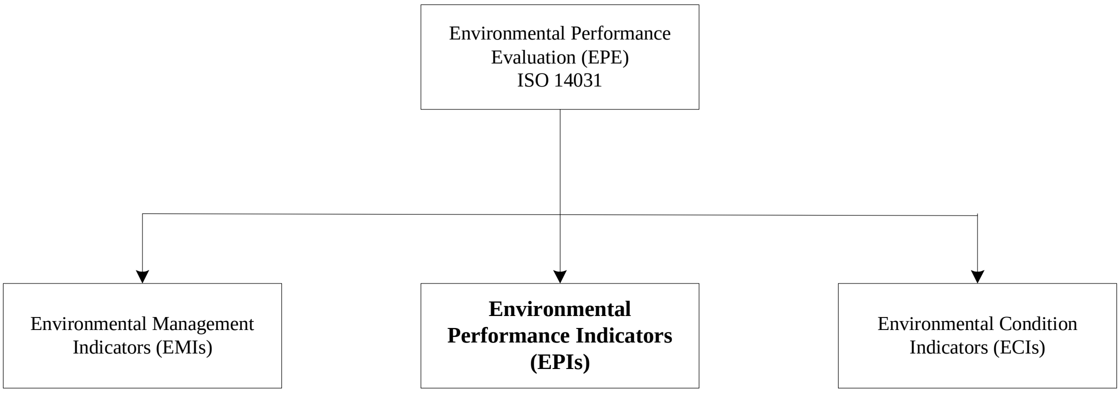


Figure 2-2 Components of an environmental performance evaluation

ISO 14031 defines environmental performance evaluation as a “process to facilitate management decisions regarding an organisation’s environmental performance by selecting indicators, collecting and analysing data, assessing information against environmental performance criteria, reporting and communication, and periodically reviewing and improving this process” (International Organization for Standardization, 1999). In other words, environmental performance evaluation is a tool to monitor the ongoing process by collecting and assessing data and information for evaluation purposes (International Organization for Standardization, 1999; Jasch, 2000; You & Cheng, 2008).

The advantage of an indicator is able to favour people for decision making and understanding the environmental aspects of manufacturing (Li & Hui, 2001). With the simple units of measure, indicators faciliate indecision-making and management of complex issues (Olsthoorn et al., 2001). Moreover, it is a comprehensive way to make comparisons between different products (Berkhout et al., 2000; Hui et al., 2002). Using an indicator can attract the interest of all stakeholders (internal or external) in the environmental aspects of the manufacturing processes, as well as the products (Thoresen, 1999). Compare to other environmental management approaches such as eco-label, EPI is an ongoing process of collection and assessment of data which aims to provide the current status of environmental performance. Also, EPI focuses on the comprehensive performance of the whole company other than the single product or service (Jasch, 2000). The following section illustrates some examples regarding the development of environmental performance evaluation using a single score system.

2.3.2 Previous studies on the existing EPI

Below are the examples of the various EPIs found in the literature. They use different criteria in assessing the environmental impact and are discussed are follows.

2.3.2.1 The environmental impact scoring system

The environmental impact scoring system is developed by Hui et al (2002) to assess the product’s greenness by using an environmental impact scoring system. The concept is grounded in the Life Cycle Assessment (LCA). It is suggested there are six stages altogether in a product life cycle. The environmental impact factors within these six stages are identified to assess the greenness of the product’s life cycle. The factors mentioned in the literature are resources consumed, residues, product size, durability, maintenance, disposal and recycling. Each of these factors is further divided into sub-factors as the basis to establish the scoring system. For example, the 'residue' factor is separated into gaseous residues, liquid residues and solid residues. These typical residues are then divided into components, which are ozone depletors, greenhouse gases, acidic gases, pH value, temperature, transparency, hazardous wastes and scrap. This creates a hierarchy in the scoring system. The environmental impact significance of each sub-factor is expressed by a rating as well as a weighting factor. After multiplying the rating and weighting factors together, the numerous sub-factor scores are summed up. The final environmental impact score is then calculated. An example of the rating scale for transparency is shown in Table 2-2.

Table 2-2 Rating scale for transparency

Water colour rating	Intensity
Class 3: High	3 > Regulatory limit
Class 2: Medium	2 = Regulatory limit
Class 1: Low	1 < Regulatory limit

2.3.2.2 Environmental impact evaluation model

The same group of researchers pointed out that since there were no standard rules for the evaluation of environmental performance, another model is proposed (Li & Hui, 2001). This model is based on the concept of environmental impact, which again originated from Life Cycle Assessment (LCA). The model's main element is based on the 'unit process'. It refers to the input, process and output of the industrial activity.

Each of the unit processes is studied in order to distinguish the potential hazard in the output inventory. The next step is classifying the inventories into different groups and further categorising them into two environmental impact divisions: ecological health and human health. After inserting different weighing factors for each group, the environmental impact score is finalised. The model framework is shown in Figure 2-3. This model can provide product designers with the necessary information on environmental aspects within operations.

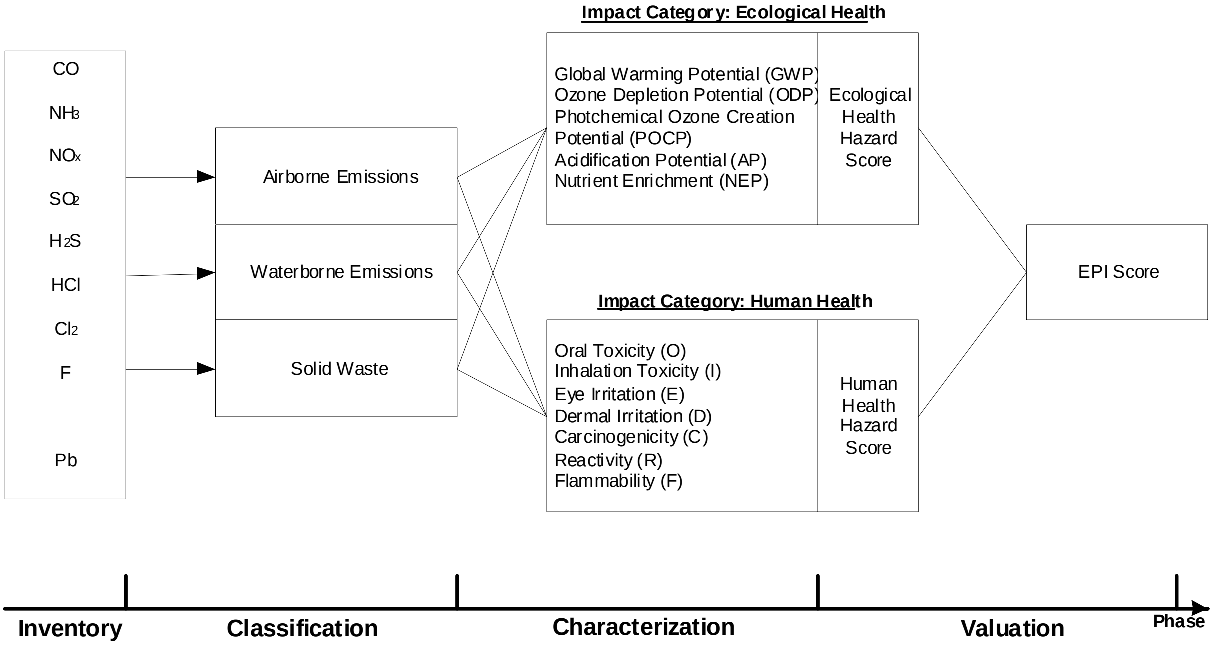


Figure 2-3 The framework of the environmental impact evaluation model

2.3.2.3 *EPI for textile industry*

There are environmental performance indicators developed specifically for textile processes and products by identifying the best available values in production (Mirata, 2001; Ren, 2000). Various formulae are employed to predict the values of the following parameters:

(1) Colour discharged;

(2) Biological Oxygen Demand (BOD);

(3) Amount of metal in effluent;

(4) Toxicity of dyes and chemicals in the receiving water;

(5) Specific water consumption; and

(6) Specific thermal energy consumption.

These theoretical formulae are useful when there is difficulty in direct measurement of environmental factors. Apart from indicating the textile processes, the study has been further expanded to develop an environmental performance indicator for textile products (Ren, 2000). However, it is difficult to determine a product’s actual life cycle, due to continually changing fashion trends and the consumer lifestyle. Therefore, the EPI for textile products is underdeveloped.

2.3.2.4 Measuring environmental performance of industry (MEPI)

The MEPI project benchmarks the environmental performance of six industries which are situated in Germany, Austria, the Netherlands, Italy, Belgium and the U.K. The industries participating in the study are electricity, printing, fertilizers, textiles, computer manufacturing, and pulp and paper (Tyteca & Carlens, 2002). With the use of “quantitative analysis of industrial environmental performance which is obtained from publicly available information”, the MEPI could standardise the environmental performance indicators of these six industries (Berkhout et al., 2000).The scheme identifies the variables within each sector after consulting industrial experts. The indicators focused on the MEPI are physical, business management and environmental impact. The project aimed to provide a uniform method for benchmarking within the same type of business, as well as cross-sectorally or even making international comparisons of industrial environmental performance. The scheme also investigates the correlations between management, business and environmental performance of the six sectors. The method of assessment is not illustrated in the literature; however, the outline of the methodology applied is clarified below:

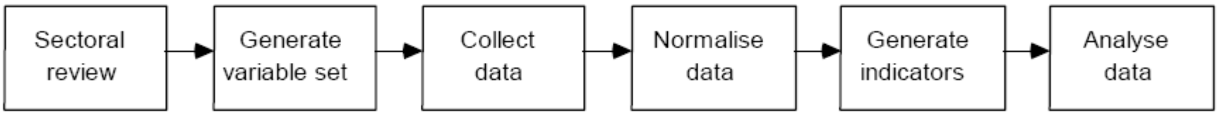


Figure 2-4 The process of indicator development (Berkhout et al., 2000)

2.4 Research Gap with Previous Studies of the Existing EPI

The previous sections discuss the literature on the several approaches of environmental performance indicators. Regardless of their popularity in the textile industry, these EPIs suffer from insufficiency in their design and applications. There are three associated problems and they are discussed as below.

2.4.1 Inconsistency of the EPI framework

There are numerous studies attempted to develop a framework for environmental performance indicators (Berkhout et al., 2000; Hui et al., 2002; Hui et al., 2003; Li & Hui, 2001; Mirata, 2001; Olsthoorn et al., 2001; Ren, 2000; Young et al., 1996). However, they have different approaches in evaluating the environmental performance For instance, one uses equations to calculate the environmental impact of the manufacturing process (Ren, 2000) and one determines the environmental performance based on the data available (Berkhout et al., 2000). It is necessary to set a consistent framework and criteria when developing an index. This can ensure an uniform output for each indicator and favour a better communication among the plant, local authorities or even international stakeholders (Olsthoorn et al., 2001; Ren, 2000).

2.4.2 Lack of comprehensive view

Even the EPI is developed for the textile industry, they are mainly used to evaluate the wet processing (Alanya et al., 2006; Mirata, 2001; Ren, 2000). Other textile manufacturing processes such as yarn or cloth formation are ignored. It is acknowledged that each textile process would have a negative impact on the environment. Therefore, there is a need to develop an EPI which can evaluate the textile industry from a more comprehensive perspective.

2.4.3 Weight subjectivity

Another common problem in constructing an environmental performance indicator is the issue of weight subjectivity in estimating the relative importance of the variables being evaluated. During the design of an EPI, there are numerous environmental issues to be evaluated such as polluted air, wastewater and solid waste. These pollutants have different impact to the environment therefore weights are used to differentiate their impact levels. Greater the weight of the environmental variable, greater the environmental impact. Most of the previous research is not based on a scientific approach in determining the relative rating of the variables. For instance, the EPI developed by Hui et al. (2002), the questionnaire approach was used to determine the weighting system and eight recipients responded. The authors then decided the weights of the factors and sub-factors based on the results of the responded questionnaire. Another example is the EPI designed by (Li & Hui, 2001). The analytic hierarch process (AHP) approach is adopted to identify the importance of the factors determined by experts on the related field. These preceding indicators or scoring systems rely on the subjective judgment of management to decide the relative importance of the numerous variables.

Based on the above research gaps, a Green Index is developed from this study. The Green Index introduces a simple and consistent framework for environmental performance evaluation. Relevant data is collected and followed by the calculation of performance by data envelopment analysis (DEA), which is a tool applied in this present study. The details of DEA are covered in the next section. Additionally, the Green Index investigates into the manufacturing process of yarn, cloth and chemical fibre. This approach provides a more inclusive view to look into the environmental performance of the textile industry than the previous EPIs. Furthermore, DEA is a tool to calculate the performance of organisations according to their inputs and outputs. As the weights for various inputs and outputs are determined by the DEA itself, therefore, it is not necessary to rely on the subjective opinion to decide the relative importance of the variable. In fact, DEA is also recommended by a profusion of literature that it can be applied to solve the weighing problem (Epstein & Henderson, 1989; Kortelainen, 2008; Kuosmanen & Kortelainen, 2005; Lam & Shiu, 2001; Shimshak et al., 2009). Therefore, DEA is an appropriate tool to calculate the environmental performance of the textile industry in the Green Index. Details of DEA are discussed in the next section.

2.5 Data Envelopment Analysis (DEA)

Apart from the ISO 14000 series, there are indeed a number of environmental management tools which encourage companies to integrate sustainable development into corporate business strategy at different levels. For instance, one way to gain insight into the environmental condition of a production process or product, is to analyse its eco-efficiency. Data Envelopment Analysis (DEA) is a new approach of applying eco-efficiency for environmental assessment (Hua et al., 2007; Korhonen & Luptacik, 2004; Kortelainen, 2008; Kuosmanen & Kortelainen, 2005; Park & Tahara, 2008; Sarkis, 2004)

Eco-efficiency can be a simple ratio or indicator to examine the environmental impact resulting from a production process or industrial activity. It joins monetary value and sustainable development as an assessment to achieve optimum operating conditions. According to Kuosmanen and Kortelainen (2005), two reasons explain the increasing popularity of eco-efficiency. Firstly, the authors believed that eco-efficiency is the “most cost-effective way of reducing environmental pressures”. It is possible that an option might be slightly inferior in terms of pollution reduction when compared with other alternatives, but it is of the lowest cost. From an eco-efficiency point of view, this option might not be the worst. Hence, this increases the availability of different eco-management alternatives. Secondly, it is less demanding to implement policy which is “targeted at efficiency improvements” rather than “restricting the level of economic activity”.

2.5.1 Description and justifications of DEA

DEA was introduced by Charnes, Cooper and Rhodes (1978) in 1978. It is a nonparametric linear programming-based technique to measure the relative efficiency of decision units (Zhou et al., 2008b). The word “relative” is employed because different sets of units are subject to comparison based on their multi-inputs and multi-outputs (Düzakın & Düzakın, 2007). These sets of units are referred to as decision making units (DMU). Each DMU being evaluated must have a homogeneous role that converts the same group of resources (inputs) into the same type of products or services (outputs) (Zhou et al., 2008b). It is of significance to delineate both the unit of assessment and its related input and output. This helps the assessment to be more accurate and less biased (Thanassoulis, 2001). Subsequently, the DMUs are then classified as either efficient or inefficient. The efficient DMUs are grouped together and form a border line, called the efficient frontier. This line acts like an envelope that encloses the inefficient units. This characteristic explains the term “envelopment” (Düzakın & Düzakın, 2007) (with detailed graphical description in Section 2.3.2). The aim of DEA is to increase the efficiency of each DMU in the sense that it can yield more outputs for a given input or use fewer inputs for a given output. Ultimately, the DMU can emulate to improve its performance.

Hence, DEA has been applied to a wide range of industries such as education (schools and universities), health care (hospitals, clinics), railroads, coal mining, the military, financial services, agricultural production, regulation, power plants, the police service and operations and management science (Cooper et al., 2004; Forsund & Sarafoglou, 2002, 2005; Ramanathan, 2003; Thanassoulis, 2001). DEA has also been applied in the textile industry as well to tackle various kind of issues (Chandra et al., 1998; Cooper et al., 1995; Jahanshahloo & Khodabakhshi, 2004; Zhu, 1996).

According to Thanassoulis (2001), DEA offers the following advantages:

(1) To decompose efficiency into components attributable to different layers of management or agents involved in the operations of the units being assessed;

(2) To assess the impact of policy initiatives on productivity; and

(3) To measure the change over time in the productivity of the industry as distinct from that of the units operating within it.

2.5.2 Basic DEA

Assume that there are *R* DMUs that convert *M* inputs to *N* outputs. DMU_k is one of the *R* DMUs being evaluated. Further assume that DMU_k consumes *m* input $X_i^k (i = 1, 2, ..., m)$ to produce *n* output $Y_j^k (j = 1, 2, ..., n)$ and each DMU has at least one positive and one positive output. The measure of efficiency of DMU_k is then obtained by:

$$E_k = \frac{\sum_{j=1}^{n} u_j^k Y_j^k}{\sum_{i=1}^{m} v_i^k X_i^k}, \tag{2-1}$$

$$X_i^k, Y_j^k \geq 0, \quad i=1,...,m$$
$$u_j^k, v_i^k \geq 0, \quad j=1,...,n$$

where u_j^k, v_i^k are the optimal weights for the *jth* output and *ith* input when maximisation of DMU$_k$ is obtained. The objective of DEA is to maximise the efficiency E_k of DMU$_k$, and compute a most favourable weighted combination of inputs $v_1^k, v_2^k, ..., v_m^k$ to a most favourable weighted combination of outputs $u_1^k, u_2^k, ..., u_n^k$ while keeping the ratios for all the DMUs not more than 1. All these conditions give the following model (2-2):

$$\max \quad \frac{\sum_{j=1}^{n} u_j^k Y_j^k}{\sum_{i=1}^{m} v_i^k X_i^k} = E_k$$

$$\text{s.t} \quad \frac{\sum_{j=1}^{n} u_j^k Y_j^r}{\sum_{i=1}^{m} v_i^k X_i^r} \leq 1 \qquad r=1,2,...,R \tag{2-2}$$

$$u_j^k > 0, \qquad j=1,...,n$$
$$v_i^k > 0, \qquad i=1,...,m$$

where DMU$_r$ = any of the decision making units being evaluated;

DMU$_k$ = the particular decision making unit being evaluated;

X_i^r, Y_j^r = the inputs and outputs of every DMU$_r$; and

u_j^k, v_i^k = the unknown weights.

Therefore, the weights for each input and output are not assigned in advance. The weights are determined by obtaining the maximum value of efficiency E_k^* of DMU$_k$. The weights present the most favourable performance of the evaluated DMU (Kuosmanen & Kortelainen, 2005). If E_k^* =1, that means DMU$_{k.}$ is efficient. If E_k^*<1, that means DMU$_{k.}$ is inefficient. The preceding model (2-2) is regarded as an output-oriented DEA model, which aims to maximise the DMU output with the same input. Model (2-2) can be further transformed into an input-oriented model (2-3) which aims to minimise the input by keeping the output amount unchanged. Both approaches have the same efficiency result and provide the same value.

The dual of the output maximising program is the input-oriented envelopment programme. In a similar way, the dual of the input oriented model is the output maximising envelopment programme (Ramanathan, 2003). The input-oriented reciprocal linear programming problem is shown below:

$$\begin{aligned}
&\min \quad h_\mathrm{k} = \theta \\
&\text{s.t} \quad \sum_{r=1}^{R} \lambda_r X_i^r - \theta X_i^k + s_i^- = 0 \qquad i = 1, 2, \ldots, m \\
&\qquad \sum_{r=1}^{R} \lambda_r Y_j^r - s_j^+ = Y_j^k \qquad j = 1,2,\ldots,n \\
&\qquad \lambda_r, s_i^-, s_j^+ \geq 0, \qquad r = 1, \ldots, R
\end{aligned} \tag{2-3}$$

where θ = represents the efficiency of DMU;

λ_r = the dual variable corresponding to the other inequality constraint of the primal;

s_i^-, s_j^+ = the slack variables which turn the inequality constraint into an equal form; and

$\lambda_r^*, s_i^{-*}, s_j^{+*}$ = the optimal solutions when the relative efficiency of DMU$_k$ is $\theta^*=1$ and $s_i^{-*} = s_j^{+*} = 0$.

If the relative efficiency is <1 and one wants to improve it to reach the efficient frontier, the constraints in model (2-3) $\sum_{r=1}^{R}\lambda_r^* X_i^r = \theta^* X_i^k - s_i^{-*}, \sum_{r=1}^{R}\lambda_r^* Y_j^r = Y_j^k + s_j^{+*}$ can be utilised for further adjustment:

$$\Delta X_i^k = X_i^k - \sum_{r=1}^{R}\lambda_r^* X_i^r = X_i^k - (\theta^* X_i^k - s_i^{-*})$$
$$\Delta Y_j^k = \sum_{r=1}^{R}\lambda_r^* Y_j^r - Y_j^k = (Y_j^k + s_j^{+*}) - Y_j^k \qquad (2\text{-}4)$$

When the relative efficiency of DMU$_k$ is $\theta^*=1$, the slack variables $s_i^{-*} = s_j^{+*} = 0$ and $\Delta X_i^k = \Delta Y_j^k = 0$, the amount of inputs and outputs do not have to be adjusted. However, if the relative efficiency of DMU$_k$ is <1, it is necessary to decrease the input ΔX_i^k and increase the output ΔY_j^k in order to reach the efficient frontier.

The foregoing DEA was introduced by Charnes, Cooper and Rhodes (1978), thus it is referred to as the CCR DEA Model. In the literature, the CCR DEA Model is typically considered as constant return to scale (CRS), therefore the CCR DEA Model is also called CRS DEA Model. CRS assumes all firms are operating at an optimal scale. This is the appropriate assumption for single output only (Banker et al., 2004). However, this situation would not be the same for multiple outputs. The proportional increase in all inputs would be the necessary result of the proportional increase in output. In addition, according to Coelli et al (2005), conditions such as imperfect competition, government regulations and constraints on finance would cause a firm to not be operating at optimal scale. Thus, Banker, Charnes and Cooper (1984) suggested the BCC DEA Model with the assumption of variable returns to scale (VRS) DEA Model. Hence, the BCC DEA Model is also known as VRS DEA Model. The CCR DEA Model can be modified to BCC DEA Model by adding a convexity constraint $\sum_{r=1}^{R}\lambda_r = 1$ to give:

$$
\begin{aligned}
\min \quad & \theta \\
\text{s.t} \quad & \sum_{r=1}^{R}\lambda_r X_i^r - \theta X_i^k + s_i^- = 0 \qquad i = 1, 2, \ldots, m \\
& \sum_{r=1}^{R}\lambda_r Y_j^r - s_j^+ = Y_j^k \qquad j = 1, 2, \ldots, n \\
& \sum_{r=1}^{R}\lambda_r = 1 \\
& \lambda_r, s_i^-, s_j^+ \geq 0, \qquad r = 1, \ldots, R
\end{aligned}
\tag{2-5}
$$

This approach enables the data points to be enveloped more tightly by the convex hull of the intersecting planes and provides the technical efficiency scores which are greater than or equal to those attained by the CRS DEA Model (Coelli et al., 2005).

2.5.3 Graphical description of DEA

Figure 2-5 shows a generic DEA which consists of an efficient frontier that set benchmarks for the DMU, i.e. A, B, D, F, G.. There are two outputs and a common input value for all DMU. DMU B, F and G are efficient because they have the most output with the same input, thus the highest ratio. They form the efficient frontier. DMU A and D, which are not on the frontier, are regarded as inefficient and can be improved by increasing the output/input ratio distance to reach Q and P respectively. On the other hand, Q and P can be referred to as the benchmark for DMU A and D respectively.

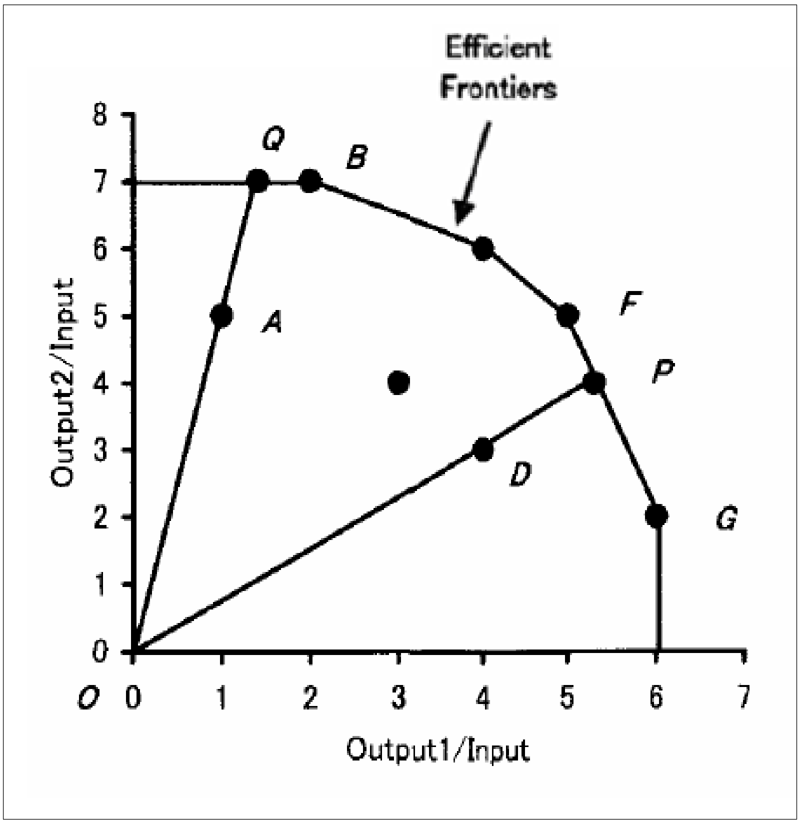


Figure 2-5 The generic DEA (Cooper et al., 2007)

2.5.4 Introduction of Eco-DEA

As mentioned in the previous section, with the increasing attention on the environment, researchers have started to include undesirable outputs into their study of DEA (Allen, 1999; Chung et al., 1997; Dyckhoff & Allen, 2001; Faere et al., 1989; Färe & Grosskopf, 2004; Färe et al., 2004; Färe et al., 1996; Golany & Roll, 1989; Gomes & Lins, 2008; Hailu & Veeman, 2001; Hua et al., 2007; Jahanshahloo et al., 2005; Korhonen & Luptacik, 2004; Kortelainen, 2008;

Kuosmanen & Kortelainen, 2005, 2007; Liang et al., 2008; Lozano & Gutiérrez, 2008; Lu & Lo, 2007a; Lu & Lo, 2007b; Park & Tahara, 2008; Sarkis, 2004; Scheel, 2001; Seiford & Zhu, 2002; Yang et al., 2008a; Yörük & Zaim, 2008; Zhang et al., 2008; Zhou et al., 2008a; Zhou et al., 2007; Zofio & Prieto, 2001). In the context of environmental assessment, the outputs in DEA are treated differently in order to differentiate their desirable and undesirable nature. Therefore, pollutants are characterised as undesirable outputs or factors. The DEA with the presence of undesirable output, the DEA approach is termed as eco-DEA.

Dyckhoff and Allen (2001) argued that when applying DEA in eco-related studies, it was not appropriate to embrace the assumption used by traditional DEA: maximising output quantities while minimising input quantities. Conceivably, not all outputs are “good” and not all inputs are “bad”. For example, ecologically undesirable outputs (waste emissions) and ecologically desirable inputs (waste in a waste-burning power plant or in a recycling plant). Zhou et al. (2007) and Lu and Lo (2007b) took the same point of view. They emphasised the DMU should be considered as inefficient when undesirable outputs are produced along with the desirable outputs in a production process. Therefore, it is only the desirable outputs, not the undesirable outputs that are preferred. The term ‘undesirable outputs’ can also be applied in health care (complications of medical operations) and business applications (tax payments) (Dyckhoff & Allen, 2001).

The concept of undesirable outputs was supported by a great deal of literature, and their numbers are increasing. Zhou et al. (2008b) divided the period from 1983-2006 into a time frame of three eight-year periods (1983-1990, 1991-1998 and 1999-2006). They found that the publications on undesirable outputs within these three periods are 7, 21 and 72 respectively. It is widely applied in various fields such as electric utility industry (Burnett & Hansen, 2008), logistic (Quariguasi Frota Neto et al., 2008) and energy (Mukherjee, 2008). However, there are many approaches in calculating the effects of pollutants to a decision making unit (DMU). In the same way, there exists various ways to treat undesirable outputs with the model chosen.

2.5.5 Previous Studies on the existing eco-DEA

As there are numerous approaches on incorporating undesirable outputs in DEA, the following section divides them into four main alternatives, followed by examples of their application. It would be of interest to show the range of DEA application in the ecological extension.

2.5.5.1 Ignoring undesirable outputs

This refers to the traditional DEA, which neglects undesirable output (Hua & Bian, 2007; Lu & Lo, 2007a, 2007b; Nakashima et al., 2006). Undesirable outputs are not included in the calculation and the output variables are not further divided into desirable and undesirable outputs.

2.5.5.2 Treating undesirable outputs as inputs

Dyckhoff and Allen (2001) considered DEA as a multi-criteria approach in which the undesirable output is modelled as input. This application of the model measures the environmental efficiency of Dutch dairy farms (Reinhard et al.,

2000) and also evaluates their carbon dioxide emission quota in light of the Kyoto Protocol (Gomes & Lins, 2008).

2.5.5.3 Non-linear monotonic decreasing transformation approach (data transformation)

This data transformation approach is suggested by Golany and Roll (1989). It converts an undesirable output as “normal” output by a monotonic decreasing function f (since after retransformation, increasing these values means decreasing the undesirable outputs) (Scheel, 2001). The undesirable output is modelled as being desirable $f(u_i^k) = 1/u_i^k$ where u_i^k is one of the elements of the matrix u of the undesirable outputs i of the decision-making unit DMU_k (Gomes & Lins, 2008). Lovell et al (1995) compared the macroeconomic performance of 19 OECD countries using the same approach. The undesirable outputs (carbon and nitrogen emissions) are treated as normal outputs after taking their reciprocals.

2.5.5.4 Linear monotonic decreasing transformation approach

This is a method suggested by Seiford and Zhu (2002). A sufficiently large positive scalar β_i is added to the reciprocal additive transformation of the undesirable output i so that the final values are positive for each DMU_k so the environmental DEA technology becomes $f(u_i^k) = -u_i^k + \beta_i$. Lu and Lo (2007b) utilised the above model to examine the overall performance for different regions in China, based on economics and environmental factors. In this analysis, the desirable output being considered was GDP and the undesirable outputs were emissions such as soot, dust and sulphur dioxide. Hua, Bian and Liang (2007) used the same approach to assess the ecological efficiency of paper mills along China’s Huai River.

Despite the popularity of this approach the data must be transformed back when interpreting the results and are valid for the BCC model only (Gomes & Lins, 2008). This model is criticised for its invariance to data transformation within the DEA (Lu & Lo, 2007a, 2007b) and the possibility of having a biased efficiency score (Yang et al., 2008a).

2.6 Research Gap with Previous Studies of the Existing Eco-DEA

After conducting the comprehensive review as the previous eco-DEA studies, it is found that there are two problems concerning the four approaches and they are discussed in the following.

2.6.1 Ignorance of undesirable output

It is wrong to ignore the presence of undesirable output. During production, as undesirable outputs and desirable outputs are generated at the same time during production. Undesirable output is of a different nature, therefore it should be distinguished when computed with the desirable factors. For textile manufacturing, pollutants are produced along with the end products. Therefore, under the umbrella of environmental concern, the traditional DEA is not suitable to assess the situation in the textile industry. A conventional DEA regards input and output as positive and desirable. Pollutants are discharged in any textile manufacturing process. Thus, undesirable outputs should be considered and included in the DEA.

Based on the above research gap, the new eco-DEA is developed. In the context of environmental concern, the new eco-DEA accommodates the undesirable output. The details on the manipulation of the undesirable output is covered in Chapter 4.

2.6.2 Improper description of undesirable output

The present of approaches fail to describe the undesirable output. For example, treating undesirable outputs as inputs (Dyckhoff & Allen, 2001) fails to reflect the true production process. Conceivably, input and output have a direct relationship, and all outputs are interconnected. On the other hand, the potential reduction in pollutants (outputs) as expressed in an input-oriented measure does not have a natural interpretation. Moreover, an unlimited decrease in undesirables (holding other inputs constant) is not technically possible (Yang et al., 2008a). Also, when using the linear and non-linear monotonic decreasing transformation approach, the efficiency scores tend to increase. These existing approaches fail to take into account the logic behind the efficiency score obtained. Consequently, a new eco-DEA is needed to solve the mentioned research problems.

To further illustrate and discuss how these prior approaches incorporating undesirable output inappropriately, a more in-depth study is conducted in Chapter 4. Based on the literature review in this chapter together with the results of the comparative study in Chapter 4, a new eco-DEA is therefore developed to provide a new attempt to describe the nature of the undesirable output in a more proper and advanced way.

2.7 Chapter Summary

This chapter reviews the relevant literature and highlighted the research gaps of the present study. It is widely acknowledged that industrial activities causes pollution in the aspects of air, water and land. Therefore, the production of textile products evaluated such as yarn, cloth and chemical fibres are review to indicate the environmental impact induced from these industrial activities. Besides, the potential health impact resulted from the textile manufacturing processes are also examined. Environmental protection becomes one of the indispensable elements in regulating the textile manufacturing processes. Environmental performance indicator (EPI) which has an increasing popularity to be a common way in resolving the subject of green management in the textile industry is discussed. With the examples of the prior studies on EPIs, the research gaps on the development of EPIs are identified. In turn, DEA is introduced as a new method to measure environmental performance. The theory of DEA is outlined and it is acknowledged that the wide application of DEA makes it a common tool to measure performance efficiency. Although there is a considerable research published on the undesirable aspects of production outputs, the suitability of the DEA for incorporating the undesirable outputs are yet being properly discussed and examined. Based on the literature reviewed in this chapter, the research gaps calls for further extensive research work on environmental performance indicator of the textile industry. Therefore, the present study aims to develop a Green

Index, with DEA as tool, for the Textile Industry to strengthen the practice of environmental management. The following chapter gives details on how the study is performed.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Introduction

With the knowledge gained from the previous chapter, it is believed that an effective and consistent environment management tool is indispensable for the textile industry. Also to achieve the mentioned research gap, the objective of the present study is to develop an environmental performance index (EPI), which is termed as the Green Index. In particular, the Green Index aims to assess the environmental impact textile production in China.

Figure 3-1 shows the research approach of the present study which is divided into two stages. Stage One is further divided into three steps which aim to address the development of the new eco-DEA named as the Ratio Model. A comparative study is conducted to indicate the prior eco-DEA, as discussed in Section 2.6, is insufficient to characterise the impact of the undesirable output in a DEA. Thus, a new approach, the Ratio Model is introduced. Verification of the Ratio Model is then conducted to further confirm and show it is a better way to measure the impact of the undesirable output. Stage Two is also further divided into three steps which illustrate the environmental performance assessment of China’s textile industry. The newly developed eco-DEA is adopted to construct the Green Index. The Green Index is then applied in four case studies which are designated for the environmental performance evaluation of the textile industry in China and Jiangsu respectively.

Based on the above research approach, this chapter reviews the research methodology applied in the present study. Corresponding to Stage One, Section 3.2 outlines the method on the development of the new eco-DEA, which is called the Ratio Model. Section 3.3 corresponds to Stage Two which provides details on how the environmental performance of China's textile industry is assessed by the Green Index.

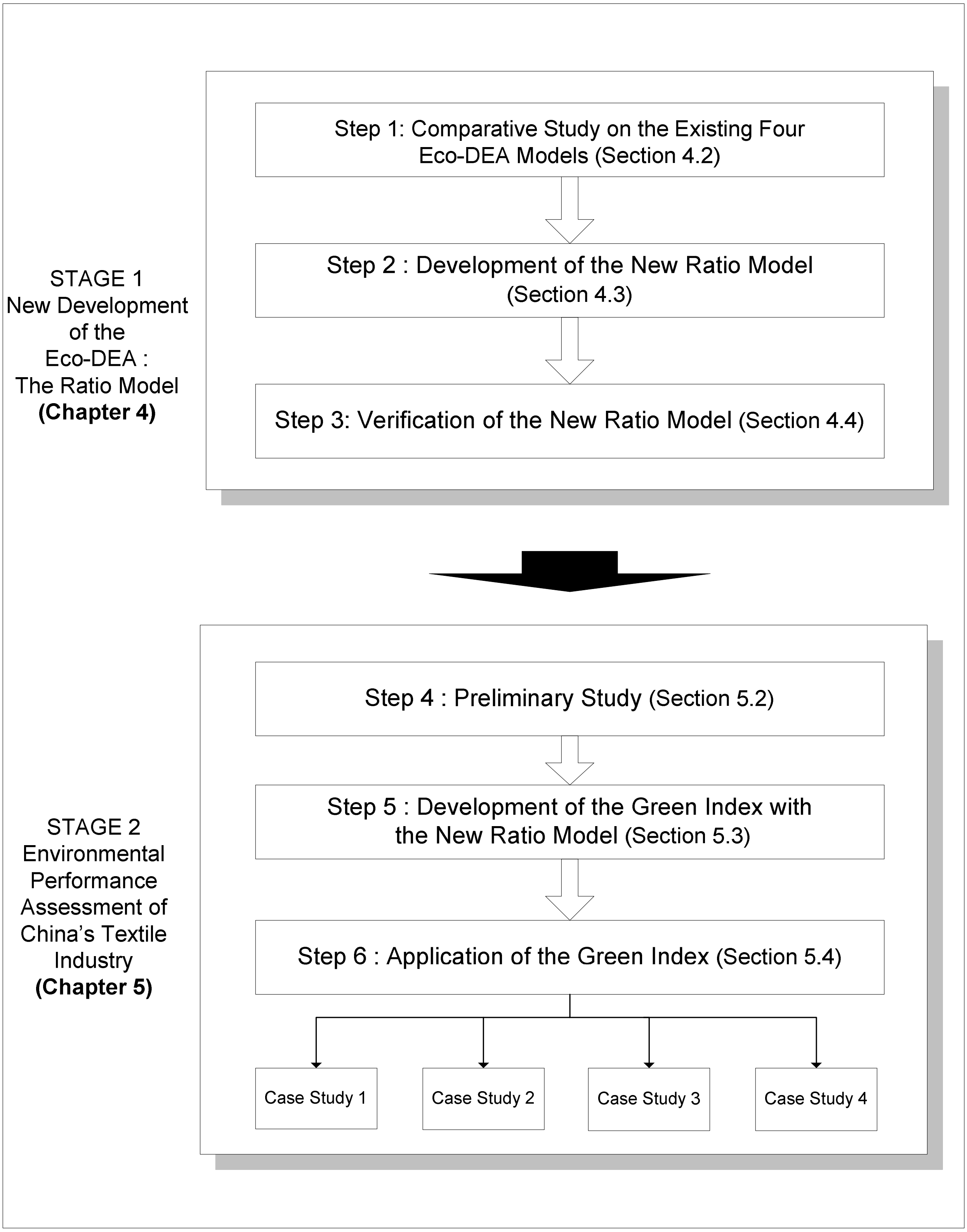


Figure 3-1 Research approach of the present study

3.2 Stage One: New Development of the Eco-DEA: The Ratio Model

As concluded in Chapter 2, there is an urge to develop an EPI which is consistent and objective to evaluate the environmental performance of the textile industry. To achieve this aim, a Green Index is developed from the present study and data envelopment analysis (DEA) is adopted as a methodology to measure the environmental impact from the perspective of eco-efficiency.

Data envelopment analysis is a methodology adopted to construct the Green Index. The primary application of DEA is to measure the performance of similar units from the aspect of efficiency. By comparing their common outputs and inputs, a score is assigned to each examined unit. With this score, one can compare and tell how efficient each unit is performing. The conventional DEA regards the input and output variables as positive and desirable. However, from the literature review in Section 2.2, it is known that pollutants are commonly produced along with the end products in any textile manufacturing process. The output variables should, therefore, be further differentiated into desirable and undesirable outputs (Dyckhoff & Allen, 2001).

There are many approaches to incorporate undesirable outputs into the DEA and they are illustrated in Section 2.5.5. Nevertheless, the research gap in Section 2.6 concludes that these approaches are defective to some extent. In turn, a new eco-DEA is needed. The objective of Stage One is to develop a new eco-DEA which is called the Ratio Model. Stage One is further divided into three steps. The following sections describe these three steps accordingly.

3.2.1 Comparative study on the four existing eco-DEA

The first step of Stage One is to conduct a comparative study in order to explore the discrepancy of the efficiency scores under different approaches of eco-DEA. The common problems of the existing measures are therefore observed and examined in depth. There are three components attributing to the achievement of this step.

3.2.1.1 Existing eco-DEA

As a comparative study is conducted at the first stage to examine the prior eco-DEA, four different approaches of eco-DEA are chosen. They are summarised in Table 3-1. These are the four common methods in incorporating undesirable outputs. Details of these four approaches are illustrated in Sections 2.5.5.1 to 2.5.5.4 respectively.

Table 3-1 The four chosen methods for comparison

	Definition	**References**
Method 1	Ignoring undesirable outputs in DEA	Hua & Bian, 2007; Lu & Lo, 2007a; Lu & Lo, 2007b
Method 2	Treating undesirable outputs as inputs	Dyckhoff & Allen, 2001
Method 3	Applying a nonlinear monotonic decreasing transformation, e.g., 1/b, to the undesirable outputs	Golany & Roll, 1989
Method 4	Using a linear monotonic decreasing transformation to deal with undesirable outputs	Seiford & Zhu, 2002

3.2.1.2 Data source

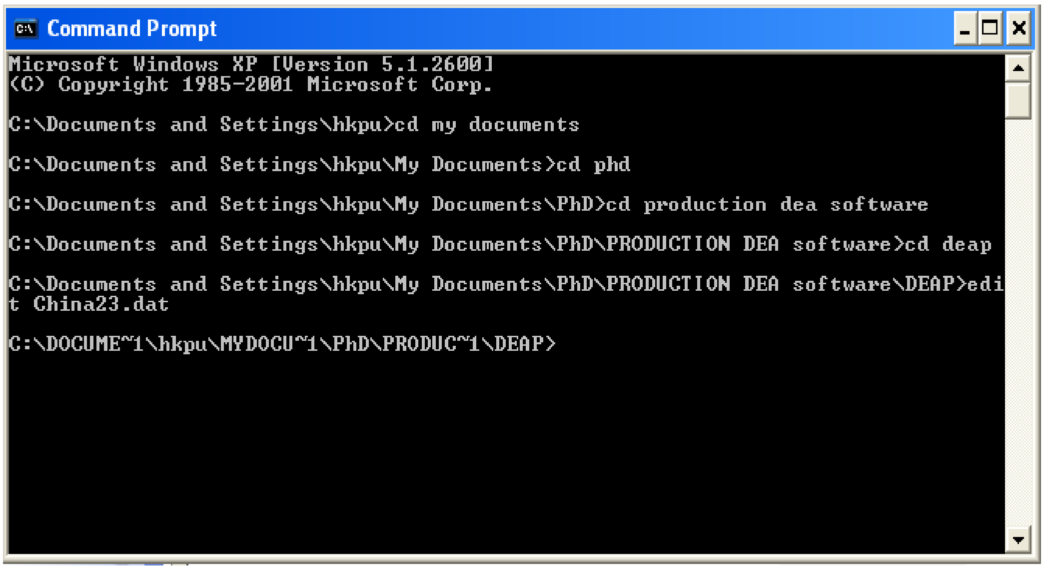
The data of input, desirable output and undesirable output are needed to study the difference between the existing eco-DEA. As this step is conducted to compare the results of the various approaches of eco-DEA, only secondary data are therefore adopted. Hua and Bian (2007) has done a similar study before therefore the data used by the researchers are employed. There are two inputs, two desirable outputs, one undesirable output and 30 DMUs. The translation parameter for method 4 is set as *w* = 1500.

3.2.1.3 Software

A computer program was employed to run the DEA. It is called DEAP and the version used is DEAP 2.1. DEAP 2.1 is used because it provides a user-friendly program for users to conduct a DEA study. The software is a DOS programme and was created by Coelli (1996). To execute the DEAP, it generally involves five files: the command prompt file, executable file DEAP.EXE, data file, instruction file, and output file.

The command prompt file

The following figure is the interface of the command prompt file, in which commands are typed in to execute the DEAP programme as well as to open the data, instruction and output file.

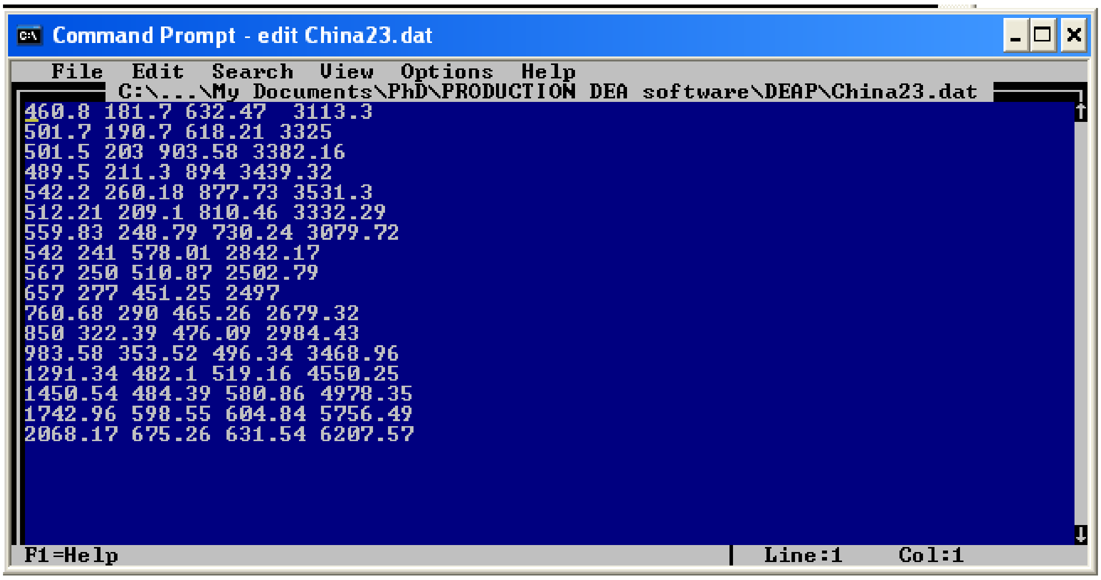


```
Microsoft Windows XP [Version 5.1.2600]
(C) Copyright 1985-2001 Microsoft Corp.

C:\Documents and Settings\hkpu>cd my documents

C:\Documents and Settings\hkpu\My Documents>cd phd

C:\Documents and Settings\hkpu\My Documents\PhD>cd production dea software

C:\Documents and Settings\hkpu\My Documents\PhD\PRODUCTION DEA software>cd deap

C:\Documents and Settings\hkpu\My Documents\PhD\PRODUCTION DEA software\DEAP>edi
t China23.dat

C:\DOCUME~1\hkpu\MYDOCU~1\PhD\PRODUC~1\DEAP>
```

Figure 3-2 Interface of the Command prompt file

The data file

All the data is stored in the data file and the DEAP expects the data to be listed according to a specific order. If there are five DMUs being assessed, then there will be five rows of data in the data file. From left to right across the file, the column of output is listed followed by the input column. For example, Figure 3-3 shows the data file “China23.dat”. The 17 rows mean there are 17 DMUs for assessment. The four columns state the first two columns are output data, and the other two columns are input data.



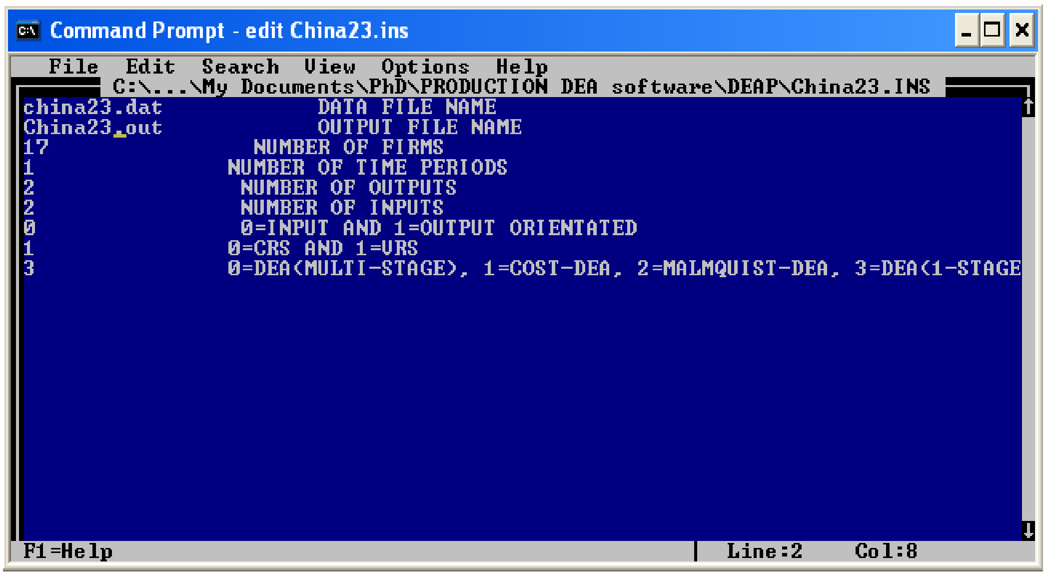
```
460.8 181.7 632.47  3113.3
501.7 190.7 618.21 3325
501.5 203 903.58 3382.16
489.5 211.3 894 3439.32
542.2 260.18 877.73 3531.3
512.21 209.1 810.46 3332.29
559.83 248.79 730.24 3079.72
542 241 578.01 2842.17
567 250 510.87 2502.79
657 277 451.25 2497
760.68 290 465.26 2679.32
850 322.39 476.09 2984.43
983.58 353.52 496.34 3468.96
1291.34 482.1 519.16 4550.25
1450.54 484.39 580.86 4978.35
1742.96 598.55 604.84 5756.49
2068.17 675.26 631.54 6207.57
```

Figure 3-3 Interface of the data file

The instruction file

The instruction file contains all the necessary information required for the programme to give the results. Using Figure 3-4 as an illustration, the instruction file holds information on the data file name, output file name, number of firms (i.e. the number of DMUs), number of time periods, number of outputs, number of inputs, choice of input or output orientation, assumption of constant returns-to-scale (CRS) or variable returns-to-scale VRS assumption and the selection of various approaches of DEA.

The constant returns to scale (CCR) assumes all firms are operating at an optimal scale. However, according to Coelli et al (2005), conditions such as imperfect competition, government regulations, and constraints on finance would result in a firm operating at a sub-optimal scale. Thus, the variable returns to scale (BCC) DEA model is utilised in this study to treat the undesirable outputs. The model has an assumption of variant return to scale. Although the previous environmental DEA studies followed the CCR DEA model, which assumed a constant return to scale, Zhou et al (2008a) believed the case of variant returns to scale (VRS) (Hu et al., 2005) is observed in the actual situation. "Variable return" means that different output levels are produced due to reduced performance or economies of scale (Park & Tahara, 2008). Therefore, one cannot follow the traditional DEA, as this may not withstand the basis of eco-DEA.

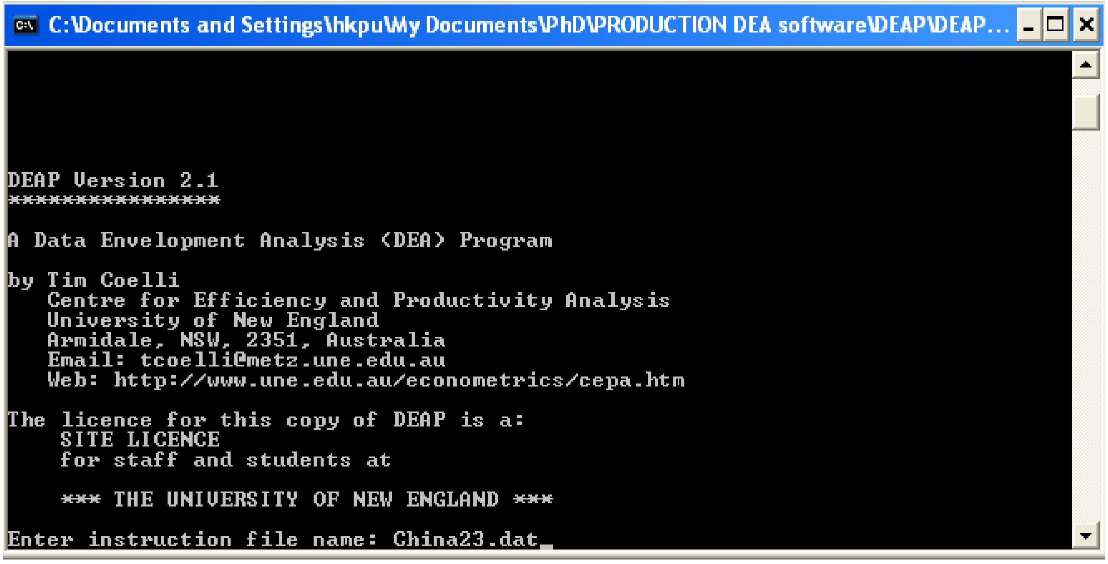


```
china23.dat                 DATA FILE NAME
China23.out                 OUTPUT FILE NAME
17                     NUMBER OF FIRMS
1                    NUMBER OF TIME PERIODS
2                     NUMBER OF OUTPUTS
2                     NUMBER OF INPUTS
0                     0=INPUT AND 1=OUTPUT ORIENTATED
1                    0=CRS AND 1=VRS
3                    0=DEA(MULTI-STAGE), 1=COST-DEA, 2=MALMQUIST-DEA, 3=DEA(1-STAGE
```

Figure 3-4 Listing of Instruction File "China23.ins"

The executable file DEAP.EXE

The main function of the executable file is to type in the name of the instruction file when it is created. When an instruction file name is typed, which is "China23.dat" in this example, the programme takes a few seconds to run the required linear programme and then sends the results to the output file "China23.out".

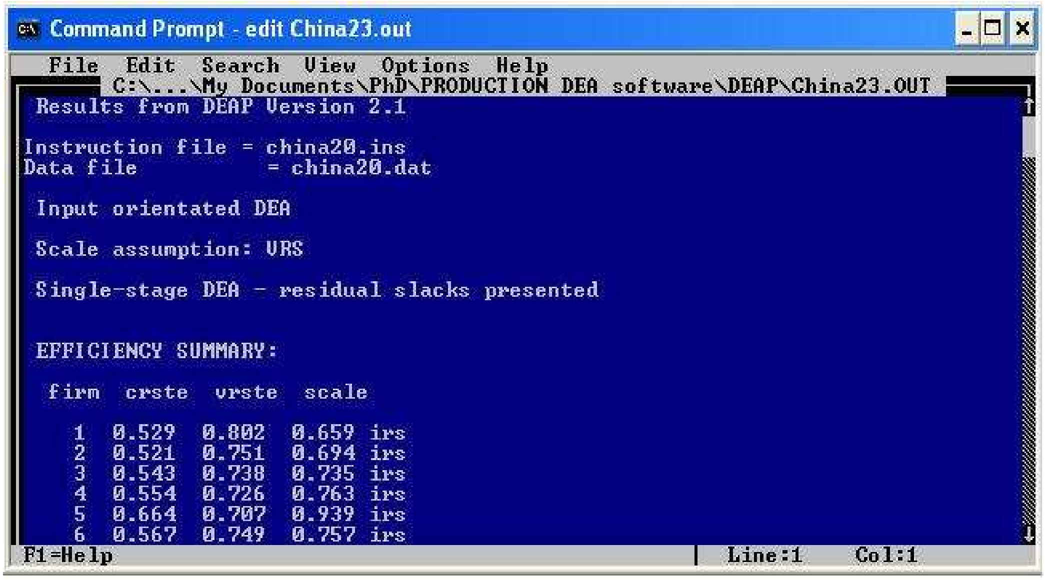


```
DEAP Version 2.1
****************

A Data Envelopment Analysis (DEA) Program

by Tim Coelli
   Centre for Efficiency and Productivity Analysis
   University of New England
   Armidale, NSW, 2351, Australia
   Email: tcoelli@metz.une.edu.au
   Web: http://www.une.edu.au/econometrics/cepa.htm

The licence for this copy of DEAP is a:
    SITE LICENCE
    for staff and students at

    *** THE UNIVERSITY OF NEW ENGLAND ***

Enter instruction file name: China23.dat_
```

Figure 3-5 Interface of the executable file

The output file

The following figure shows the interface of the output file "China23.out". The output file gives the efficiency score of each DMU and other results such as slack and weight.



```
C:\...\My Documents\PhD\PRODUCTION DEA software\DEAP\China23.OUT
 Results from DEAP Version 2.1

Instruction file = china20.ins
Data file        = china20.dat

 Input orientated DEA

 Scale assumption: VRS

 Single-stage DEA - residual slacks presented


 EFFICIENCY SUMMARY:

  firm  crste  vrste  scale

    1  0.529  0.802  0.659 irs
    2  0.521  0.751  0.694 irs
    3  0.543  0.738  0.735 irs
    4  0.554  0.726  0.763 irs
    5  0.664  0.707  0.939 irs
    6  0.567  0.749  0.757 irs
```

Figure 3-6 Interface of the output file

3.2.2 Development of the new Ratio Model

Based on the findings in step one, there is a need to develop a new eco-DEA. Therefore the objective of this step is to introduce the new eco-DEA which is named as the Ratio Model and the theory behind. The newly developed Ratio Model is illustrated and the differences between the new and old approaches of eco-DEA are identified as well.

3.2.3 Verification of the new Ratio Model

This is the third step in Stage One which aims to verify the two findings concluded from step one. Also, the newly developed Ratio Model is compared to the prior eco-DEA to verify that the new approach is more comprehensive in describing the undesirable output than the previous ones.

The data source and choice of eco-DEA to verify the newly developed Ratio Model is identical to step one which are illustrated in Section 3.2.1.1 and 3.2.1.2. As mentioned in Section 3.2.1.3, DEAP 2.1 is adopted as the software to perform the DEA. For the calculation of the Ratio Model, as the undesirable output is modelled with a new aspect, the data of the desirable and undesirable outputs has to be treated before entering into the DEAP 2.1. Thus, it is necessary to yield the ratio value between the desirable and undesirable outputs before proceeding to the calculation of the Ratio Model by DEAP 2.1. The ratio values obtained is then entered into the DEAP 2.1 as output variables. In this study, the software employed to calculate the ratio values is Microsoft Office Excel 2003.

3.3 Stage Two: Environmental Performance Assessment of China's Textile Industry

The previous section outlines the research methodology of Stage One which aims to develop the new eco-DEA. This section describes the establishment of the Green Index in Stage Two.

The ultimate objective of the present study is to assess the textile industry environmental performance by the newly developed Green Index, which is a form of environmental performance indicator (EPI). As mentioned in Section 2.4, one of the main problems in the present EPIs is that the EPIs rely on subjective judgement to prioritise the importance of the factors studied. Different parties have different perspectives concerning the importance of environmental impacts (Dyckhoff & Allen, 2001; Zhao et al., 2006). The bias in the weight assignment is a significant hurdle for the common application of the indicator. Hence, DEA is an appropriate approach to construct the Green Index by enhancing the overall efficiency and at the same time, reducing the negative environmental impact. A weight is assigned to each factor programmed by the DEA. This approach makes it suitable for performance measurement.

Concerning other research gaps on the EPIs studied in Section 2.4, the Green Index provides a consistent approach with an objective judgement on the weighting, as well as design specifically for the nature of the textile industry. The objective of Stage Two is to construct the Green Index with the new eco-DEA developed in Stage One and employ the Green Index to assess the environmental performance of China's textile industry. Stage Two is further divided into three steps. The following sections describe these three steps accordingly.

3.3.1 Preliminary Study

Before the development of the Green Index, a preliminary study is conducted to ratify the possibility of applying the Green Index in a textile mill. Therefore, a factory visit is arranged and the textile mill is located in Shenzhen, China. The main purpose of this preliminary study is to collect the polluted air samples and examine the mill's practice in producing environmental friendly products.

The data on wastewater and solid waste are not collected in the present preliminary study because the senior manager of the textile mill does not allow the disclosure of their records on wastewater and they do not have any records on the solid waste.

3.3.1.1 Sample collection

The collection of air samples is conducted to explore the air quality of textile dyeing and familiarize with the necessary assessment technique. The study was endorsed by the indoor air quality experts from the Department of Civil and Structural Engineering, the Hong Kong Polytechnic University.

Due to limited time, only two spots of the dyeing room are assessed. Both of the sample collection spots are next to a dyeing machine. For each spot, two air samples are collected by stainless canister and the airbag, with the help of air pump -airchek sampler (Model 224-44XR). The apparatuses used for sample air collection are shown in Figure 3-7. It takes 45 minutes and 15 minutes respectively for the stainless canister and airbag to be filled up. After the samples are collected, they are analysed within 24 hours for accurate results.

Stainless canister

Airbag

Airchek sampler

Figure 3-7 Apparatuses for sample collection

3.3.1.2 Sample Analysis

As the samples have to be analysed by different appliances within 24 hours, they are sent to the air laboratory of the Department of Civil and Structural

Engineering, The Hong Kong Polytechnic University. The various polluted air samples parameters detected are shown in Table 3-2. The samples are analysed by different apparatuses which detect specific polluted air species and they are shown in Table 3-2.

Table 3-2 Polluted air samples parameters

Types of air emission	
SO_2	Toluene
CO	1,2-Dibromoethane
NO_2	Ethylbenzene
HCHO	m,p-Xylene
TVOC	o-Xylene
Methylene chloride	4-Ethyltoluene
Benzene	1,3,5-Trimethylbenzene

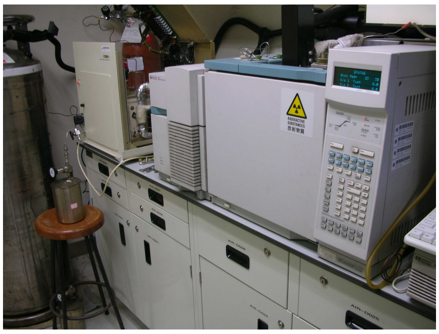
	
Carbon monoxide and sulphur dioxide detector	Nitrogen oxides detector
	
Volatile organic compounds detector	Gas chromatograhy/mass spectrometry (GCMS)

Figure 3-8 Apparatuses for air quality assessment

3.3.2 Development of the Green Index with the new Ratio Model

In light of the findings from the previous chapters, the generic framework of the Green Index is developed as shown in Figure 3-9. The framework provides a general outline of how to carry out the Green Index in various circumstances. It consists of three main phases: data collection, Ratio Model and the Green Index.

The first phase is about data collection, from the various production processes of China’s textile industry. Data include the inputs and outputs of the relevant DMU. Obviously, the number of inputs and outputs as well as the DMU must follow the rule of thumb indicated in Section 3.3.3.4 to ensure reasonable results. As this present study attempts to incorporate environmental aspects into the Green Index, therefore, the output variables are further divided into desirable and undesirable outputs. The sub-index is then derived from the Ratio Model which incorporates undesirable outputs into the evaluation of performance and the Green Index is accomplished by the sum of the three sub-indices. In fact, the number of the sub-index depends on the research situation or application. For the present study, there are three sub-indices which represent the three common pollutants found in the textile manufacturing process. The details of these three pollutants are discussed in Chapter 5. The dotted line that links the first and third phases presents the repetitive need for data collection for the sub-indices.

Thus, the general framework presented in this section constitutes the core objective of the study. Details on the development of the Green Index and its application to China’s textile industry are covered in Chapter 5.

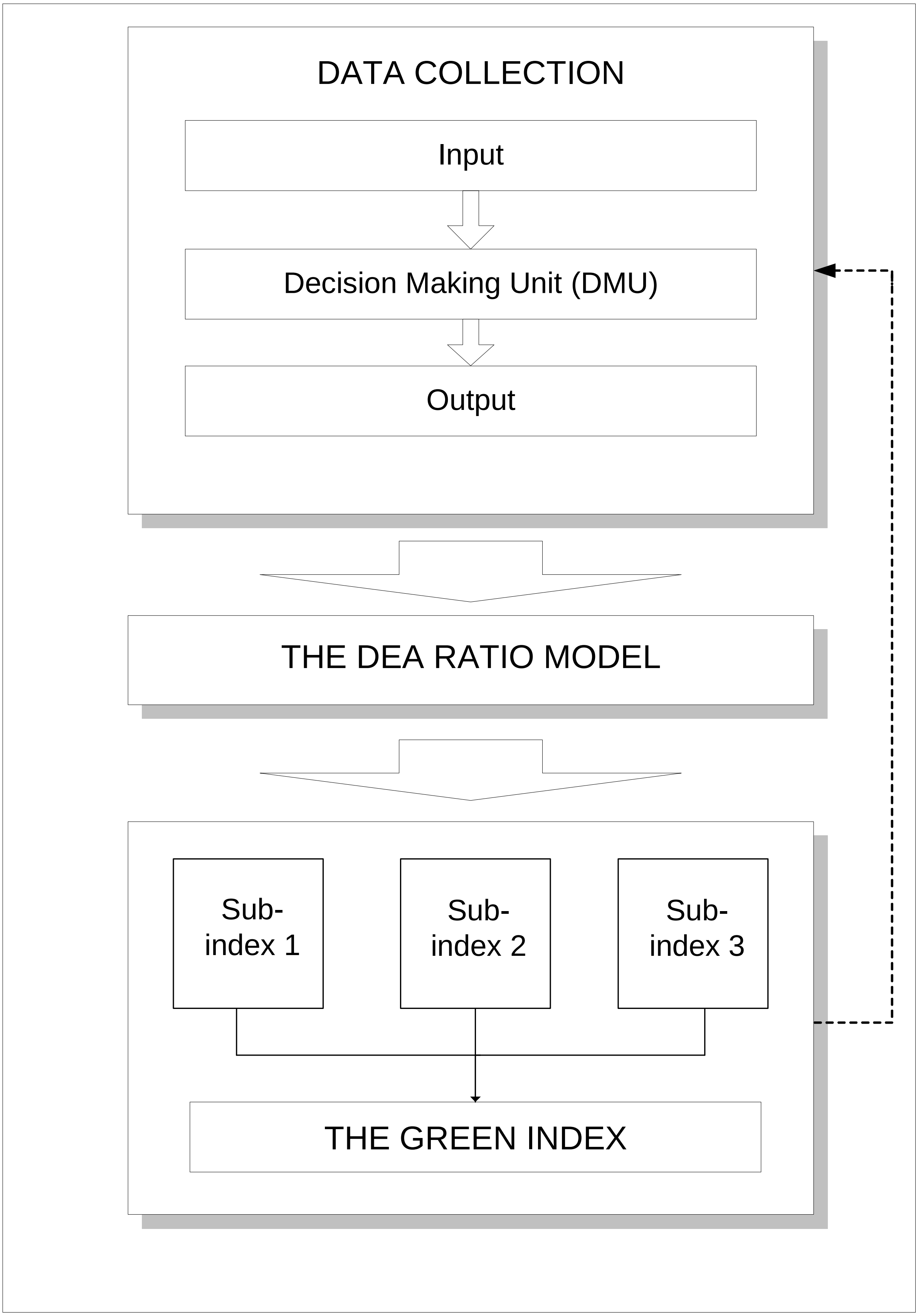


Figure 3-9 The conceptual framework of the Green Index

3.3.3 Application of the Green Index by four case studies

After establishing the framework, the Green Index is then applied to four case studies which represent four different scenarios of China’s textile industry. There are four components attributing to the achievement of the present step.

3.3.3.1 Case study

The present study uses case study as an approach to apply the newly developed Green Index at various scenarios of the China’s textile industry. Case study is considered as a qualitative research method to investigate the real-life context and can link real-life interventions with the complex phenomenon (Yin, 1994). Therefore, it is an common and acceptable form of study in the environmental research (Jiang, 2009; Song et al., 2009; Zhang et al., 2007).

The objective of the four case studies is to verify the Green Index as well as to evaluate the environmental performance of China’s textile industry in the past decade. To further illustrate the mentioned research question, the perspective of China’s textile industry is further divided into two levels: national and provincial level. The national level examines the environmental performance of China’s textile industry as a whole while the provincial level studies the impact of Jiangsu textile industry on the environment. The rationales behind the choice of these two subjects and the details of the case studies are covered in Chapter 5.

3.3.3.2 Data Source

The data source of the present study mainly comes from the China Statistical Yearbook (The People's Republic of China State Statistical Bureau, Various issues). If necessary, the China Textile Industry Development Report (Zhongguo fang zhi gong ye xie hui, various issues) is referred as a backup reference.

The China Statistical Yearbook is an annual statistical publication which is a widely used reference. It covers a wide range of data to reflect the social and economic development of the country. There are over twenty chapters in each of the statistical year that records the necessary data on various aspects of the country such as population, agricultural and construction. The data for the present study is collected under the category “industry” and “resources and environment”.

3.3.3.3 Selection of DMU

There are certain requirements in DMU selection. The DMU should be similar for comparison purpose, yet easily differentiated for competition. In computing a DEA study, the homogeneity of the DMU chosen is also a significant factor in its selection (Ramanathan, 2003). The units should have similar objectives for sensible comparison. With these constraints in mind, the Green Index is applied to the textile manufacturing sector from both the national and provincial levels.

As the study concentrates in the comprehensive scope of assessing the annual performance of Chinese textile industry, hence the analysis undertaken is across the period which data is available. Each year is treated as a separate DMU and this DMU choice has also been accepted in the literature (Cooper et al., 2001; Cooper et al., 1995; Jahanshahloo & Khodabakhshi, 2004; Sueyoshi, 1992). For Case Studies 1 and 2, the period under evaluation is from 1991-2007, while for Case Studies 3 and 4, it is from 1998-2007. This period is chosen because there is no environmental data on industrial activities recorded before 1991 and 1998. Therefore, the data is chosen based on data availability, which starts from 1991 and 1998. The details of the DMU cover the present study are discussed in Chapter 5.

3.3.3.4 Selection of input and output variables

In the context of designing a DEA study, input and output factors should have a direct relationship. That means an input is any resource that is used by the DMU to produce the outputs. Moreover, in the selection of inputs and outputs, it is necessary to ensure that data is available for the chosen inputs and outputs (Zhou et al., 2008b). Although input and output selection is relatively subjective, it is suggested that the choice and the number of inputs and outputs is restricted by regulations. Cooper et al. (2007) provided the following rule of thumb for guidance in determining the number of inputs and outputs:

$$n \geq \max\{m \times s, 3(m+s)\} \tag{3-1}$$

where n = number of DMUs;

m = number of inputs; and

s = number of outputs.

In the present study, the input variables are labour and total energy consumption; while the desirable output are the amount of yarn, cloth and chemical fibre produced and the total industrial output value of the individual textile product. The undesirable outputs studied are polluted air, wastewater and solid waste. Details on the selection of these variables and the rationale are explained in Chapter 5.

3.4 Chapter Summary

With the research gap identified in the previous chapter, this chapter describes the research methodology adopted to answer the research questions. In this study, there are two stages which aim to develop a Green Index to assess the environmental performance of China’s textile industry. Stage One which is about the development of the new eco-DEA is discussed. The three steps that contribute to the achievement of Stage One are also covered. Sequentially, Stage Two which is the environmental performance assessment of China’s textile industry is reviewed. Correspondingly, Stage Two is divided into three steps and they are described with details in this chapter. Based on the research framework indicated, the next chapter starts the establishment of the Green Index by the development of the new eco-DEA which is the Stage One of the present study.

CHAPTER 4 NEW DEVELOPMENT OF THE ECO-DEA: THE RATIO MODEL

4.1 Introduction

The previous chapter illustrates the research approach adopted in the present study. Considering the objective is to develop a Green Index for the textile industry, the present study is divided into two stages. Stage One is about the development of a new eco-DEA and Stage Two describes the establishment of the Green Index by the new eco-DEA. This chapter describes with details the steps involved in Stage One.

Recalling the literature viewed in Chapter 2, due to the unavoidable emission of pollutants as part of the production process of all industrial activities, environmental management is particularly desired for the manufacturing sector. Under current production conditions, the presence of negative outputs, also described as undesirable outputs, cannot be ignored. For instance, in the textile industry, a company that produces a high amount of desirable output (cloth or yarn) is associated with a certain amount of undesirable output as well (water pollutants from the dyeing process). One way to gain insight into the environmental condition of a production process is to analyse its eco-efficiency. Eco-efficiency examines the environmental impact of an industrial activity. Among the extant literature, data envelopment analysis (DEA) is a new perspective in measuring eco-efficiency.

DEA is an established methodology to measure the efficiency of organisations by comparing the relative productivity with the same input and output set, expressed as a non-linear problem. As more attention is being paid to the environment, researchers have extended the conventional DEA by integrating undesirable outputs to measure eco-efficiency. With the presence of undesirable outputs, it is not appropriate to use the assumption of the traditional DEA: maximising output quantities of output while minimising the quantities of input to achieve higher efficiency (Dyckhoff & Allen, 2001). Thus, new approaches are proposed to incorporate undesirable outputs in a DEA framework.

Measuring the impact of undesirable variables is important from an environmental management perspective. Nonetheless, as mentioned in the research gaps in Section 2.6, the existing studies fail to properly describe the characteristics of undesirable outputs. To fill the research gaps, this chapter aims to develop a new eco-DEA (Stage One) which incorporates both desirable and undesirable outputs in an alternative way, so that prior knowledge of eco-DEA is questioned.

There are three steps involved in Stage One and they are described in this chapter accordingly. Firstly, Section 4.2 describes a study which is performed by comparing existing eco-DEA so as to explore the discrepancy of the efficiency scores under the various approaches of eco-DEA. This provides a further validation for the research gaps mentioned in Section 2.6. Thus, the common problems of the existing measures are be observed and examined. With the findings concluded from the comparative study, Section 4.3 introduces a new eco-DEA which is developed to address the discriminating power of the undesirable output, contrary to the traditional eco-DEA. Lastly, Section 4.4 verifies the newly developed model with the prior eco-DEA to confirm the new approach is able to manipulate the undesirable output with a preferred method.

4.2 Comparative Study on the Four Existing Eco-DEA

With increasing public attention on the natural environment, one of the major research thrusts in Data Envelopment Analysis (DEA) is to manipulate the undesirable output in the conventional DEA. The traditional output variable in a DEA computation is further divided into desirable and undesirable outputs. With the dissimilar nature of both outputs, it is important to define the two outputs in such a way that the undesirable output can be discriminative. There are numerous aspects to incorporating undesirable outputs discussed in the literature and they are covered in Section 2.5.5.1-2.5.5.4 respectively. However, the economic implications and the suitability to the DEA research background of the undesirable outputs have yet to be seriously investigated and discussed. Therefore, it is necessary to conduct a comparative study to explore how existing approaches that measure environmental performance differ from one another. By comparing the efficiency scores computed from the various measures, the effect of undesirable output on the results can be distinguished.

Using data from Hua and Bian (2007), this section reviews the models as discussed in the previous text with undesirable outputs. The four identified methods as discussed in Section 2.5.5, representing the different approaches of treating undesirable outputs in DEA, are as follows:

Method 1: Ignoring undesirable outputs in DEA;

Method 2: Treating undesirable outputs as inputs;

Method 3: Applying a nonlinear monotonic decreasing transformation, 1/b, to the undesirable outputs; and

Method 4: Using linear monotonic decreasing transformation to deal with undesirable outputs.

As reported in Table 4-1, the first column identifies the 30 DMUs, while the second and third columns list the two inputs. Columns 4 and 5 provide the two desirable outputs, and the last column indicates the undesirable output. The translation parameter for method 4 is set as w = 1500. DEAP 2.1 used the computer programme (Hu et al., 2005; Lam & Shiu, 2001) to run the various DEA approaches, and the study is based on the assumption of variable return-to-scale. Table 4-2 records the results of the comparative study under methods 1 to 4.

Table 4-1 Data of the 30 DMU

DMU	Desirable Input 1	Desirable Input 2	Desirable Output 1	Desirable Output 2	Undesirable Output 1
1	437	1438	2015	14667	665
2	884	1061	3452	2822	491
3	1160	9171	2276	2484	417
4	626	10151	953	16434	302
5	374	8416	2578	19715	229
6	597	3038	3003	20743	1083
7	870	3342	1860	20494	1053
8	685	9984	3338	17126	740
9	582	8877	2859	9548	845
10	763	2829	1889	18683	517
11	689	6057	2583	15732	664
12	355	1609	1096	13104	313
13	851	2352	3924	3723	1206
14	926	1222	1107	13095	377
15	203	9698	2440	15588	792
16	1109	7141	4366	10550	524
17	861	4391	2601	5258	307
18	249	7856	1788	15869	1449
19	652	3173	793	12383	1131
20	364	3314	3456	18010	826
21	670	5422	3336	17568	1357
22	1023	4338	3791	20560	1089
23	1049	3665	4797	16524	652
24	1164	8549	2161	3907	999
25	1012	5162	812	10985	526
26	464	10504	4403	21532	218
27	406	9365	1825	21378	1339
28	1132	9958	2990	14905	231
29	593	3552	4019	3854	1431
30	262	6211	815	17440	965

Source: Hua and Bian (2007)

Table 4-2 Results of the DMU's efficiency scores for method 1 to method 4

DMU	Method 1	Method 2	Method 3	Method 4
1	1.000	1.000	1.000	1.000
2	1.000	1.000	1.000	1.000
3	0.304	0.633	0.312	0.359
4	0.472	0.779	0.545	0.566
5	0.988	1.000	1.000	1.000
6	1.000	1.000	1.000	1.000
7	0.889	0.944	0.890	0.892
8	0.499	0.601	0.499	0.510
9	0.547	0.622	0.547	0.547
10	0.882	1.000	1.000	1.000
11	0.510	0.644	0.510	0.510
12	1.000	1.000	1.000	1.000
13	0.995	0.995	0.995	0.995
14	1.000	1.000	1.000	1.000
15	1.000	1.000	1.000	1.000
16	0.665	0.839	0.677	0.721
17	0.488	1.000	0.876	1.000
18	0.967	0.967	0.967	0.967
19	0.541	0.541	0.541	0.541
20	1.000	1.000	1.000	1.000
21	0.576	0.583	0.576	0.576
22	1.000	1.000	1.000	1.000
23	1.000	1.000	1.000	1.000
24	0.304	0.373	0.304	0.304
25	0.347	0.564	0.347	0.347
26	1.000	1.000	1.000	1.000
27	1.000	1.000	1.000	1.000
28	0.317	0.964	0.847	0.862
29	1.000	1.000	1.000	1.000
30	1.000	1.000	1.000	1.000
Mean	0.776	0.868	0.814	0.823
No. of efficient DMU	13	16	15	16

4.2.1 Finding from the comparative study

When an undesirable output is incorporated into the eco-DEA, it gives efficiency scores that are either increased or remain unchanged. The various approaches in dealing with undesirable output tend to give a better efficiency score and greater number of efficient DMUs when compared with the method that ignores the undesirable output.

According to Table 4-2, when comparing method 1 to other approaches, the efficiency scores show either no difference or increase. In general, the number of efficient DMUs and the mean efficiency score under method 2 to method 4 increase. For example, DMU 17 sees a significant rise in its efficiency score after adding undesirable output into computation. With method 1, the value is 0.488 which is one of the least inefficient DMUs. It becomes efficient under method 2 and method 4. DMU 28 is another obvious example showing the discrepancy in the results between the calculation of various approaches. Its efficiency score is 0.317 under method 1 but abruptly increases up to above 0.84 under other methods.

Unlike the obvious ascent of DMUs 17 and 28, an improvement in their performance is commonly observed for other DMUs. For method 2, the increase in the efficiency score is considerately more obvious than in methods 3 and 4. For those DMUs with no increase in the efficiency score, their results remain constant under all the approaches. For example, the efficiency scores of DMU 18 and 19 are the same under methods 1 to 4. The DMUs with a 1.000 efficiency score, such as DMUs 1, 2, 6, 12, 14, 15, 20, 22, 23, 26, 27, 29 and 30, are efficient despite the methods used in incorporating the undesirable outputs. The observation above illustrates a common finding encountered from existing approaches in dealing with undesirable outputs in DEA. In fact, these observations are also found in the research of Seiford and Zhu (2002) and Hua and Bian (2007).

Under methods 2 to 4, when the input remains unchanged and the number of output increases or vice versa, the efficiency score of the inefficient DMU increases. The traditional DEA is restricted by the condition that the ratio between weighted sum of inputs and weighted sum of outputs must be positive. Besides, when the nature of the outputs varies, they cannot be subtracted from each other. Thus, when considering an undesirable output, it must be treated as an individual and positive number in the DEA. It appears that any extra positive output tends to improve the DMU efficiency. The presence of the undesirable output implies that with the same amount of input, the DMU can produce extra outputs. Therefore, the DEA perceives the DMU as more efficient when compared with the previous combination set of input and output.

Based on this comparative study, a research gap is raised. In modelling undesirable output, there is a strong possibility that whenever an extra positive output or input is included in the DEA, the efficiency of the DMU tends to increase. The finding of the present study is concluded as:

The existing approaches of eco-DEA tend to increase efficiency scores.

4.2.2 Discussion of the comparative study

Based on the observations found in Table 4-2, it is suggested that after incorporating the undesirable output, the results will either improve or remain constant. This change could not reflect a reasonable logic behind the presence of undesirable output. When one more factor is considered, the competition condition between the DMU has altered and the efficient DMU could become less efficient after considering the undesirable output. In fact, the efficiency score should change in such a way that it might increase or decrease. For example, the desirable output of plant A is greater than plant B. However, when accommodating the pollutants produced by both plants, plant B produces less pollutant than plant A. Putting these 2 considerations together for comparison, plant B behaves better in the environmental aspect because it produces less pollutant per desirable product. Therefore, plant B can be regarded as more environmentally efficient compared with plant A.

The assessment of efficiency is based on the combination of the inputs and outputs of the DMU. Therefore, each variable should be properly defined in the eco-DEA so as to give an accurate result to the stakeholder for reference. All these variables should be favourable or unfavourable to the performance of the DMU which depends on the amount of input, and the desirable and undesirable outputs it produces. Therefore, when an extra variable, which is environmentally related in this study, is incorporated into an assessment, it should not be restricted to simply as a neutral or favourable impact to the DMU.

In this study, it can be deduced that after considering the undesirable outputs, the mean efficiency score increases as well as the number of efficient DMU. In this context, it can only be explained the difference between the results is due to the various techniques used in modelling the undesirable outputs. It is important to characterise the undesirable output correctly. The undesirable output should be discriminative enough so that its presence would affect the efficiency score that would not only increase or remain constant, but it could also worsen the efficiency score. Moreover, the difference in the efficiency scores calculated is simply based on the different calculation methods in dealing with the undesirable outputs. In principle, the results are the same. The existing literature failed to explain the deeper issue concerning undesirable output. The undesirable output's effect to the efficiency score should not be strictly positive. The discussion of the impact of undesirable output on the whole DEA and the efficiency score has received little attention. In order to address this problem, one model is proposed in the following section.

4.3 Development of the New Ratio Model

The various existing approaches of eco-DEA fail to characterise undesirable outputs in a proper manner. With the four methods diverged from the literature, the efficiency score and the number of efficient DMUs tend to either increase or remain unchanged when undesirable output is considered. In fact, the undesirable output in the eco-DEA should have either a favourable or an unfavourable impact on the DMU. The existing approaches fail to satisfy this significant nature of an undesirable output. Under the current limitation and research gap, there is a need to develop a new model which treats undesirable output in a way that its impact can be accurately described and interpreted. In this section, a new DEA efficiency measure called the “Ratio Model” is proposed. It is believed able to characterise the undesirable output in a more advanced and effective way than previous approaches. This alternative avoids the common problems mentioned.

4.3.1 Definition of the new Ratio Model

In recalling the convention BCC DEA model and assumes that there are *R* DMUs that convert *M* inputs to *N* outputs, DMU$_k$ is one of the *R* DMUs being evaluated. It is further assumed that DMU$_k$ consumes *m* input $X_i^k (i=1,2,...,m)$ to produce *n* output $Y_j^k (j=1,2,...,n)$ and each DMU has at least one positive output. The measure of efficiency of DMU$_k$ is then obtained by:

$$
\begin{array}{lll}
\min & \theta & \\
s.t & \sum_{r=1}^{R} \lambda_r X_i^r - \theta X_i^k + s_i^- = 0 & i=1,2,...,m \\
 & \sum_{r=1}^{R} \lambda_r Y_j^r - s_j^+ = Y_j^k & j=1,2,...,n \\
 & \sum_{r=1}^{R} \lambda_r = 1 & \\
 & \lambda_r, s_i^-, s_j^+ \geq 0, & r=1,...,R
\end{array}
\tag{4-1}
$$

where DMU$_r$ = any of the decision making units being evaluated;

DMU$_k$ = the particular decision making unit being evaluated;

X_i^r, Y_j^r = the inputs and outputs of every DMU$_r$;

θ = the efficiency of DMU;

λ_r = the dual variable corresponding to the other inequality constraint of the primal;

s_i^-, s_j^+ = the slack variables which turn the inequality constraint into an equal form; and

$\lambda_r^*, s_i^{-*}, s_j^{+*}$ = the optimal solutions when the relative efficiency of DMU*k* is $\theta^*=1$ and $s_i^{-*} = s_j^{+*} = 0$

The traditional DEA does not consider undesirable output. In the Ratio Model, the undesirable output and desirable output are defined as O_q^- and O_p^+ respectively. The undesirable output O_q^- is treated as a new variable, ψ , which is called the penalty parameter. ψ is written as:

$$\psi_k = \rho_1 O_{1k}^- + \ldots + \rho_q O_{qk}^- \qquad q = 1, 2, \ldots, t_2 \tag{4-2}$$

where Ψ_k = penalty parameter for DMU$_{k;}$

ρ_q = the penalty for individual undesirable output; and

O_q^- = the undesirable output.

Since ρ is the penalty charged for producing the outputs, the ψ obtained from problem (4-2) gives a measure of the total monetary value of undesirable outputs. From the definition of ψ , the greater the amount of undesirable output, the greater is the value of the penalty parameter. Further, the respective value of ρ is associated with the individual undesirable output, therefore ρ has the same value for every DMU. With this model, desirable and undesirable outputs can relate to one another, regardless of disagreement in the units. In addition, the government levy on industrial pollutant emissions can be incorporated as ρ into the eco-DEA. Thus, stakeholders can be reminded of both the operational and environmental costs in producing dirty industrial output. With the new approach of treating undesirable output in (4-2), the output of the Ratio Model is defined as:

$$Y_p^{'} = \frac{1}{\psi_p} O_p^{+} \qquad p = 1, 2, ..., t_1 \qquad (4\text{-}3)$$

where O_p^{+} = the desirable output; and

$Y_p^{'}$ = the penalty factor.

The new Ratio Model computes desirable output and undesirable output as a fraction that the undesirable output O_q^{-} is the denominator and the desirable output O_p^{+} is the numerator. In this case, the output value is interpreted as a ratio of desirable output to undesirable output. The use of ratio provides a more straightforward and sensitive way to expose the impact of undesirable outputs in a DEA. As the undesirable output is the denominator, the greater amount of pollutant produced, the less will be the value of the overall output Y'. On the other hand, with a smaller amount of undesirable output produced, the output amount Y' increases. By using this transformative approach, desirable and undesirable outputs are directly proportionate to one another. The ratio form can satisfy the restrictions of the conventional DEA, which the output variable states must be a positive value. Furthermore, the ratio form gives both desirable and undesirable outputs a more distinguished way to describe the effect of the presence of the pollutant on the DMU efficiency. The existing eco-DEA simply incorporates the undesirable outputs into the conventional DEA, which the efficiency score would either increase or remain the same. This new linkage, a ratio form, between the two outputs gives the eco-quality a more discriminative power in the eco-DEA, thus is a more appropriate way to characterise undesirable output. With the new expression of output Y', the Ratio Model can be written as :

$$
\begin{aligned}
&\min \quad \theta' \\
&\text{s.t} \quad \sum_{r=1}^{R} \lambda_r X_i^r - \theta X_i^k + s_i^- = 0 \qquad i = 1,2,...,m \\
&\qquad \sum_{r=1}^{R} \lambda_r Y'^r_j - s_j^+ = Y'^k_j \qquad j = 1,2,...,n \\
&\qquad \sum_{r=1}^{R} \lambda_r = 1 \\
&\qquad \lambda_r, s_i^-, s_j^+ \geq 0, \qquad r = 1,...,R
\end{aligned}
\tag{4-4}
$$

By comparing models (4-1) and (4-4), it can be seen that the form of the Ratio Model and the original DEA are similar. However, this has also introduced a new way to treat both desirable and undesirable outputs. The difference between the output Y and Y' is that Y' includes undesirable outputs which assess the DMU based on all of the good and bad outputs generated. The output Y' in the Ratio Model formulates the desirable and undesirable outputs as a ratio, and associates the undesirable outputs with a monetary value. This gives a new definition and computation approach to the DEA ecological model. The following table summarises the difference between the traditional DEA/eco-DEA and the Ratio Model.

Table 4-3 Difference between the existing eco-DEA and the newly developed Ratio Model

	Existing eco-DEA	**Newly developed Ratio Model**
Presence of the undesirable output	Method 1 ignores undesirable output; method 2 to method 4 incorporates undesirable output	Undesirable output is incorporated
Form of the undesirable output	Undesirable output is modelled as a positive value in the eco-DEA	Desirable and undesirable outputs are formulated as a ratio form
Effect of the undesirable output on the efficiency score	The efficiency score either increases or remains the same	The efficiency score would decrease, increase or remain the same according to the DMU performance

4.4 Verification of the New Ratio Model

Based on the new eco-DEA developed in the previous section, the present section aims to verify the new approach. A comparative study is conducted between the prior approaches of eco-DEA and the newly developed Ratio Model, conducted in a similar fashion as in Section 4.2. As the Ratio Model formulates the desirable and undesirable outputs in a ratio form, therefore the ratio values of these two outputs have to be calculated. Table 4-4 shows the ratio between the two desirable outputs and one undesirable output. Table 4-5 compares the results of all the methods discussed in the preceding sections as well as the Ratio Model.

Table 4-4 Ratio of the two desirable outputs and one undesirable output

DMU	Output ratio 1	Output ratio 2
1	3.03	22.06
2	7.03	5.75
3	5.46	5.96
4	3.16	54.42
5	11.26	86.09
6	2.77	19.15
7	1.77	19.46
8	4.51	23.14
9	3.38	11.30
10	3.65	36.14
11	3.89	23.69
12	3.50	41.87
13	3.25	3.09
14	2.94	34.73
15	3.08	19.68
16	8.33	20.13
17	8.47	17.13
18	1.23	10.95
19	0.70	10.95
20	4.18	21.80
21	2.46	12.95
22	3.48	18.88
23	7.36	25.34
24	2.16	3.91
25	1.54	20.88
26	20.20	98.77
27	1.36	15.97
28	12.94	64.52
29	2.81	2.69
30	0.84	18.07

Table 4-5 Results of the DMU efficiency score under the five methods

DMU	Method 1	Method 2	Method 3	Method 4	Ratio Model
1	1.000	1.000	1.000	1.000	1.000
2	1.000	1.000	1.000	1.000	1.000
3	0.304	0.633	0.312	0.359	0.314
4	0.472	0.779	0.545	0.566	0.538
5	0.988	1.000	1.000	1.000	1.000
6	1.000	1.000	1.000	1.000	0.589
7	0.889	0.944	0.890	0.892	0.456
8	0.499	0.601	0.499	0.510	0.463
9	0.547	0.622	0.547	0.547	0.515
10	0.882	1.000	1.000	1.000	0.543
11	0.510	0.644	0.510	0.510	0.489
12	1.000	1.000	1.000	1.000	1.000
13	0.995	0.995	0.995	0.995	0.589
14	1.000	1.000	1.000	1.000	1.000
15	1.000	1.000	1.000	1.000	1.000
16	0.665	0.839	0.677	0.721	0.484
17	0.488	1.000	0.876	1.000	0.718
18	0.967	0.967	0.967	0.967	0.961
19	0.541	0.541	0.541	0.541	0.541
20	1.000	1.000	1.000	1.000	0.932
21	0.576	0.583	0.576	0.576	0.497
22	1.000	1.000	1.000	1.000	0.364
23	1.000	1.000	1.000	1.000	0.631
24	0.304	0.373	0.304	0.304	0.290
25	0.347	0.564	0.347	0.347	0.347
26	1.000	1.000	1.000	1.000	1.000
27	1.000	1.000	1.000	1.000	0.653
28	0.317	0.964	0.847	0.862	0.618
29	1.000	1.000	1.000	1.000	0.583
30	1.000	1.000	1.000	1.000	1.000
Mean	0.776	0.868	0.814	0.823	0.670
No. of efficient DMU	12	16	15	16	8

Concerning the finding in Section 4.2.1, the Ratio Model gives three different results when compared to the efficiency scores under method 1 to method 4. From the results shown in Table 4-5, the disparity between the efficiency scores under method 1 and other eco-DEA states that the presence of undesirable output has an impact on DMU performance. Similar to the previous findings, the performance under method 2 to method 4 is improved when an undesirable output is incorporated into the assessment. The mean efficiency score under the newly developed Ratio Model decreases when compared with other methods. The difference in the results is attributed to the simultaneous incorporation of undesirable and desirable factors as single outputs. When one extra variable is considered, it could exert a potential favourable or unfavourable impact on DMU performance. Therefore, it is believed that the mere improvement in the efficiency score after pollutants are accounted is a false idea. The new Ratio Model developed in this study provides a new perspective which formulates the desirable and undesirable outputs as a ratio form so that the two outputs are directly related. This gives a strong discriminative power in distinguishing the impact of the undesirable output on the DMU performance.

For example, DMUs 6, 20, 22, 23, 27 and 29 were considered efficient beforehand, but under the Ratio Model, their efficiency scores drop. The discrepancy is due to the perspective in viewing the desirable outputs. Although these DMUs produce a relative higher amount of desirable output, at the same time they also produce a higher amount of undesirable output. As the newly developed Ratio Model accommodates the desirable output and the undesirable output as a ratio form, this exposes the impact of the undesirable output in a more discriminative approach. Thus, as observed in Table 4-4, the mentioned DMUs have a lower output ratio when compared with other DMUs that produce less desirable outputs. These findings prove that the previous approaches failed to appropriately characterise the undesirable outputs. Conversely, they gave credit to the polluted DMUs.

DMUs 3, 4, 5, 17 and 28 are less efficient under method 1 than other eco-DEA and also the newly developed Ratio Model. This is because method 1 does not consider the undesirable output in the calculation and solely shows the performance evaluation concluded from the amount of inputs and desirable outputs. As method 1 does not include the undesirable outputs into computation, thus, simply judging the amount of desirable output distorts the environmental performance of the DMUs.

There is a sharp decrease in the number of efficient DMUs under the newly developed Ratio Model because this comparative study indicates the impact of the undesirable output is discriminative enough when compared to other approaches of eco-DEA. Based on the Ratio Model, the undesirable output is taken into consideration as a ratio form with the desirable output. When the undesirable output is accommodated in this approach, the presence of the undesirable output directly affects the output ratios of the DMU, thus changes the performance of the DMU. For example, even though DMU 18 has the greatest amount of undesirable output, it also has a relatively large amount of desirable output produced. Thus, its efficiency score is 0.961. The performance is assessed in such a way that all the variables considered in the study should have a positive or negative impact on DMU performance.

To conclude, the newly developed Ratio Model is more advanced in characterising the presence of the undesirable output in the content of eco-DEA. The findings in this comparative study provide evidence that the presence of undesirable outputs can be either a favourable or unfavourable factor in the efficiency score. The Ratio Model manages to consider this condition in the assessment of environmental performance.

4.5 Chapter Summary

This chapter illustrates Stage One of the present study. Firstly, a comparative study is conducted between various existing eco-DEA to examine the impact of an undesirable output. It is found that the existing eco-DEA fails in incorporating the undesirable outputs in an appropriate way. Following is the introduction of the development of the new Ratio Model which simultaneously incorporates undesirable and desirable outputs. They are defined as a ratio from which the desirable output is directly proportionate to the undesirable output. Thus, this increases the discriminative power of the undesirable output on the DMU performance. The impact of pollutants is well characterised under the newly developed Ratio Model. From the verification study in Section 4.4, the results further show that the prior approaches of eco-DEA fail to credit the undesirable output. Thus, the DMU efficiency score is exceptionally high. With the application of the new Ratio Model, the efficiency score and the number of efficient DMUs are adjusted. Under the new Ratio Model, some of the efficient DMUs are no longer regarded as efficient from an environmental perspective, while some of the DMUs have an improved efficiency score after undesirable output is incorporated.

CHAPTER 5 ENVIRONMENTAL PERFORMANCE ASSESSMENT OF CHINA’S TEXTILE INDUSTRY

5.1 Introduction

Recalling the objective is to develop a Green Index for the textile industry, the present study constitutes two stages which are shown in Chapter 3. Stage One, which is covered in Chapter 4, illustrates the development of a new eco-DEA. In this chapter, Stage Two is examined. Stage Two demonstrates how the Green Index is applied to evaluate the environmental performance of the textile industry in China. Adopting the framework as revealed in Chapter 3, this chapter firstly discuss the preliminary study in Section 5.2. Followed by is Section 5.3, the components of the four case studies are addressed and the rationale behind the selection of these factors are verified. Lastly, Section 5.4 discusses the four case studies accordingly.

5.2 Preliminary Study

The aim of this assessment was to identify the rooms for improvement regarding the environmental management tool. From this preliminary study, some of the data was collected and it could help a better understanding in the daily operation of the company. Additionally, from the process of gathering data, the company’s principles and daily monitoring system on environmental management, if necessary, could be identified. This study examined the pre-treatment stage of the textile wet finishing processes. This could provide a new perspective for the future development and application of the Green Index for the manufacturing processes.

5.2.1 Background of the textile mill

The textile mill (also referred as the company) is located in Shenzhen, China which owns six highly integrated subsidiaries. The products ranges from yarn, elastic, embroidery, lace to knitted fabric and haberdasheries. The company has been devoted to provide an “one-stop” service to all its customers since its establishment in 1974. Its market-driven and customer-oriented approaches have propelled since then and led to the substantial growth in the manufacture of diversified products. The company is currently the pioneer in the manufacture of lingerie fabrics and accessories. Its high quality and innovated products are internationally renowned. The textile plant has acquired ISO 9001 and 14001 for its customer and environmentally satisfactory products. Figure 5-1 outlines the knitted fabrics production process at the company.

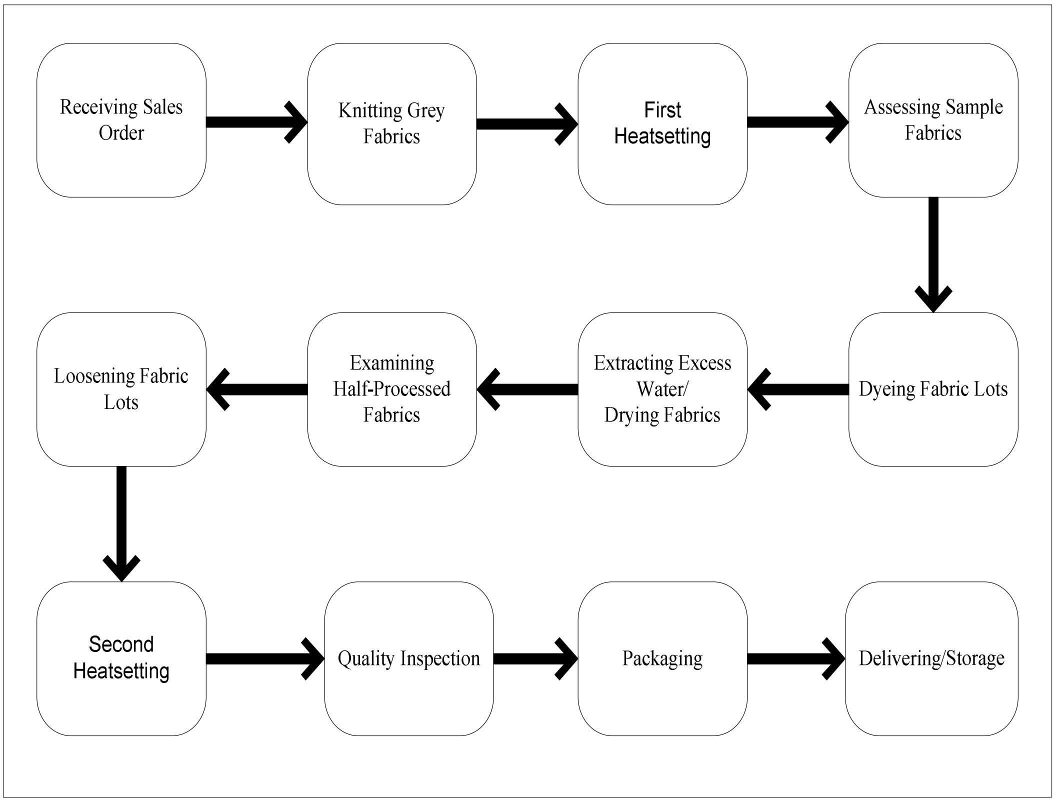


Figure 5-1 Production process of knitted fabrics at the textile mill

At the company, an in-depth conversation with two managers from the top management level was conducted. From the conversation, it is known that one of the company’s future targets is to develop its brand image as an environmental friendly manufacturer. Hence, the company’s strategy is to be a pioneer in developing environmental friendly production. With its own existing procedures in environmental management, the company also follows numerous eco-standards which are required by the European and American buyers. These countries are more environmental conscious when concerning the manufacturing processes. The company is qualified for the Öeko-tex Standard in using harmless substance as the raw material. Moreover, the quality level of the mill’s products has met the Marks and Spencer standard and has been well recognized by the latter. Besides from complying with different companies’ standards, the company establishes its own eco-standard to regulate the product quality.

Apart from complying with the rules and regulations of the customers, it is recommended that the company is able to play a more proactive role in developing a monitoring system to oversee each manufacturing stage. It is feasible for the company to regulate its environmental performance by comparing its previous record with the present. Therefore, the Green Index is suitable for this type of eco-conscious textile plant.

5.2.2 Polluted air sample collection

In this preliminary study, only polluted air is collected but not wastewater and solid waste. This is because the senior manager of the textile mill does not allow the disclosure of their records on wastewater and they do not have any records on the solid waste.

As covered in Section 3.3, after the polluted air samples are collected, they are immediately sent to the air laboratory for further analysis. The results of the analysis are shown in Table 5-1.

Table 5-1 Types of air emission from the two batches

Types of air emission	Quantities	
	First batch	Second batch
SO_2	3.4 ppb	12.4 ppb
CO	1.715 ppm	1.558 ppm
NO_2	30.8 ppb	28.1 ppb
HCHO	0.12 ppm	0.1 ppm
TVOC	508 ppb	423 ppb
Methylene chloride	Nil	0.80 ppb
Benzene	0.89 ppb	0.89 ppb
Toluene	2.83 ppb	2.38 ppb
1,2-Dibromoethane	1.51 ppb	1.07 ppb
Ethylbenzene	0.92 ppb	0.45 ppb
m,p-Xylene	0.46 ppb	0.18 ppb
o-Xylene	0.20 ppb	Nil
4-Ethyltoluene	0.62 ppb	0.51 ppb
1,3,5-Trimethylbenzene	0.65 ppb	0.46 ppb

From the table above, there are thirteen types of gases which contribute to the air quality of the textile mill. When reaching certain level of concentration, these gases would become toxic and poisonous which greatly impact the human health environment (Lacasse & Baumann, 2004). However, under the restricted time and location, only two batches of air samples are collected. They are not representative enough to examine the condition of this textile mill.

Even though the Green Index has been intended to be applied in one or two actual production mills in the very early stage of the study, the data collected was not sufficient to run the new model. During the completion of this study, there is a change in the senior management of the company and the new manager forbade the disclosure of the relevant data and considered the data as confidential. In addition, as this is a Teaching Company Scheme project, it is restricted to work with the sponsoring company only but not other companies. Therefore, only one textile mill is visited for the preliminary study. With these obstacles, the Green Index to be developed is thus applied with the data collected from the China

Statistical Yearbook to evaluate the environmental performance of China's textile industry in the past seventeen years.

5.3 Development of the Green Index with the New Ratio Model

The previous section addressed the notion of applying the developed Green Index with the database from the China Statistical Yearbook instead of the textile mill in China. Determining the source of the data, this section illustrates how the Green Index is accounted and the rationale of the factors involved in the case studies is verified.

In Section 3.3.2, the general framework of the Green Index is outlined. It is known that there are three phases involved in the execution of the Green Index, which included data collection, Ratio Model and the Green Index. Based on the same framework, Figure 5-2 illustrates the factors of the Green Index specifically designed for the four cases which are discussed in Section 5.4 accordingly.

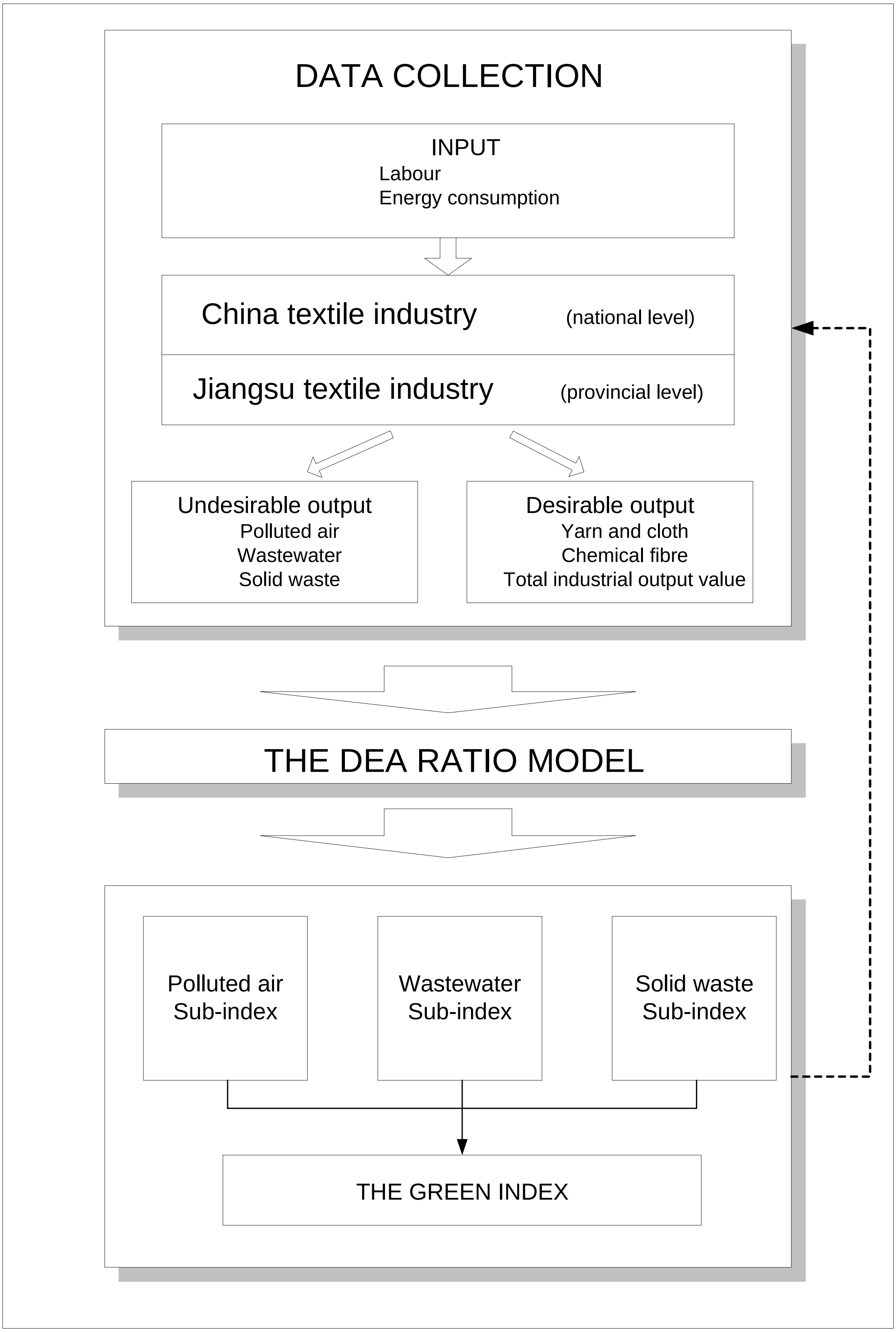


Figure 5-2 Components of the Green Index

To enhance the comprehensiveness of the application of the Green Index, the subject of the study, China’s textile industry, is further divided into two levels, the national level and the provincial level. The national level describes the environmental performance of textile production of China as a whole; while the provincial level focuses on the evaluation of Jiangsu Province. The textile products to be assessed are yarn, cloth and chemical fibres and the three undesirable outputs are polluted air, wastewater and solid waste. The rationale on the selection of these factors is verified in the following subsections.

5.3.1 Subjects of the case studies

The national level: China

Since the introduction of China’s open door policy in late 1979, the world has been amazed by its surging economy, whose growth rate is unmatched by any other country’s (Cheung, 1998). China has gradually transformed itself from an agricultural economy to a fully modern industrial economy. World Bank statistics indicates that China’s average income was USD2,025 in 2006, compared to USD293 in 1985 (Kahn & Yardley, 26 August 2007). Among the myriad commodities produced in China, textiles are one of its main income-generating sources.

For years, as one of the largest and highly diverse industries in China, the textile industry has boosted China’s economy and employed large numbers of workers. The industry employed about seven million people in 2008, which accounted for over 7.8% of the country’s total labour force. As seen from Figure 5-3, the production of yarn, cloth and chemical fibre has increased noticeably over the past decade. Based on the factors described above, it can be concluded that the textile industry has made a remarkable contribution to the growth of China's economy.

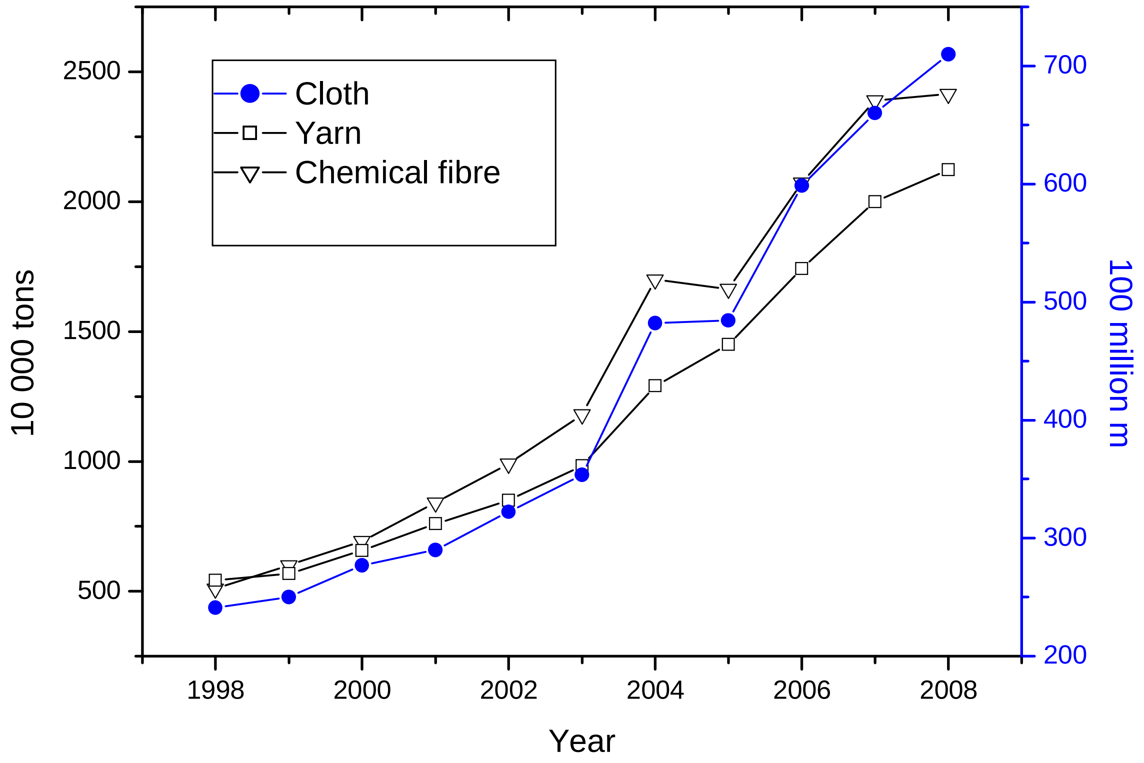


Figure 5-3 Output of China's major textile products (1998-2008)

However, the expanding scale of the textile industry deteriorates the environment. In terms of existing textile enterprises, most are medium to small sized firms. This occurs because the textile sector provides relatively easy start-up opportunities compared to other sectors, since financial and technical requirements are low (Jahiel, 2007). However, these small firms have a great impact on the environment due to limited investment into superior machinery and technology. Moreover, because of China's lack of "rural environmental protection personnel…the development of these small firms is difficult to regulate" (Jahiel, 2007). Cheng et al. (2004) have done in-depth research on the impact of China's admission to the World Trade Organization (WTO) and the environment. After China became a WTO member in 2001, foreign investment in these small plants increased. The advantage, is that this increases the capital of these small plants, which allows improvements to the industry's technological level. Foreign investment also positively affected the industry, by regulating environmental policy (Cheng & Shen, 2004). However, these benefits cannot compensate for the losses brought to the environment as a result of industry activities (Jahiel, 2007).

The provincial level: Jiangsu

Besides the perspective from the whole nation, Jiangsu Province is adopted as an example to discuss the impact of textile manufacturing on the environment. Situated along China's east coast with the famous Changjiang (Yangtze) River running through its southern half, Jiangsu Province is one of the major provinces which is recognized for its economic and industrial development (Hong Kong Trade Development Council Research Department, 1996). GDP in Jiangsu Province rose sharply from CNY668 billion in 1997 to CNY2574 billion in 2007. Jiangsu enjoys a rich number of water resources. There are lakes and rivers throughout the province, such as Changjiang (Yangtze) River, Huaihe River, Yihe River, Taihu Lake, Hongzehu Lake, Gaobaohu Lake, Grand Canal and Chuanchanghe River. With Jiangsu's superior geographical location, many foreign investors are attracted to start up their businesses there. Among the vast varieties of commodities produced in Jiangsu, textiles are one of the most prosperous industries. In 2008, the respective amounts of yarn, cloth and chemical fibre produced in Jiangsu stood at approximately 33%, 17% and 11% of total national output. However, the textile industry’s rapid development has unfavourably impacted Jiangsu’s environment. For example, the ongoing use of DDT in cotton field has seriously polluted the Changjiang (Yangtze) River (Yang et al., 2008b), water quality of in Taihu Lake has been deteriorating since the economic development of the 1980s (Shen et al., 2001), and abnormally high concentrations of nitrogen have been found in the Kuihe River (Wu et al., 2007).

5.3.2 Input

Following the guidance covered in Section 3.3.3.4, the inputs are labour (Chandra et al., 1998; Cooper, 1978; Jahanshahloo & Khodabakhshi, 2004; Zhu & Shen, 1993) and the total energy consumption (Zhu & Shen, 1993).

The textile industry is relatively labour intensive (Cooper et al., 1995; Duan & Gao, 2008; Ormerod, 1999; Tian et al., 2007), therefore, it is understandable to use labour as an input of textile production.

As textile production is heavily reliant on the use of machinery, total energy consumption therefore has a direct relationship with end product output. In addition, there is an explicit affiliation between energy consumption and air pollutants (Tian et al., 2007).The total energy consumption includes raw coal, crude petroleum and their products, natural gas and electricity, but excludes fuel of low calorific value, bio-energy and solar energy.

5.3.3 Desirable outputs

As discussed in Section 3.3.3.4, the outputs should be the common measures of the achievement of the DMU. Therefore, the desirable outputs are yarn, cloth and chemical fibre produced, as well as the total industrial output value of the respective textile products.

From Figure 5-4, it is observed that yarn, cloth and chemical fibre are chosen to be the textile products studied in the four case studies. As stated in Section 3.3.3.2, China Statistical Yearbook is the official database of the Chinese Government, indicates that yarn, cloth and chemical fibre are the major industrial products of China. It is believed they are popular and welcomed by most consumers. As seen in Figure 5-4, the respective textile products include the following items:

(1) Yarn includes pure and blended cotton yarn, and pure chemical fibre yarn, but excludes cotton thread, substitute fibre yarn and hand-made yarn;
(2) Cloth includes pure and blended cotton cloth, pure chemical-fibre cloth and canvas, but excludes substitute fibre cloth, hand-woven cloth and cord cloth; and
(3) Chemical fibre includes synthetic fibre such as polyester fibre, acrylic fibre, polyvinyl fibre and manmade/ cellulose fibre.

Yarn and cloth are grouped under the category named “textile” and chemical fibre belongs to a separate category. This classification is responding to the principle of the United Nations which yarn and cloth are classified as SITC 65 while chemical fibre is classified as SITC 26 (United Nations Statistics Division, 2010). Therefore, from the Statistical Yearbook of China (The People's Republic of China State Statistical Bureau, Various issues), the relevant data on yarn, cloth and chemical fibre are collected under the product categories "textile" and "chemical fibre" respectively.

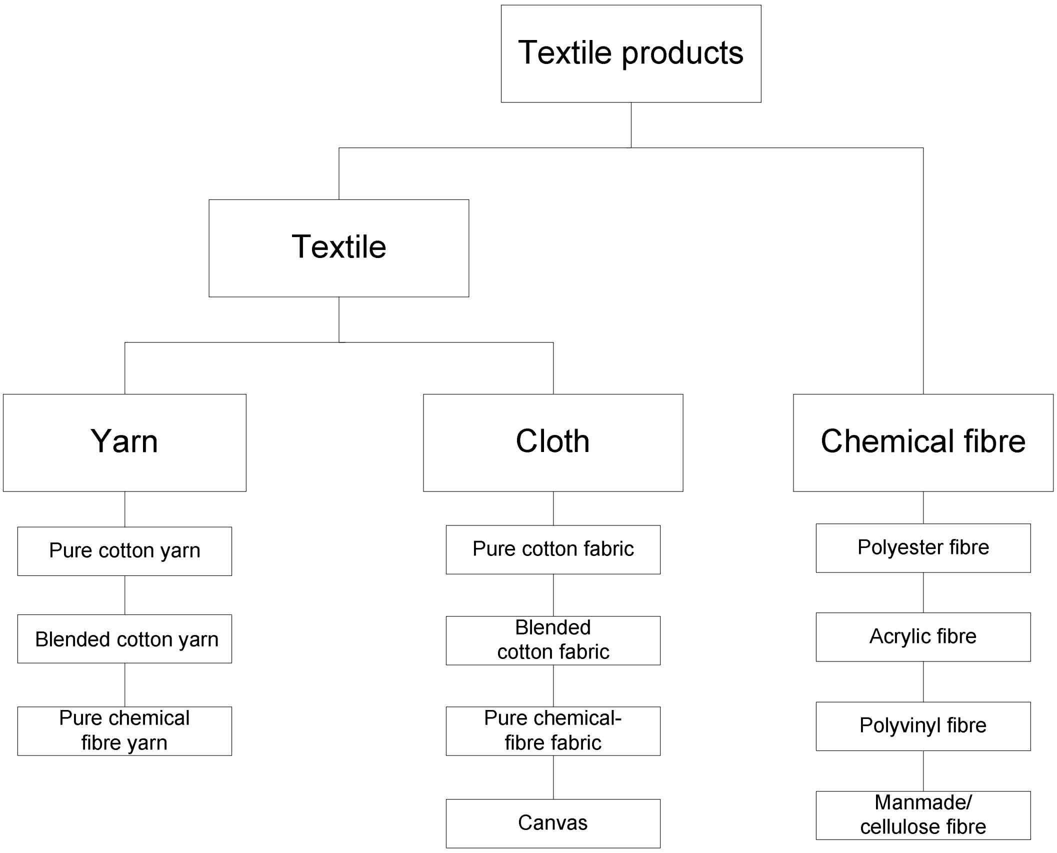


Figure 5-4 Components of the desirable outputs

Other than yarn, cloth and chemical fibre, cotton fibre and silk are not studied because the relevant environmental data on the manufacturing of cotton fibre and silk is not available in the database. In additionally, due to the prosperous development of China's textile industry, China has a great demand in the supply of cotton fibre. Therefore, a great amount of cotton fibre is imported from countries such as USA and India (China Customs, 2008). From the statistics (The People's Republic of China State Statistical Bureau, Various issues), the amount of imported cotton fibre has significantly increased from 0.03 million tons in 1991 to 2.5 million tons in 2007. Thus, China is seen to rely more on imported cotton fibres.

Apart from the three textile products, the total industrial output value of the textile products are also considered as one of the desirable outputs. The total industrial output value indicates the monetary value of the respective textile product and it provides another source of evidence to examine the growth and the performance of textile industry. The total output value is measured in RMB and adjusted to 1978 prices, based on the official consumer index of prices. The details of the price adjustment are recorded in Appendix A.

5.3.4 Undesirable outputs

The index is further divided into three sub-indices which reflect three types of undesirable outputs discharged during the production of textile products. This project focuses on quantifying the textile industry's environmental impact. Before collecting the relative data, it is crucial to understand the different undesirable outputs that are affecting the manufacturing system.

From Figure 5-5, the three undesirable outputs to be studied are polluted air, wastewater and solid waste. They form the three sub-indices in the Green Index respectively. For each production process, the environmental impact is caused by a number of polluting factors. In developing an environmental performance indicator, these factors should be representative and significant enough to reflect the significance and conditions of production performance. As acknowledged in Chapter 2, the mentioned undesirable outputs represent the common pollutants discharged during the production of textile products. The figure overleaf illustrates the pollution problem induced from the textile manufacturing process.

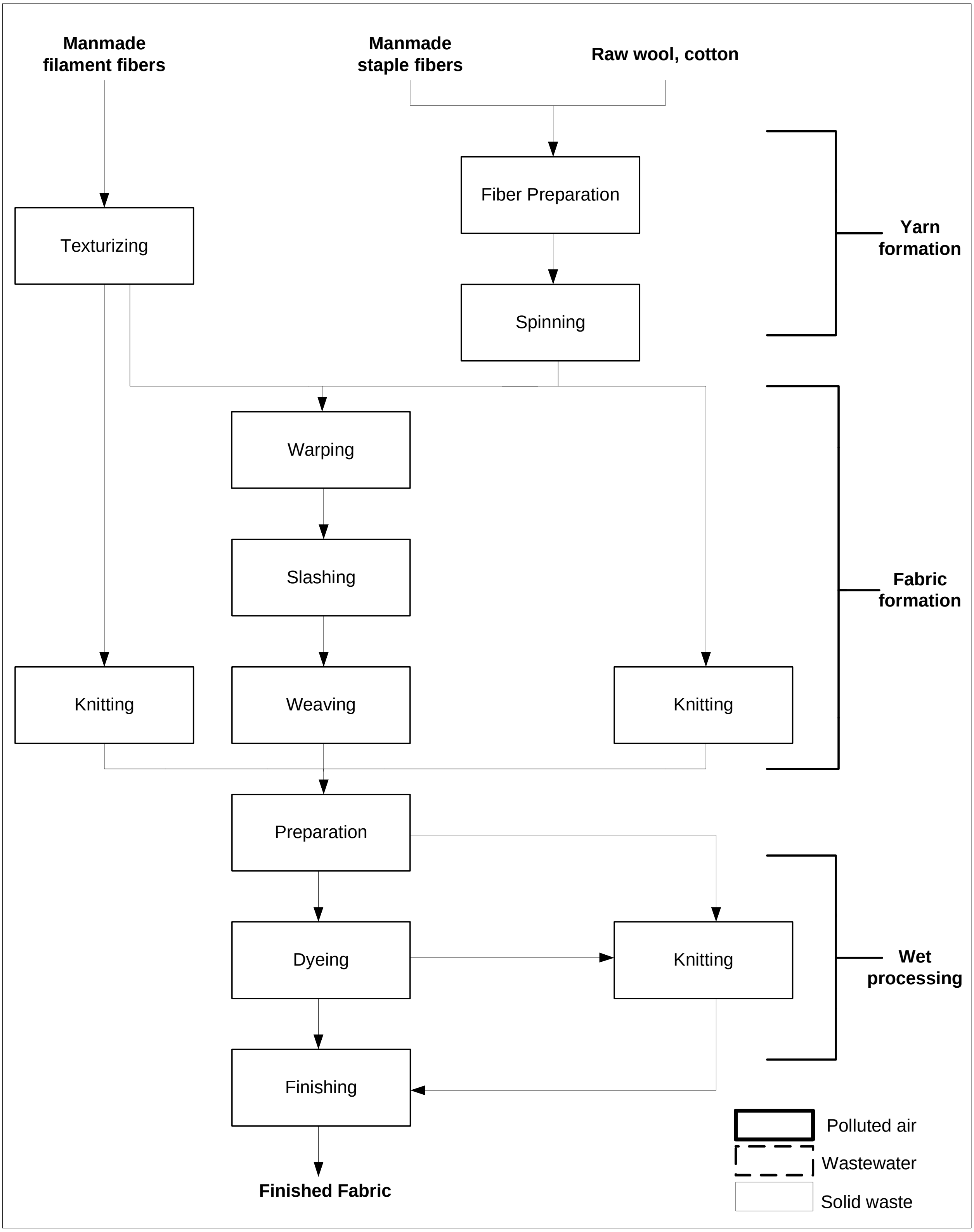


Figure 5-5 Pollutants originated from the textile processing activities

As seen from Figure 5-5, air particulates are constantly emitted in the textile production because industrial activities largely rely on machine manufacturing. These airborne particulates are harmful to human health. Air pollutants generated from textile finishing processes originate mainly from textile processes such as singeing, functional finishing or bleaching (Buonicore, 2000; Lacasse & Baumann, 2004). According to the Environmental Protection Agency (USA Environmental Protection Agency, 1996), high-temperature drying and curing ovens are the most common source of air emissions in a textile operation. All of these high temperature operations are needed to process textile material coatings. Heat-setting and thermofixation, with a typical operation temperature ranging from 250^{o}F to 400^{o}F, emit certain levels of air particles and waste detergent, which can cause air and water pollution (Slater, 2003).

Water is a necessity means for wet processing treatments. This is especially true for the dyeing process, in which water acts as a solvent to fix the dyes onto the fabrics. Water is also a medium for the finishing process. Water consumption varies between processes and the machines used. For example, there are numerous dyeing techniques under the two main principles in dyeing: discontinuous and continuous/ semi-continuous dyeing. Each dyeing method has a different liquor ratio which determines the water consumption used per kg of fabric (Lacasse & Baumann, 2004). Common factors for indicating water pollution are pH, total alkalinity, total dissolved solids, suspended solids, biochemical oxygen demand (BOD), chemical oxygen demand (DOB), chlorides, sulphates, calcium, magnesium, sodium and potassium (Jhala et al., 1981). The characteristics of each sample of wastewater are determined by the range of chemicals, dyes and auxiliaries.

Solid waste is produced continuously during the manufacturing process. As the unit of textile products is non-biogradable fibre, the disposal of textile products can pollute the environment. Industrial waste can include cut selvage ends, roll-ends, reject lots, set-up yardage, and other waste materials generated during the manufacturing process (USA Environmental Protection Agency, 1996). Reprocessing of industrial fabric scrap is impossible because it is often a mixture of chemicals and substrates. Examples are fabrics coated with lamination and coloured with dyes. These properties make them difficult to be recycled and reprocessed. The following table (Table 5-2) summarises the possible source of solid wastes generated from some of the textile manufacturing processes.

Table 5-2 Residual waste from textile manufacturing (USA Environmental Protection Agency, 1997)

Process	Residual wastes
Fibre preparation	Fibre waste, packaging waste and hard waste
Yarn spinning	Packaging wastes, sized yarn, fibre waste, cleaning and processing waste
Slashing/sizing	Fibre lint, yarn waste, packaging waste, unused starch-based sizes
Weaving	Packaging waste, yarn and fabric scarps, off-spec fabric, used oil
Knitting	Packaging waste, yarn and fabric scarps, off -spec fabric
Tufting	Packaging waste, yarn and fabric scarps, off -spec fabric

5.3.5 The Green Index

With the above factors, there will be four case studies which respectively assess the environmental performance of China's yarn and cloth production, China's chemical fibre production, Jiangsu yarn and cloth production and Jiangsu chemical fibre production. As the subject for each study is different, therefore the data adopted for each case varies. After collecting the relevant data, the three sub-indices, which represent the three common pollutants in the textile industry, are calculated by the new eco-DEA, the Ratio Model. Adding the sub-indices, the Green Index of that particular case study is then obtained. The following equation illustrates the general idea on how the Green Index is attained:

I+II+III=the Green Index (5-1)

where I is the sub-index of wastewater;

II is the sub-index of solid waste; and

III is the sub-index of polluted air.

The efficiency score obtained from the three respective assessments are summed up to be the Green Index of the respective case. As the maximum score for each sub-index is 1.000, the pollution indices are added to arrive at a value ranging from 0.000 to 3.000, i.e. the highest value of the Green Index is 3.000 and the lowest is 0.000. For the DMU which obtains a score lower than 3.000, it is regarded as inefficient. Conversely, the DMU is regarded as efficient with the Green Index equals to 3.000.

To ensure any merit in any of the sub-indices does not make up for the deficiency in another sub-index, the three sub-indices have equivalent weight. In other words, if the sub-indices have different weights, people tend to obtain a higher Green Index by lowering the pollutants in the heavily weighted sub-indices. Additionally, due to constraints such as cost and time, the pollutants of the less weighted sub-indices are ignored. This in turn increases the emissions of that particular less weighted pollutant. Thus, this shifts the pollution from one form to another instead of reducing the total amount of pollution.

As a new Ratio Model has been developed in this study, it is used as a tool to evaluate the environmental performance of China and Jiangsu textile industry. Similar to Section 4.4, comparison is made between the different approaches in modelling undesirable output in each case study. This is to demonstrate the superiority of the newly developed Ratio Model when compared to other existing eco-DEA in characterising undesirable outputs. Analysis is given to describe the impact of both the desirable and undesirable outputs on the efficiency score. Finally, suggestion is given to the less efficient DMUs so as to increase the ratio between desirable output and undesirable output to reach the benchmark.

5.4 Case Study 1: China Yarn and Cloth Production 1991-2007

The first scenario considers the environmental performance of yarn and cloth production in the whole country from 1991-2007. In order to give the Green Index for each DMU, it is necessary to compute the relative efficiency score for each sub-index. The DMU selected in this study is the annual performance of the yarn and cloth manufacturing factory in China from 1991-2007. Therefore, there are altogether 17 DMUs being evaluated. The details of all the chosen variables for the case studies are described in Chapter 3 and summarised in Table 5-6. The following sections analyse the data and the ratios of the outputs computed for each sub-index.

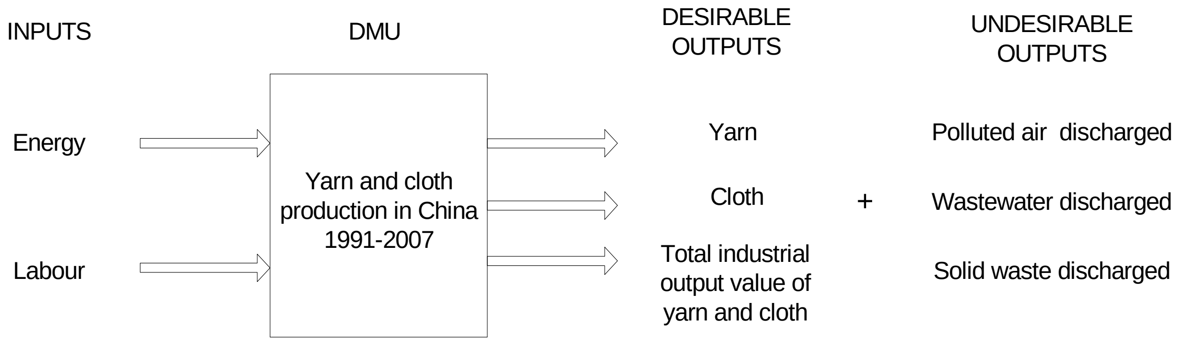


Figure 5-6 The inputs and outputs of Case Study 1

5.4.1 Polluted air sub-index of Case Study 1

Table 5-3 shows the textile industry data and the amount of polluted air produced. The first column identifies the 17 years as DMUs, while the second and third column list the two inputs for the study. Columns 4, 5 and 6 provide the three desirable outputs and the seventh column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Columns 2, 3 and 4 in Table 5-4 show the ratios of the three desirable outputs to the total volume of polluted air emission, and the last column illustrates the results of the polluted air sub-index of the 17 DMUs computed by the new eco-DEA Ratio Model.

Table 5-3 Data of the polluted air sub-index (Case Study 1)

DMU	**Inputs**		**Desirable output**			**Undesirable output**
	1	**2**	**1**	**2**	**3**	**1**
Year	**Labour (10 000 persons)**	**Total energy consumption (10 000 tn SCE)**	**Yarn output (10 000 tons)**	**Cloth output (100 million m)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial polluted air emission (100 million cu.m)**
1991	632.47	3113.30	460.80	181.70	729.27	2139.00
1992	618.21	3325.00	501.70	190.70	731.88	1814.00
1993	903.58	3382.16	501.50	203.00	1289.18	1800.00
1994	894.00	3439.32	489.50	211.30	1460.16	1815.00
1995	877.73	3531.30	542.20	260.18	1159.99	1633.00
1996	810.46	3332.29	512.21	209.10	1098.46	1373.00
1997	730.24	3079.72	559.83	248.79	1077.23	1650.00
1998	578.01	2842.17	542.00	241.00	998.24	1500.00
1999	510.87	2502.79	567.00	250.00	1048.08	1447.00
2000	451.25	2497.00	657.00	277.00	1072.85	1577.00
2001	465.26	2679.32	760.68	290.00	1226.21	1817.00
2002	476.09	2984.43	850.00	322.39	1423.69	2022.00
2003	496.34	3468.96	983.58	353.52	1762.23	2428.00
2004	519.16	4550.25	1291.34	482.10	2126.55	2629.00
2005	580.86	4978.35	1450.54	484.39	2697.79	3020.00
2006	604.84	5756.49	1742.96	598.55	3247.02	3492.00
2007	631.54	6207.57	2068.17	675.26	3424.00	3990.00

Source: Statistical Yearbook of China, various issues

Table 5-4 Output ratios and results under the polluted air sub-index
(Case Study 1)

Year	Yarn ratio ($x10^{-2}$)	Cloth ratio ($x10^{-2}$)	Total industrial output value ratio ($x10^{-4}$)	Polluted air sub-index
1991	21.54	8.49	3409.38	0.802
1992	27.66	10.51	4034.61	0.751
1993	27.86	11.28	7162.09	0.740
1994	26.97	11.64	8044.94	0.992
1995	33.20	15.93	7103.43	0.708
1996	37.31	15.23	8000.45	1.000
1997	33.93	15.08	6528.67	0.811
1998	36.13	16.07	6654.91	0.879
1999	39.18	17.28	7243.15	1.000
2000	41.66	17.56	6803.12	1.000
2001	41.86	15.96	6748.56	0.974
2002	42.04	15.94	7041.00	0.974
2003	40.51	14.56	7257.97	0.958
2004	49.12	18.34	8088.81	1.000
2005	48.03	16.04	8933.08	1.000
2006	49.91	17.14.	9298.45	1.000
2007	51.83	16.92	8581.45	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the polluted air sub-index. Therefore, the results titled polluted air sub-index in Table 5-4 and Table 5-5 are calculated by the Ratio Model.

There are seven efficient DMUs identified by the polluted air sub-index which obtain a relative efficiency score of 1.000. They are year 1996, 1999, 2000, 2001, 2005, 2006 and 2007. The remaining DMUs are considered to be inefficient, because the efficiency score is less than 1.000. The average performance of 1991-1998 is noticeably worse than the performance after 1998. However, there is a consecutive drop in the efficiency score between 2001 and 2003. There is an increasing trend for the yarn, cloth and total industrial output value ratio. This suggests the amount of desirable output produced is increasing for each unit of polluted air generated. It is important that the computation of the parameters is significantly discriminative, so that the diversity in the data can be well characterised by DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-5.

Table 5-5 Efficiency score of the 4 eco-DEA and the polluted air sub-index (Case Study 1)

Year	Method 1	Method 2	Method 3	Method 4	Polluted air sub-index
1991	0.802	0.802	0.802	0.802	0.802
1992	0.751	0.810	0.751	0.751	0.751
1993	0.820	0.909	0.824	0.829	0.740
1994	0.879	0.984	0.890	0.933	0.992
1995	0.736	0.938	0.742	0.746	0.708
1996	0.758	1.000	1.000	1.000	1.000
1997	0.812	0.885	0.812	0.812	0.811
1998	0.879	0.958	0.880	0.880	0.879
1999	0.998	1.000	1.000	1.000	1.000
2000	1.000	1.000	1.000	1.000	1.000
2001	1.000	1.000	1.000	1.000	0.974
2002	1.000	1.000	1.000	1.000	0.974
2003	1.000	1.000	1.000	1.000	0.958
2004	1.000	1.000	1.000	1.000	1.000
2005	0.986	0.992	0.986	0.990	1.000
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	1.000

Table 5-5 shows a discrepancy between the efficiency score under method 1 and the polluted air sub-index. For example, the efficiency score in 1996 of method 1 is unexceptionally low, when compared to 1.000 under the polluted air sub-index. This is because method 1 does not consider the environmental quality in the calculation and solely shows the manufacturing efficiency of the yarn and cloth production in China from 1991-2007. However, the Ratio Model incorporates undesirable output into computation, thus the parameters are viewed from a different perspective. Under the polluted air sub-index, the unit of desirable output produced per unit of polluted air is relatively high in 1996. Therefore, the polluted air sub-index for that year is 1.000. As method 1 does not include the polluted air parameter into computation, thus, simply judging the amount of desirable output distorts the environmental performance of the textile industry.

The efficiency scores for method 2 are generally higher when compared to the results of the polluted air sub-index. This result agrees with Hua and Bian (2007) that treating undesirable outputs as inputs cannot reflect the true production process and easily distorts the DMU’s eco-efficiency. Also, the results also confirm the finding in Chapter 4 which states that the existing eco-DEA tends to increase the efficiency scores. The eco-related parameter has been a factor that simply favours the efficiency of the DMU.

When comparing method 3, method 4 with the polluted air sub-index, the results agree with the finding in Section 4.2.1. The existing eco-DEA methods fail to characterise the undesirable output in an accurate way that leading s to a distortion in the DMU performance of the DMU. For example, the efficiency scores of 2001-2003 achieve 1.000 under method 3 and method 4, while the polluted air sub-index are 0.974 and 0.958 respectively. The discrepancy between the efficiency scores and the sub-index score is due to the perspective in viewing the desirable outputs. Although the three desirable outputs have seen a general increase over the years, the total volume of industrial emissions is increasing at the same time. Therefore, from table 5-2, the yarn, cloth ratio does not show a parallel increasing trend in general. The output amount, which originates from the ratio between the desirable output and the undesirable output is adjusted accordingly. The ratio approach regards the desirable output as per unit of polluted air emitted. Therefore, the increasing amount of undesirable output in that period does not favour the performance of the DMU. Another example is to confirm the discussion in Section 4.2.2. The efficiency score under method 3 and method 4 is 0.89 and 0.933, while it is 0.992 for the polluted air sub-index for DMU 1994. Due to the comparatively small amount of polluted air in that year, the cloth ratio and the industrial output ratio increase from 11.28 to 11.64 and 7162.09 to 8044.94. Thus, 1994 has a relatively good environmental performance and the newly developed Ratio Model is able to give credit for the presence of pollutants. Thus, as a newly developed eco-DEA, the Ratio Model provides a more sensitive way to characterise the pollutants.

5.4.2 Wastewater sub-index of Case Study 1

Table 5-6 shows the textile industry data of Textile industry and the amount of wastewater discharged. The first column identifies the 17 years as DMUs, while the second and third column list the two inputs for the study. Columns 4, 5 and 6 provide the three desirable outputs, and the seventh column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Columns 2, 3 and 4 in Table 5-7 show the ratios of the three desirable outputs to the total volume of wastewater generated, and the last column illustrates the results of the wastewater sub-index of the 17 DMUs computed by the new eco-DEA Ratio Model.

The table below shows the textile industry data and the amount of wastewater produced. There is an increasing trend for the yarn output and cloth output since 1991. The total volume of industrial wastewater discharged fluctuates slightly in the beginning but starts to rise from 1999 onward. The amount of labour and energy consumed shows a steady increase in the early stage, and fluctuates in the middle stage. The drop might be attributed to the economic crisis of the late 20th century, which led to the closure of many textile plants. However, both the input variables start to increase from 2000 onward.

Table 5-6 Data of the wastewater sub-index (Case Study 1)

DMU	**Inputs**		**Desirable output**			**Undesirable output**
	1	**2**	**1**	**2**	**3**	**1**
Year	**Labour (10 000 persons)**	**Total energy consumption (10 000 tn SCE)**	**Yarn output (10 000 tons)**	**Cloth output (100 million m)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial wastewater discharge (10 000tons)**
1991	632.47	3113.30	460.80	181.70	729.27	140353.00
1992	618.21	3325.00	501.70	190.70	731.88	138483.00
1993	903.58	3382.16	501.50	203.00	1289.18	129410.00
1994	894.00	3439.32	489.50	211.30	1460.16	121964.00
1995	877.73	3531.30	542.20	260.18	1159.99	116425.00
1996	810.46	3332.29	512.21	209.10	1098.46	87100.00
1997	730.24	3079.72	559.83	248.79	1077.23	102767.00
1998	578.01	2842.17	542.00	241.00	998.24	110128.00
1999	510.87	2502.79	567.00	250.00	1048.08	121240.00
2000	451.25	2497.00	657.00	277.00	1072.85	125649.00
2001	465.26	2679.32	760.68	290.00	1226.21	128974.00
2002	476.09	2984.43	850.00	322.39	1423.69	132208.00
2003	496.34	3468.96	983.58	353.52	1762.23	141264.00
2004	519.16	4550.25	1291.34	482.10	2126.55	153875.00
2005	580.86	4978.35	1450.54	484.39	2697.79	172232.00
2006	604.84	5756.49	1742.96	598.55	3247.02	197934.00
2007	631.54	6207.57	2068.17	675.26	3424.00	225169.00

Source: Statistical Yearbook of China, various issues

Table 5-7 Output ratios and results under the wastewater sub-index (Case Study 1)

Year	Yarn ratio ($x10^{-4}$)	Cloth ratio ($x10^{-4}$)	Total industrial output value ratio ($x10^{-4}$)	Wastewater sub-index
1991	32.83	12.95	51.96	0.802
1992	36.23	13.77	52.85	0.751
1993	38.75	15.69	99.62	0.82
1994	40.13	17.32	119.72	0.93
1995	46.57	22.35	99.63	0.786
1996	58.81	24.01	126.12	1.000
1997	54.48	24.21	104.82	0.957
1998	49.22	21.88	90.64	0.912
1999	46.77	20.62	86.45	1.000
2000	52.29	22.05	85.38	1.000
2001	58.98	22.49	95.07	1.000
2002	64.29	24.39	107.69	1.000
2003	69.63	25.03	124.75	1.000
2004	83.92	31.33	138.20	1.000
2005	84.22	28.12	156.64	1.000
2006	88.06	30.24	164.05	1.000
2007	91.85	29.99	152.06	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the wastewater sub-index. Therefore, the results titled wastewater sub-index in Table 5-7 and Table 5-8 are calculated by the Ratio Model.

There are 10 efficient DMUs identified by the wastewater sub-index which obtain a relative efficiency score of 1.000. They are year 1996, 1999-2007. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. The efficiency scores attained in 1991-1995 are noticeably lower than the DMUs after 1996. The wastewater sub-index has remained to be 1.000 since 1999. It is important that the computation of the parameters is significantly discriminative so that the diversity in the data can be well characterised by the

DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-8.

Table 5-8 Efficiency score of the four eco-DEA and the wastewater sub-index (Case Study 1)

Year	Method 1	Method 2	Method 3	Method 4	Wastewater Sub-index
1991	0.802	0.839	0.802	0.802	0.802
1992	0.751	0.845	0.751	0.751	0.751
1993	0.820	0.904	0.823	0.825	0.820
1994	0.879	0.975	0.930	0.956	0.930
1995	0.736	0.903	0.783	0.799	0.786
1996	0.758	1.000	1.000	1.000	1.000
1997	0.812	1.000	0.973	1.000	0.957
1998	0.879	1.000	0.979	1.000	0.912
1999	0.998	1.000	1.000	1.000	1.000
2000	1.000	1.000	1.000	1.000	1.000
2001	1.000	1.000	1.000	1.000	1.000
2002	1.000	1.000	1.000	1.000	1.000
2003	1.000	1.000	1.000	1.000	1.000
2004	1.000	1.000	1.000	1.000	1.000
2005	0.986	1.000	0.987	1.000	1.000
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-8, the efficiency score of 1991-1995 under method 1 is remarkably low, because the model does not consider environmental quality in its calculation. The inclusion of undesirable outputs into assessing environmental performance is necessary. Therefore, method 1 distorts the performance of yarn and cloth manufacturing in that period.

The efficiency scores under method 2 are generally higher than other approaches. This result agrees with Hua and Bian (2007) that treating undesirable outputs as inputs cannot reflect the true production process and easily distorts the eco-efficiency of the DMU. For example, under method 2, the undesirable output is treated as input. Therefore, when compared the performance of 1991 and 1992, the drop in the wastewater (which is the “input” under method 2), and the increase in the desirable output computes a better efficiency in 1992.

The wastewater sub-index has similar results with method 3 and method 4, except in 1997 and 1998. Although the amount of yarn and cloth produced and the total industrial output value in 1997 and 1998 are greater than in 1996, at the same time the amount of wastewater generated in both 1997 and 1998 had increased. As the Ratio Model incorporates undesirable outputs and desirable output as a form of ratio, the efficiency score would be sensitive to the change in the amount of undesirable output. Therefore, the wastewater sub-index decreases spontaneously in 1997 and 1998. This phenomenon can also be illustrated by the 2007 performance. According to Table 5-6, 2007 records the largest amount of wastewater. On the other hand, an enormous amount of yarn and cloth output was also produced in that period. Therefore, it is considered an efficient DMU with an efficiency score equal to 1.000.

5.4.3 Solid waste sub-index of Case Study 1

Table 5-9 shows the textile industry data and the amount of solid waste produced. The first column identifies the 17 years as DMUs, while the second and third column list the two inputs for the study. Columns 4, 5 and 6 provide the three desirable outputs, and the seventh column indicates the undesirable output, which is the environmental quality to be assessed in this sub-index. Columns 2, 3 and 4 in Table 5-10 show the ratios of the three desirable outputs to the total volume of solid waste generated, and the last column illustrates the results of the solid waste sub-index of the 17 DMUs, computed by the new eco-DEA Ratio Model. Table 5-9 shows the textile industry data and the amount of solid waste produced. In terms of the volume of solid industrial waste, there is a fluctuation over this period.

Table 5-9 Data of the solid waste sub-index (Case Study 1)

DMU	**Inputs**		**Desirable output**			**Undesirable output**
	1	**2**	**1**	**2**	**3**	**3**
Year	**Labour (10 000 persons)**	**Total energy consumption (10 000 tn SCE)**	**Yarn output (10 000 tons)**	**Cloth output (100 million m)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Volume of industrial solid waste generated (10 000 tons)**
1991	632.47	3113.30	460.80	181.70	729.27	605.00
1992	618.21	3325.00	501.70	190.70	731.88	638.00
1993	903.58	3382.16	501.50	203.00	1289.18	548.00
1994	894.00	3439.32	489.50	211.30	1460.16	534.00
1995	877.73	3531.30	542.20	260.18	1159.99	511.00
1996	810.46	3332.29	512.21	209.10	1098.46	411.00
1997	730.24	3079.72	559.83	248.79	1077.23	507.00
1998	578.01	2842.17	542.00	241.00	998.24	435.00
1999	510.87	2502.79	567.00	250.00	1048.08	425.69
2000	451.25	2497.00	657.00	277.00	1072.85	437.04
2001	465.26	2679.32	760.68	290.00	1226.21	513.00
2002	476.09	2984.43	850.00	322.39	1423.69	511.00
2003	496.34	3468.96	983.58	353.52	1762.23	33.00
2004	519.16	4550.25	1291.34	482.10	2126.55	870.00
2005	580.86	4978.35	1450.54	484.39	2697.79	690.00
2006	604.84	5756.49	1742.96	598.55	3247.02	679.00
2007	631.54	6207.57	2068.17	675.26	3424.00	660.40

Source: Statistical Yearbook of China, various issues

Table 5-10 Output ratios and results under the solid waste sub-index (Case Study 1)

Year	Yarn ratio (x10^{-2})	Cloth ratio (x10^{-2})	Total industrial output value ratio (x10^{-4})	Solid waste sub-index
1991	76.17	30.03	12054.00	0.802
1992	78.64	29.89	11471.43	0.751
1993	91.51	37.04	23525.11	0.738
1994	91.67	39.57	27343.75	0.728
1995	106.11	50.92	22700.39	0.707
1996	124.63	50.88	26726.58	0.751
1997	110.42	49.07	21247.14	0.811
1998	124.60	55.40	22947.97	0.879
1999	133.20	58.73	24620.83	0.998
2000	150.33	63.38	24548.15	1.000
2001	148.28	56.53	23902.78	0.970
2002	166.34	63.09	27860.85	0.948
2003	2980.55	1071.27	534010.29	1.000
2004	148.43	55.41	24443.07	0.869
2005	210.22	70.20	39098.40	0.779
2006	256.70	88.15	47820.60	0.749
2007	313.17	102.25	51847.42	0.719

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the solid waste sub-index. Therefore, the results titled solid waste sub-index in Table 5-10 and Table 5-11 are calculated by the Ratio Model.

There are two efficient DMUs identified by the solid waste sub-index which obtain a relative efficiency score of 1.000. They are year 2000 and 2002. The remaining DMU is considered to be inefficient because the efficiency score is less than 1.000. The sub-index for solid waste fluctuates from time to time. In general, in terms of yarn and cloth production, the industry performed better from 1998 to 2003. In 2003, only 33,000 tons of waste were generated. With no means to clarify the data validity, it is assumed the data are accurate (Cooper et al., 1995). One possible explanation is the breakout of SARS in 2003, which marks the discrepancy, with an exceptionally low volume of industrial solid wastes generated when compared to other DMUs (You et al., 2009). The yarn and cloth ratios, and the total industrial output value ratio score the highest in that year, which favours the efficiency score. Therefore, the solid waste sub-index of 2003 is 1.000. It is important that the parameter computation is significantly discriminative, so that diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable outputs, the results are shown in Table 5-11.

Table 5-11 Efficiency score of the four eco-DEA and the solid waste sub-index (Case Study 1)

Year	Method 1	Method 2	Method 3	Method 4	Solid waste Sub-index
1991	0.802	0.802	0.802	0.802	0.802
1992	0.751	0.751	0.751	0.751	0.751
1993	0.820	0.820	0.820	0.820	0.738
1994	0.879	0.879	0.879	0.879	0.728
1995	0.736	0.744	0.736	0.736	0.707
1996	0.758	0.817	0.759	0.765	0.751
1997	0.812	0.822	0.812	0.812	0.811
1998	0.879	0.908	0.879	0.879	0.879
1999	0.998	1.000	0.999	1.000	0.998
2000	1.000	1.000	1.000	1.000	1.000
2001	1.000	1.000	1.000	1.000	0.970
2002	1.000	1.000	1.000	1.000	0.948
2003	1.000	1.000	1.000	1.000	1.000
2004	1.000	1.000	1.000	1.000	0.869
2005	0.986	0.986	0.986	0.986	0.779
2006	1.000	1.000	1.000	1.000	0.749
2007	1.000	1.000	1.000	1.000	0.719

From Table 5-11, most of the DMU has a lower efficiency score under method 1 than under the solid waste sub-index. This is because method 1 does not include solid waste parameters in its calculation, therefore the efficiency score resulting from method 1 could not reflect the DMU environmental performance.

With method 2, the efficiency scores are generally higher when compared to the solid waste sub-index results. This result agrees with Hua and Bian’s findings (2007) that treating undesirable outputs as inputs cannot reflect the true production process and easily distorts the DMU’s eco-efficiency. The results also confirm the finding in Section 4.2.1 which states that the existing eco-DEA tends to increase efficiency scores. The eco-related parameter has been a factor that favours the efficiency of the DMU.

For DMU 1993 - 1994, 2001 and 2003 and 2004-2007, there is a significant discrepancy between the solid waste sub-index and the efficiency scores obtained by method 3 and method 4. The solid waste sub-index is generally lower in these eight DMUs. For method 3 and method 4, the undesirable output is considered a positive extra output for the DEA. Therefore, the efficiency score would accordingly be higher for these DEA approaches. With the support of the finding in Section 4.2.1, it is believed that the Ratio Model can reflect the environmental performance in the most appropriate way, so the amount of desirable and undesirable outputs are proportionate to each other, normalising the desirable output by the undesirable output. An increase in the undesirable output can directly affect the amount of desirable output.

5.4.4 The Green Index of Case Study 1

The overall Green Index is obtained as the sum of the three environmental sub-indices, as discussed in the previous sections. Table 5-12 describes the grading results of the 17 DMUs, based on the Green Index.

Table 5-12 Efficiency score of the four eco-DEA and the Green Index (Case Study 1)

Year	Method 1	Method 2	Method 3	Method 4	Green Index
1991	2.406	2.443	2.406	2.406	2.406
1992	2.253	2.406	2.253	2.253	2.253
1993	2.460	2.633	2.467	2.474	2.298
1994	2.637	2.838	2.699	2.768	2.650
1995	2.208	2.585	2.261	2.281	2.201
1996	2.274	2.817	2.759	2.765	2.751
1997	2.436	2.707	2.597	2.624	2.579
1998	2.637	2.866	2.738	2.759	2.670
1999	2.994	3.000	2.999	3.000	2.998
2000	3.000	3.000	3.000	3.000	3.000
2001	3.000	3.000	3.000	3.000	2.944
2002	3.000	3.000	3.000	3.000	2.922
2003	3.000	3.000	3.000	3.000	2.958
2004	3.000	3.000	3.000	3.000	2.869
2005	2.958	2.978	2.959	2.976	2.779
2006	3.000	3.000	3.000	3.000	2.749
2007	3.000	3.000	3.000	3.000	2.719

From the comparative studies conducted in the previous sections, it is concluded that method 2-4 tend to yield higher efficiency scores than method 1 and the Ratio Model. In the computation in method 2-4, the total volume of polluted air, wastewater and solid waste generated from yarn and cloth manufacturing in China is regarded as either input or output. However, with the repetitive studies completed in Chapters 4 and 5, it is commonly observed that the existing eco-DEA would tend to give a higher efficiency scores. This observation further proves that these methods fail to characterise the undesirable outputs in an appropriate manner. They are not sensitive enough to characterise the changes in the amount of desirable and undesirable outputs at the same time. Whereas for method 1, as environmental quality is not included in the computation, the results from method 1 cannot be a reference for stakeholders when looking into environmental problems or carrying out related management procedures. As a result, the efficiency score can be easily distorted without considering the appropriate factors. There are chances that the original DEA will give false credit to the DMU which does not perform that well from an environmental perspective. Therefore, the Green Index is able to evaluate the green performance of the DMU. To further validate the Ratio Model, the environmental performance of the yarn and cloth manufacturing in the past seventeen years is assessed by policies implemented in related areas.

Although the Chinese government has been encouraging the textile industry to control pollution, there are indeed some limitations in the textile industry that induce fluctuations in the environmental performance from time to time. According to the China Textile Industry Development Report (Zhongguo fang zhi gong ye xie hui, various issues), cost is one of the factors that discourages textile plants from executing environmental policies. They may find the cost too high to set up wastewater treatment facilities. To reduce expenses, instead of using the latest model, textile plants use the old machinery that consumes more energy. Also, there are numerous textile plants scattered around the country, which some of them do not possess the concept of environmental protection. In addition, a plant may find it hard to keep up with the latest technology, simply because it does not have enough space or its existing facilities are not compatible.

All these factors increase the difficulty in the implementation of laws and regulations. Another limitation is textile product quality. China produces mainly middle to low quality textile goods. In order to maintain production costs as low as possible, the raw materials used may be of inferior quality, requiring extra energy and resources to process. For instance, poor quality dyes are less efficient and remain in the water after the dyeing process.

5.4.5 Improvement for the inefficient DMUs of Case Study 1

In DEA, the DMUs with less than 1.000 efficiency score are considered as inefficient. For the DMUs with 1.000, they are regarded as benchmark for the inefficient DMUs. Therefore, in order to achieve an efficient performance, the inefficient DMUs can improve in both their input and output to reach the frontier which is formed by the efficient DMUs. The efficiency frontier acts as a standard performance for the inefficient DMUs as reference. By simple calculation, the output ratios can be converted to the target output amount suggested by the programme. The targets for the inputs and outputs of the inefficient DMUs computed by the Ratio Model for the respective sub-indices can be found in Appendix B.

5.5 Case Study 2: China's Chemical Fibre Production 1991-2007

The second scenario focuses on the environmental performance of chemical fibre production in the entire country from 1991-2007. In order to give the Green Index for each DMU, it is necessary to compute the relative efficiency score for each sub-index. The DMU selected in this study is the annual performance of the chemical fibre manufacturing factory in China from 1991-2007. Therefore, there are altogether 17 DMUs being evaluated. The details of all the chosen variables for the case studies are described in Chapter 3 and summarised in Figure 5-7. The following sections analyse the data and ratios of the outputs computed for each sub-index.

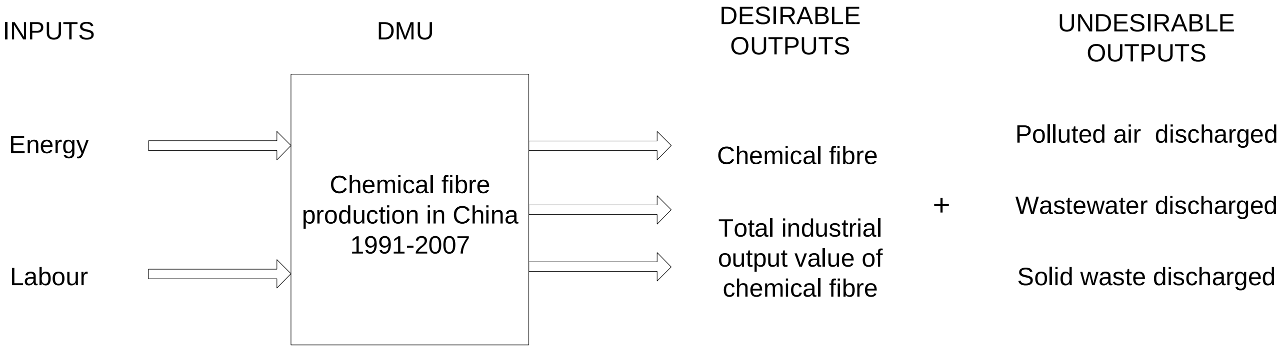


Figure 5-7 The inputs and outputs of Case Study 2

5.5.1 Polluted air sub-index of Case Study 2

Table 5-13 shows the textile industry data and the amount of polluted air produced. The first column identifies the 17 years as DMUs, while the second and third columns list the two inputs for the study. Columns 4, 5 and 6 provide the three desirable outputs, and the seventh column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Columns 2, 3 and 4 in Table 5-14 show the ratios of the three desirable outputs to the total volume of polluted air emissions, and the last column illustrates the results of the polluted air sub-index of the 17 DMUs, computed by the new eco-DEA Ratio Model.

Table 5-13 Data of the polluted air sub-index (Case Study 2)

DMU	Inputs		Desirable output		Undesirable output
	1	2	1	2	1
Year	**Labour (10 000 persons)**	**Total energy consumption (10 000 tn SCE)**	**Chemical fibre output (10 000 tons)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial polluted air emission (100 million cu.m)**
1991	30.75	855.60	191.03	102.32	1857
1992	32.42	932.00	213.04	102.98	2327
1993	50.28	962.57	237.37	166.17	2269
1994	52.36	993.13	280.33	187.98	2219
1995	56.61	1278.00	341.17	204.07	2543
1996	57.37	1079.82	375.45	186.66	2541
1997	60.11	1434.52	471.62	195.06	2909
1998	48.13	1600.07	510.00	190.81	2893
1999	46.24	1538.20	600.00	225.65	2961
2000	44.33	1677.96	694.00	284.92	2750
2001	43.57	1705.02	841.38	281.99	2811
2002	38.88	1942.76	991.20	254.93	3090
2003	34.85	2199.87	1181.15	317.23	2724
2004	38.67	1303.03	1699.80	422.82	2557
2005	40.76	1342.00	1664.79	551.64	2886
2006	41.12	1423.97	2073.18	668.57	2617
2007	44.58	1553.97	2413.78	752.40	2504

Source: Statistical Yearbook of China, various issues

Table 5-14 Output ratios and results under the polluted air sub-index (Case Study 2)

Year	Chemical fibre ratio ($x10^{-3}$)	Total industrial output value ratio ($x10^{-3}$)	Polluted air sub-index
1991	102.87	55.10	1.000
1992	91.55	44.26	0.948
1993	104.61	73.23	0.956
1994	126.33	84.71	0.968
1995	134.16	80.25	0.740
1996	147.76	73.46	0.853
1997	162.12	67.05	0.630
1998	176.29	65.96	0.659
1999	202.63	76.21	0.696
2000	252.36	103.61	0.767
2001	299.32	100.32	0.776
2002	320.78	82.50	0.861
2003	433.61	116.46	1.000
2004	664.76	165.36	1.000
2005	576.85	191.14	1.000
2006	792.20	255.47	1.000
2007	963.97	300.48	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the polluted air sub-index. Therefore, the results titled polluted air sub-index in Table 5-14 and Table 5-15 are calculated by the Ratio Model.

There are six efficient DMUs identified by the polluted air sub-index which obtain a relative efficiency score of 1.000. They are years 1991, 2003, 2004, 2005, 2006 and 2007. The remaining DMUs are considered to be inefficient, because the efficiency score is less than 1.000. The environmental performance of China’s chemical fibre production fluctuates in the period 1995-2002, and has achieved 100% efficiency since 2003. It is important that the parameter computation is significantly discriminative, so that the diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-15.

Table 5-15 Efficiency score of the four eco-DEA and the polluted air sub-index (Case Study 2)

Year	Method 1	Method 2	Method 3	Method 4	Polluted air Sub-index
1991	1.000	1.000	1.000	1.000	1.000
1992	0.951	0.951	0.951	0.951	0.948
1993	0.955	0.955	0.955	0.955	0.942
1994	0.948	0.948	0.948	0.948	0.946
1995	0.749	0.770	0.749	0.749	0.725
1996	0.871	0.871	0.871	0.871	0.841
1997	0.661	0.670	0.661	0.661	0.629
1998	0.673	0.678	0.673	0.673	0.659
1999	0.714	0.714	0.714	0.714	0.694
2000	0.769	0.769	0.769	0.769	0.750
2001	0.782	0.783	0.782	0.782	0.768
2002	0.882	0.882	0.882	0.882	0.861
2003	1.000	1.000	1.000	1.000	1.000
2004	1.000	1.000	1.000	1.000	1.000
2005	0.974	0.974	0.974	0.974	0.929
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-15, the efficiency score in 1995-1998 for method 1 is remarkably low because the model does not consider the environmental quality in the calculation. The inclusion of the undesirable output in assessing the environmental performance is necessary. Therefore, method 1 deforms the performance of yarn and cloth manufacturing in that period.

The efficiency score for method 2 is generally higher than other approaches, such as DMU 1995, 1997, 1998, 2000 and 2001. This result agrees with Hua and Bian (2007) that treating undesirable outputs as inputs cannot reflect the true production process and easily distorts the eco-efficiency of the DMU. Also, the results confirm the finding in Chapter 4 which states that the existing eco-DEA tends to increase the efficiency scores. The eco-related parameter has been a factor that simply favours the efficiency of the DMU.

According to the Ratio Model, the increase in the chemical fibre ratio and the total industrial output value ratio is due to the low industrial polluted air emissions in that particular year. This benefits an increase in the polluted air sub-index and magnifies the change in the total volume of industrial polluted air. The examples are 2002 and 2003. The polluted air sub-index has fairly similar results when compared with method 1, method 3 and method 4. However, for 1996 and 1999, the polluted air sub-index is lower than the efficiency score of method 3 and method 4. This is because method 3 and 4 fail to characterise the undesirable output and they treat the undesirable output with a similar approach as the desirable output. Therefore, the Ratio Model manages to give a lower result, which gives that data more discriminative power to assess the performance of the DMU.

5.5.2 Wastewater sub-index of Case Study 2

Table 5-16 shows the textile industry data and the amount of wastewater discharged. The first column identifies the 17 years as DMUs, while the second and third columns list the two inputs for the study. Columns 4, 5 and 6 provide the three desirable outputs, and the seventh column indicates the undesirable output, which is the environmental quality to be assessed in this sub-index. Columns 2, 3 and 4 in Table 5-17 show the ratios of the three desirable outputs to the total volume of wastewater generated, and the last column illustrates the results of the wastewater sub-index of the 17 DMUs computed by the new eco-DEA Ratio Model.

Table 5-16 Data of the wastewater sub-index (Case Study 2)

DMU	Input		Desirable output		Undesirable output
	1	2	1	2	1
Year	**Labour (10 000 persons)**	**Total energy consumption (10 000 tn SCE)**	**Chemical fibre output (10 000 tons)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial wastewater discharge (10 000 tons)**
1991	30.75	855.60	191.03	102.32	51883
1992	32.42	932.00	213.04	102.98	59677
1993	50.28	962.57	237.37	166.17	57622
1994	52.36	993.13	280.33	187.98	52040
1995	56.61	1278.00	341.17	204.07	55945
1996	57.37	1079.82	375.45	186.66	52302
1997	60.11	1434.52	471.62	195.06	54344
1998	48.13	1600.07	510.00	190.81	54538
1999	46.24	1538.20	600.00	225.65	50037
2000	44.33	1677.96	694.00	284.92	53134
2001	43.57	1705.02	841.38	281.99	59695
2002	38.88	1942.76	991.20	254.93	53954
2003	34.85	2199.87	1181.15	317.23	48847
2004	38.67	1303.03	1699.80	422.82	47467
2005	40.76	1342.00	1664.79	551.64	48516
2006	41.12	1423.97	2073.18	668.57	49543
2007	44.58	1553.97	2413.78	752.40	48957

Source: Statistical Yearbook of China, various issues

Table 5-17 Output ratios and results under wastewater sub-index (Case Study 2)

Year	Chemical fibre ratio ($x10^{-4}$)	Total industrial output value ratio ($x10^{-4}$)	Wastewater sub-index
1991	36.82	19.72	1.000
1992	35.70	17.26	0.948
1993	41.19	28.84	0.936
1994	53.87	36.12	0.943
1995	60.98	36.48	0.734
1996	71.79	35.69	0.865
1997	86.78	35.89	0.652
1998	93.51	34.99	0.668
1999	119.91	45.10	0.714
2000	130.61	53.62	0.762
2001	140.95	47.24	0.763
2002	183.71	47.25	0.869
2003	241.81	64.94	1.000
2004	358.10	89.08	1.000
2005	343.14	113.70	0.983
2006	418.46	134.95	1.000
2007	493.04	153.69	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the wastewater sub-index. Therefore, the results titled wastewater sub-index in Table 5-17 and Table 5-18 are calculated by the Ratio Model.

There are five efficient DMUs identified by the wastewater sub-index which obtain a relative efficiency score of 1.000. They are the year 1991, 2003, 2004, 2006 and 2007. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. The average efficiency scores from 1995-2002 are noticeably lower when compared to the efficiency scores before 1995 and after 2002. The efficiency score fluctuates between 1995 and 2002. It is important that the computation of the parameters is significantly discriminative so that the diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-18.

Table 5-18 Efficiency score of the four eco-DEA and the wastewater sub-index (Case Study 2)

Year	Method 1	Method 2	Method 3	Method 4	Wastewater Sub-index
1991	1.000	1.000	1.000	1.000	1.000
1992	0.951	0.951	0.951	0.951	0.948
1993	0.955	0.955	0.955	0.955	0.936
1994	0.948	0.976	0.948	0.948	0.943
1995	0.749	0.880	0.749	0.749	0.734
1996	0.871	0.958	0.871	0.871	0.865
1997	0.661	0.881	0.661	0.661	0.652
1998	0.673	0.870	0.673	0.673	0.668
1999	0.714	0.949	0.731	0.734	0.714
2000	0.769	0.893	0.769	0.769	0.762
2001	0.782	0.820	0.782	0.782	0.763
2002	0.882	0.907	0.882	0.882	0.869
2003	1.000	1.000	1.000	1.000	1.000
2004	1.000	1.000	1.000	1.000	1.000
2005	0.974	1.000	1.000	1.000	0.983
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-18, although the efficiency score under method 1 and the wastewater sub-index has a moderately similar trend, method 1 does not consider the environmental quality in the calculation. Method 1 solely shows the manufacturing efficiency of chemical fibre production in China from 1991-2007. However, the Ratio Model incorporates undesirable outputs into computation, thus the variables are viewed from a different perspective.

The efficiency scores for method 2 are generally higher than other approaches. This result agrees with Hua and Bian (2007) that treating undesirable outputs as inputs cannot reflect the true production process and easily distorts the eco-efficiency of the DMU. Also, the results also confirm the finding in Section 4.2.1, which states that the existing eco-DEA tends to increase the efficiency scores. The eco-related parameter has been a factor that simply favours the efficiency of the DMU.

There are some differences in the wastewater sub-index when compared with method 3 and method 4. Generally, the environmental performance under method 3 and method 4 perform better than the wastewater sub-index for the same DMU from 1993-2002. 2005 has a significantly lower sub-index, because when environmental quality is incorporated with the computation, the chemical fibre ratio has dropped from 358.10 to 343.14 in 2005. This shows there was less chemical fibre produced per unit of wastewater discharged. Although there is a decrease in the chemical fibre output in 2005 when compared to 2004, the ratio approach magnifies the decrease. Therefore, the newly developed Ratio Model is more sensitive to change in both desirable output and undesirable output. This example could verify the findings from Chapter 4 as well. The way the existing eco-DEA incorporate the undesirable output would favour the efficiency score. The computation of the undesirable output should be properly characterised so that it can have a positive or a negative effect on the overall performance of the DMU. Therefore, it can show that the Ratio Model is more advanced when compared to other approaches.

5.5.3 Solid waste sub-index of Case Study 2

Table 5-19 shows the textile industry data and the amount of solid waste produced. The first column identifies the 17 years as DMUs, while the second and third columns list the two inputs for the study. Columns 4, 5 and 6 provide the three desirable outputs and the seventh column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Columns 2, 3 and 4 show the ratios of the three desirable outputs to the total volume of solid waste generated, and the last column illustrates the results of the solid waste sub-index of the 17 DMUs computed by the new eco-DEA Ratio Model.

Table 5-19 Data of the solid waste sub-index (Case Study 2)

DMU	Inputs		Desirable output		Undesirable output
	1	2	1	2	1
Year	**Labour (10 000 persons)**	**Total energy consumption (10 000 tn SCE)**	**Chemical fibre output (10 000 tons)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Volume of industrial solid waste generated (10 000 tons)**
1991	30.75	855.60	191.03	102.32	176
1992	32.42	932.00	213.04	102.98	245
1993	50.28	962.57	237.37	166.17	247
1994	52.36	993.13	280.33	187.98	256
1995	56.61	1278.00	341.17	204.07	262
1996	57.37	1079.82	375.45	186.66	291
1997	60.11	1434.52	471.62	195.06	322
1998	48.13	1600.07	510.00	190.81	255
1999	46.24	1538.20	600.00	225.65	286
2000	44.33	1677.96	694.00	284.92	329
2001	43.57	1705.02	841.38	281.99	355
2002	38.88	1942.76	991.20	254.93	352
2003	34.85	2199.87	1181.15	317.23	81
2004	38.67	1303.03	1699.80	422.82	322
2005	40.76	1342.00	1664.79	551.64	342
2006	41.12	1423.97	2073.18	668.57	376
2007	44.58	1553.97	2413.78	752.40	355

Source: Statistical Yearbook of China, various issues

Table 5-20 Output ratios and results under the solid waste sub-index (Case Study 2)

Year	Chemical fibre ratio ($x10^{-1}$)	Total industrial output value ratio ($x10^{-1}$)	Solid waste sub-index
1991	10.85	5.81	1.000
1992	8.70	4.20	0.948
1993	9.61	6.73	0.927
1994	10.95	7.34	0.924
1995	13.02	7.79	0.732
1996	12.90	6.41	0.815
1997	14.65	6.06	0.623
1998	20.00	7.48	0.645
1999	20.98	7.89	0.672
2000	21.09	8.66	0.702
2001	23.70	7.94	0.715
2002	28.16	7.24	0.804
2003	145.82	39.16	1.000
2004	52.79	13.13	0.977
2005	48.68	16.13	0.948
2006	55.14	17.78	0.940
2007	68.05	21.21	0.950

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the solid waste sub-index. Therefore, the results titled solid waste sub-index in Table 5-20 and Table 5-21 are calculated by the Ratio Model.

There are two efficient DMUs identified by the solid waste sub-index which obtain a relative efficiency score of 1.000. They are year 1991 and 2003. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. The average efficiency scores in 1995-2002 are noticeably lower when compared to the efficiency score before 1994 and after 2002. However, the efficiency score fluctuates between 1995 and 2002 and has continued to perform above 0.95 since 2003. It is important that the computation of the parameters is significantly discriminative, so that the diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-21 .

Table 5-21 Efficiency score of the four eco-DEA and the solid waste sub-index (Case Study 2)

Year	Method 1	Method 2	Method 3	Method 4	Solid waste Sub-index
1991	1.000	1.000	1.000	1.000	1.000
1992	0.951	0.951	0.951	0.951	0.948
1993	0.955	0.955	0.955	0.955	0.927
1994	0.948	0.948	0.948	0.948	0.924
1995	0.749	0.769	0.749	0.749	0.732
1996	0.871	0.871	0.871	0.871	0.815
1997	0.661	0.661	0.661	0.661	0.623
1998	0.673	0.697	0.673	0.673	0.645
1999	0.714	0.714	0.714	0.714	0.672
2000	0.769	0.769	0.769	0.769	0.702
2001	0.782	0.782	0.782	0.782	0.715
2002	0.882	0.882	0.882	0.882	0.804
2003	1.000	1.000	1.000	1.000	1.000
2004	1.000	1.000	1.000	1.000	0.977
2005	0.974	0.975	0.974	0.974	0.948
2006	1.000	1.000	1.000	1.000	0.940
2007	1.000	1.000	1.000	1.000	0.950

From Table 5-21, the efficiency score in 2003 is 1.000 for all methods because the solid waste generated was low that year, therefore the unit of desirable output produced per unit of solid waste is high.

The efficiency scores for method 2 are generally higher than other approaches. This result agrees with Hua and Bian’s findings (2007) that treating undesirable outputs as inputs cannot reflect the true production process and easily distorts the eco-efficiency of the DMU. The results also confirm the finding in Section 4.2.1 which states the existing eco-DEA tends to increase the efficiency scores. The eco-related parameter has been a factor that favours the DMU’s efficiency.

The efficiency scores under method 3 and method 4 are generally higher than under the solid waste sub-index. For example, the efficiency score for 2005 and 2006 are 0.974 and 1.000 respectively. However, the solid waste sub-index gives the two DMUs an efficiency score of 0.940 and 0.950. This confirms the finding in Section 4.2.1 that states the various environmental DEA technologies tend to give a better efficiency score. Method 3 and method 4 are different from the newly developed Ratio Model because method 3 and method 4 view the undesirable output as a “positive” output in the DEA, which would favour the efficiency score. For the Ratio Model, the desirable output and the undesirable output are aggregated in a ratio form, which provides a more discriminative way to expose the impact of the undesirable output in the model. As the Ratio Model is sensitive to change in the variables, the solid waste sub-index for both years decreases, while the other approaches increase.

5.5.4 The Green Index of Case Study 2

The overall Green Index can be obtained as the sum of the three environmental sub-indices as discussed in the previous sections. Table 5-22 describes the grading results of the 17 DMU based on the Green Index.

Table 5-22 Efficiency score of the four eco-DEA and the Green Index (Case Study 2)

Year	Method 1	Method 2	Method 3	Method 4	Green Index
1991	3.000	3.000	3.000	3.000	3.000
1992	2.853	2.853	2.853	2.853	2.844
1993	2.865	2.865	2.865	2.865	2.805
1994	2.844	2.872	2.844	2.844	2.813
1995	2.247	2.416	2.247	2.247	2.191
1996	2.613	2.700	2.613	2.613	2.521
1997	1.983	2.212	1.983	1.983	1.904
1998	2.019	2.245	2.019	2.019	1.972
1999	2.142	2.377	2.159	2.162	2.080
2000	2.307	2.431	2.307	2.307	2.214
2001	2.346	2.385	2.346	2.346	2.246
2002	2.646	2.671	2.646	2.646	2.534
2003	3.000	3.000	3.000	3.000	3.000
2004	3.000	3.000	3.000	3.000	2.977
2005	2.922	2.949	2.948	2.948	2.860
2006	3.000	3.000	3.000	3.000	2.940
2007	3.000	3.000	3.000	3.000	2.950

As evident from the three sub-indices of Case Study 2, it is concluded that methods 1-4 fail to characterise the environmental performance of the DMU. The Ratio Model aggregates the desirable output and the undesirable output in a ratio form so that the undesirable output is discriminative enough as a parameter to assess the DMU’s environmental performance. Thus, there is dissimilarity between the overall performance indication under the five approaches.

The Green Index in Table 5-22 is the sum of the three pollutant sub-indices. Therefore, the result of the respective sub-index would directly affect the final Green Index. As observed from the data, the increase in the chemical fibre output has a larger magnitude than the undesirable output. Therefore, environmental performance has been increasing since 1997. Under the Ratio Model, as the solid waste sub-index drops in 2005-2007, it affects the results of the Green Index in the same period.

From Table 5-22, it can be observed that the environmental performance of chemical fibre production in China has fluctuated in the past 17 years, regardless of the approaches used in evaluation. This indicates the instability of environmental performance in textile manufacturing. Similar to yarn and cloth production, the green performance of chemical fibre production has been decreasing in recent years. With a tremendous output of desirable products produced, the economic benefits are offset by the environmental consequences. As there are many variables that affect the efficiency score, it is therefore difficult to identify which particular reason affects the results. The production of chemical fibre may be due to the rise in the price of the raw material, which is petroleum (Zhongguo fang zhi gong ye xie hui, various issues). There is an increase after 1997 with the Green Index rising from 2.000 to 3.000 in 2003. The increase is due to the efforts of the Chinese government to protect the production of chemical fibres by implementing trade policies and cracking down on smuggling (Zhongguo fang zhi gong ye xie hui, various issues).

5.5.5 Improvement for the inefficient DMU of Case Study 2

In the DEA, the DMUs with less than a 1.000 efficiency score are considered inefficient. DMUs with a 1.000 score are regarded as a benchmark for the inefficient DMUs. Therefore, in order to achieve an efficient performance, the inefficient DMUs can improve both their input and output to reach the frontier formed by the efficient DMUs. The efficiency frontier acts as a standard performance for the inefficient DMUs as reference. The targets for the inputs and outputs of the inefficient DMUs computed by the Ratio Model, are shown in Appendix B.

5.6 Case Study 3: Jiangsu Yarn and Cloth Production 1998-2007

The third scenario examines the environmental performance of yarn and cloth production in Jiangsu province from 1998-2007. In order to give the Green Index for each DMU, it is necessary to compute the relative efficiency score for each sub-index. The DMU selected in this study is the annual performance of the yarn and cloth manufacturing factory in Jiangsu from 1998-2007. Therefore, there are altogether 10 DMUs being evaluated. The details of all the chosen variables for the case studies are described in Chapter 3 and summarised in Figure 5-8. The following sections analyse the data and the ratios of the outputs computed for each sub-index.

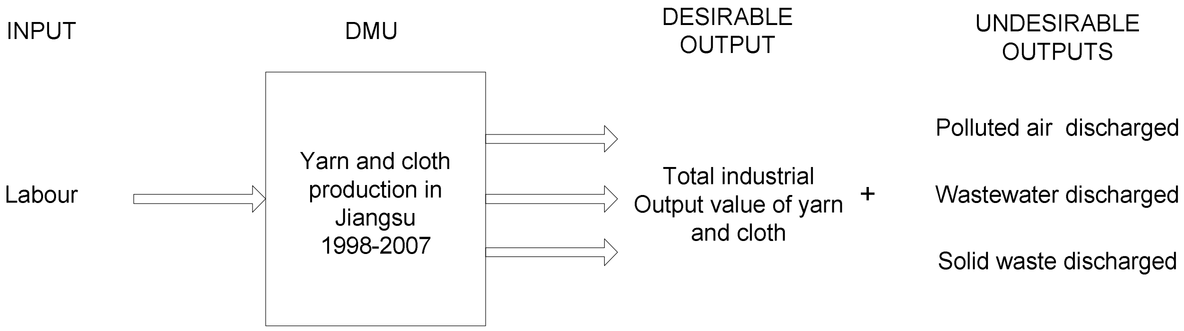


Figure 5-8 The inputs and outputs of Case Study 3

5.6.1 Polluted air sub-index of Case Study 3

Table 5-23 shows the textile industry data and the amount of polluted air produced. The first column identifies the 10 years as DMUs, while the second column lists the input for the study. Column 3 provides the desirable output and the fourth column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Column 2 in Table 5-24 shows the ratios of the desirable output to the total volume of polluted air emissions, and the last column illustrates the results of the polluted air sub-index of the 10 DMUs computed by the new eco-DEA Ratio Model.

Table 5-23 Data of the polluted air sub-index (Case Study 3)

DMU	Input	Desirable output	Undesirable output
	1	1	3
Year	Labour (10 000 persons)	Total industrial output value (100 million RMB) (at 1978 price)	Total volume of industrial polluted air emission (100 million cu.m)
1998	50.04	237.18	299.00
1999	45.81	255.49	293.00
2000	42.40	285.24	293.00
2001	38.34	309.03	402.00
2002	34.19	355.19	461.00
2003	30.60	416.97	398.59
2004	29.41	500.25	419.89
2005	29.71	652.45	400.50
2006	34.46	778.25	427.75
2007	32.05	873.97	379.19

Source: Jiangsu Statistical Yearbook, various issues

Table 5-24 Output ratios and results under the polluted air sub-index (Case Study 3)

Year	**Total textile value ratio ($x10^{-1}$)**	**Polluted air sub-index**
1998	7.93	0.588
1999	8.72	0.642
2000	9.74	0.694
2001	7.69	0.767
2002	7.70	0.860
2003	10.46	0.961
2004	11.91	1.000
2005	16.29	1.000
2006	18.19	0.881
2007	23.05	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the polluted air sub-index. Therefore, the results titled polluted air sub-index in Table 5-24 and Table 5-25 are calculated by the Ratio Model.

There are three efficient DMUs identified by the polluted air sub-index which obtain a relative efficiency score of 1.000. They are year 2004, 2005 and 2007. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. From the polluted air sub-index, the environmental performance of Jiangsu yarn and cloth production has been improving for the past 10 years. However, in 2006, the polluted air sub-index drops from 1.000 to 0.881. It is important that the computation of the parameters is significantly discriminative so that the diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-25.

Table 5-25 Efficiency score of the four eco-DEA and the polluted air sub-index (Case Study 3)

Year	Method 1	Method 2	Method 3	Method 4	Polluted air Sub-index
1998	0.588	0.980	0.828	0.833	0.588
1999	0.642	1.000	0.926	0.926	0.642
2000	0.694	1.000	1.000	1.000	0.694
2001	0.767	0.896	0.774	0.774	0.767
2002	0.860	0.869	0.860	0.860	0.860
2003	0.961	0.991	0.975	0.978	0.961
2004	1.000	1.000	1.000	1.000	1.000
2005	1.000	1.000	1.000	1.000	1.000
2006	0.901	0.905	0.901	0.901	0.881
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-25, the polluted air sub-index has similar results with the efficiency score of method 1 except DMU 2006. Despite the similarity, the sub-index of 2006 indicates the computation of the data for both methods has a discrepancy. As the ratio model includes the environmental quality, the data would show some differences that affect the results in both models.

The efficiency score of method 2 to method 4 are generally higher than method 1 and polluted air sub-index. This is because method 2 to method 4 incorporates one more positive output into computation. With the phenomenon as discussed in Chapter 4, an increase in the number of outputs may lead to an increase in the efficiency score as well. Therefore, under method 2, method 3 and method 4, the presence of the environmental parameter would benefit the performance of the DMU.

5.6.2 Wastewater sub-index of Case Study 3

Table 5-26 shows the textile industry data and the amount of wastewater discharged. The first column identifies the 10 years as DMUs, while the second column lists the input for the study. Column 3 provides the desirable output and the fourth column indicates the undesirable output, which is the environmental quality to be assessed in this sub-index. Column 2 in Table 5-27 shows the ratios of the desirable output to the total volume of wastewater discharged, and the last column illustrates the results of the wastewater sub-index of the 10 DMUs computed by the new eco-DEA Ratio Model.

Table 5-26 Data of wastewater sub-index (Case Study 3)

DMU	**Input**	**Desirable output**	**Undesirable output**
	1	**1**	**3**
Year	**Labour (10 000 persons)**	**After normalising the price effect with 1978 as the base year**	**Total volume of industrial wastewater discharge (10 000 tons)**
1998	50.04	237.18	21905.00
1999	45.81	255.49	21486.00
2000	42.40	285.24	24583.00
2001	38.34	309.03	33239.00
2002	34.19	355.19	34274.00
2003	30.60	416.97	33827.16
2004	29.41	500.25	42189.19
2005	29.71	652.45	47929.86
2006	34.46	778.25	48436.23
2007	32.05	873.97	53390.55

Source: Jiangsu Statistical Yearbook, various issues

Table 5-27 Output ratios and results under the wastewater sub-index (Case Study 3)

Year	Total textile value ratio ($x10^{-3}$)	Wastewater sub-index
1998	10.83	0.588
1999	11.89	0.642
2000	11.60	0.694
2001	9.30	0.767
2002	10.36	0.860
2003	12.33	0.964
2004	11.86	1.000
2005	13.61	1.000
2006	16.07	0.923
2007	16.37	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the wastewater sub-index. Therefore, the results titled wastewater sub-index in Table 5-27 and Table 5-28 are calculated by the Ratio Model.

There are three efficient DMUs identified by the wastewater sub-index which obtain a relative efficiency score of 1.000. They are year 2004, 2005 and 2007. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. From the wastewater sub-index, the environmental performance of Jiangsu yarn and cloth production has been improving for the past 10 years. However, in 2006, the polluted air sub-index drops from 1.000 to 0.923. It is important that the parameter computation be significantly discriminative so that diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-28

Table 5-28 Efficiency score of the four eco-DEA and the wastewater sub-index (Case Study 3)

Year	Method 1	Method 2	Method 3	Method 4	Wastewater Sub-index
1998	0.588	0.981	0.901	0.905	0.588
1999	0.642	1.000	1.000	1.000	0.642
2000	0.694	0.994	0.957	0.990	0.694
2001	0.767	0.912	0.810	0.817	0.767
2002	0.860	0.946	0.893	0.893	0.860
2003	0.961	1.000	1.000	1.000	0.964
2004	1.000	1.000	1.000	1.000	1.000
2005	1.000	1.000	1.000	1.000	1.000
2006	0.901	1.000	0.915	1.000	0.923
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-28, the wastewater sub-index has similar results with the efficiency score of method 1, except DMU 2003 and 2006. Despite the similarity, the sub-index of 2006 indicates the computation of the data for both methods has a discrepancy. As the Ratio Model includes environmental quality, the data would show some differences that affect the results in both models.

The efficiency scores of method 2 to method 4 are generally higher than method 1 and wastewater sub-index. This is because method 2 to method 4 incorporates one more positive output into computation. This phenomenon is thoroughly discussed and confirms the finding in Section 4.2.1, which states that an increase in the number of outputs may also lead to an increase in the efficiency score. Therefore, under method 2, method 3 and method 4, the presence of the environmental parameter would benefit DMU performance. The newly developed Ratio Model is more advanced in describing the undesirable output.

5.6.3 Solid waste sub-index of Case Study 3

Table 5-29 shows the textile industry data and the amount of solid waste generated. The first column identifies the 10 years as DMUs, while the second column lists the input for the study. Column 3 provides the desirable output and the fourth column indicates the undesirable output, which is the environmental quality to be assessed in this sub-index. Column 2 in Table 5-30 shows the ratios of the desirable output to the total volume of solid waste produced, and the last column illustrates the results of the solid waste sub-index of the 10 DMUs computed by the new eco-DEA Ratio Model.

Table 5-29 Data of the solid waste sub-index (Case Study 3)

DMU	**Input**	**Desirable output**	**Undesirable output**
	1	**1**	**3**
Year	**Labour (10 000 persons)**	**After normalising the price effect with 1978 as the base year**	**Total volume of industrial solid waste produced (10,000 tons)**
1998	50.04	237.18	87.00
1999	45.81	255.49	80.00
2000	42.40	285.24	87.00
2001	38.34	309.03	105.23
2002	34.19	355.19	127.70
2003	30.60	416.97	138.04
2004	29.41	500.25	156.21
2005	29.71	652.45	142.46
2006	34.46	778.25	156.01
2007	32.05	873.97	139.48

Source: Jiangsu Statistical Yearbook, various issues

Table 5-30 Output ratios and results of the solid waste sub-index (Case Study 3)

Year	Total textile value ratio	Solid waste sub-index
1998	2.73	0.588
1999	3.19	0.642
2000	3.28	0.694
2001	2.94	0.767
2002	2.78	0.860
2003	3.02	0.964
2004	3.20	1.000
2005	4.58	1.000
2006	4.99	0.923
2007	6.27	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the solid waste sub-index. Therefore, the results titled solid waste sub-index in Table 5-30 and Table 5-31 are calculated by the Ratio Model.

There are three efficient DMUs identified by the solid waste sub-index which obtain a relative efficiency score of 1.000. They are years 2004, 2005 and 2007. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. From the solid waste sub-index, the environmental performance of Jiangsu yarn and cloth production has been improving for the past 10 years. However, in 2006, the solid waste sub-index drops from 1.000 to 0.923. It is important that the computation of the parameters be significantly discriminative, so that the diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-31.

Table 5-31 Efficiency score of the four eco-DEA and the solid waste sub-index (Case Study 3)

Year	Method 1	Method 2	Method 3	Method 4	Solid waste Sub-index
1998	0.588	0.920	0.847	0.847	0.588
1999	0.642	1.000	1.000	1.000	0.642
2000	0.694	1.000	1.000	1.000	0.694
2001	0.767	0.998	0.959	0.996	0.767
2002	0.860	0.981	0.936	0.965	0.860
2003	0.961	1.000	0.991	1.000	0.964
2004	1.000	1.000	1.000	1.000	1.000
2005	1.000	1.000	1.000	1.000	1.000
2006	0.901	0.902	0.901	0.901	0.923
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-31, the solid waste sub-index has similar results with an efficiency score of method 1, except DMU 2003 and 2006. Despite the similarity, the sub-index of 2006 indicates the data computation for both methods contains a discrepancy. As the Ratio Model includes environmental quality, the data would show some differences that affect the results in both models.

The efficiency scores of method 2 to method 4 are generally higher than method 1 and the solid waste sub-index. This is because method 2 to method 4 incorporates one more positive output into computation. The results also confirm the finding in Section 4.2.1, which states that the existing eco-DEA tends to increase the efficiency scores. The eco-related parameter has been a factor that simply favours the efficiency of the DMU.

5.6.4 The Green Index of Case Study 3

The overall Green Index can be obtained as the sum of the three environmental sub-indices as discussed in the previous sections. Table 5-32 describes the grading results of the 17 DMU based on the Green Index.

Table 5-32 Efficiency score of the four eco-DEA and the Green Index (Case Study 3)

Year	Method 1	Method 2	Method 3	Method 4	Green Index
1998	1.764	2.881	2.576	2.585	1.764
1999	1.926	3.000	2.926	2.926	1.926
2000	2.082	2.994	2.957	2.990	2.082
2001	2.301	2.806	2.543	2.587	2.301
2002	2.580	2.796	2.689	2.718	2.580
2003	2.883	2.991	2.966	2.978	2.889
2004	3.000	3.000	3.000	3.000	3.000
2005	3.000	3.000	3.000	3.000	3.000
2006	2.703	2.807	2.717	2.802	2.727
2007	3.000	3.000	3.000	3.000	3.000

As evident from the three sub-indices of Case Study 3, it is concluded that methods 1-4 fail to characterise the DMU's environmental performance. The Ratio Model aggregates the desirable output and undesirable output in a ratio form so that the undesirable output is discriminative enough as a parameter to assess the DMU's environmental performance. Thus, there is a significant difference between the overall performance indication under the five approaches. The sum of efficiency scores under method 2 to method 4 is obviously higher than method 1 and the Green Index. For the results under method 1 and the Green Index, the difference in 2006 shows the disparity between the two approaches.

The Green Index in Table 5-32 is the sum of the three pollutant sub-indices. Therefore, the result of the respective sub-index would directly affect the final Green Index. For example, the drop in 2006 from 3.000 to 2.727 under the Green Index is due to the three low sub-indices in the same year.

The environmental impact of Jiangsu yarn and cloth production has seen a steadily improving trend in the past 10 years. In fact, the improving environmental performance in the Jiangsu textile industry indicates that the laws and regulations implemented have had a positive impact on the environment. Jiangsu has been pioneering and developing its green manufacturing industry since the mid-1970s, therefore it is seen as one of the more mature provinces in carrying out environmental management in industrial activities (Jiangsu Huan Bao Chan Ye Zong Shu).

5.6.5 Improvement for the inefficient DMU of Case Study 3

In the DEA, DMUs with less than a 1.000 efficiency score are considered inefficient. DMUs with a 1.000 efficiency score are regarded as a benchmark for the inefficient DMUs. Therefore, in order to achieve an efficient performance, the inefficient DMUs can improve both their input and output to reach the frontier which is formed by the efficient DMUs. The efficiency frontier acts as a standard performance for the inefficient DMUs as reference. The targets for the inputs and outputs of the inefficient DMUs computed by the Ratio Model are found in Appendix B.

5.7 Case Study 4: Jiangsu Chemical Fibre Production 1998-2007

The last scenario examines the environmental performance of chemical fibre production in Jiangsu province from 1998-2007. In order to give the Green Index for each DMU, it is necessary to compute the relative efficiency score for each sub-index. The DMU selected in this study is the annual performance of the chemical fibre manufacturing factory in Jiangsu from 1998-2007. Therefore, altogether 10 DMUs are being evaluated. The details of all the chosen variables for the case studies are described in Chapter 3 and summarised in Figure 5-9. The following sections analyse the data and the ratios of the outputs computed for each sub-index.

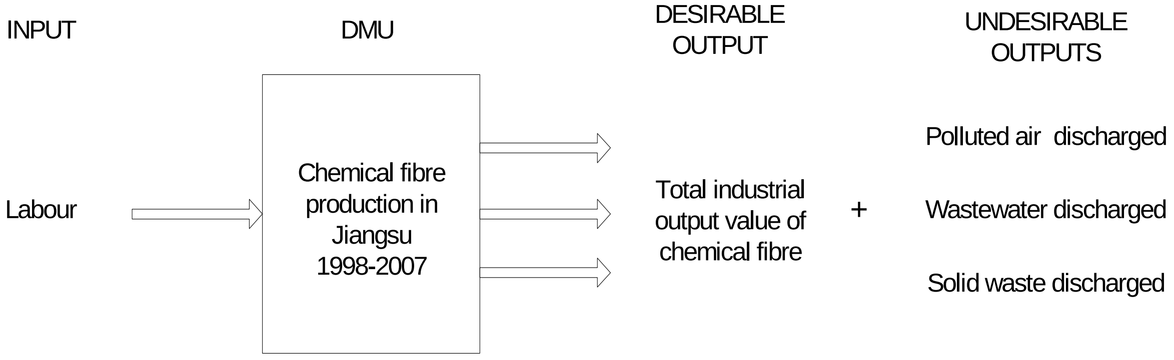


Figure 5-9 The inputs and outputs of Case Study 4

5.7.1 Polluted air sub-index of Case Study 4

Table 5-33 shows the textile industry data and the amount of polluted air produced. The first column identifies the 10 years as DMUs, while the second column lists the input for the study. Column 3 provides the desirable output and the fourth column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Column 2 in Table 5-34 shows the ratios of the desirable output to the total volume of polluted air emission, and the last column illustrates the results of the polluted air sub-index of the 10 DMUs computed by the new eco-DEA Ratio Model.

Table 5-33 Data of polluted air sub-index (Case Study 4)

DMU	**Input**	**Desirable output**	**Undesirable output**
	1	**1**	**1**
Year	**Labour (10 000 persons)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial polluted air emission (100 million cu.m)**
1998	4.48	44.78	270.00
1999	3.95	53.11	252.00
2000	4.07	66.85	316.00
2001	3.64	66.27	367.00
2002	3.56	76.73	341.00
2003	3.23	100.76	263.57
2004	2.94	134.01	433.58
2005	2.67	169.58	515.72
2006	2.83	212.20	474.60
2007	3.88	261.98	610.88

Source: Jiangsu Statistical Yearbook, various issues

Table 5-34 Output ratios and results under the polluted air sub-index (Case Study 4)

Year	Total textile value ratio ($x10^{-2}$)	Polluted air Sub-index
1998	16.58	0.596
1999	21.08	0.676
2000	21.15	0.656
2001	18.06	0.734
2002	22.50	0.750
2003	38.23	0.849
2004	30.91	0.908
2005	32.88	1.000
2006	44.71	1.000
2007	42.89	0.723

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the polluted air sub-index. Therefore, the results titled polluted air sub-index in Table 5-34 and Table 5-35 are calculated by the Ratio Model.

There are two efficient DMUs identified by the polluted air sub-index which obtain a relative efficiency score of 1.000. They are the year 2005 and 2006. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. From the polluted air sub-index, the environmental performance of Jiangsu chemical fibre production has been improving for the past 10 years. However, in 2007, the polluted air sub-index drops from 1.000 to 0.723. This is because the total volume of industrial polluted air emitted that year is so serious that it affects the total textile value ratio. The ratio decreases from 44.71 in 2006 to 42.89 in 2007. A drop in the output leads to a plummet in the polluted air sub-index. From this example, it can be seen that the importance of the data computation should be significantly discriminative so that the diversity in the data of all variables can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-35.

Table 5-35 Efficiency score of the four eco-DEA and the polluted air sub-index (Case Study 4)

Year	Method 1	Method 2	Method 3	Method 4	Polluted air Sub-index
1998	0.596	0.933	0.715	0.718	0.596
1999	0.676	1.000	1.000	1.000	0.676
2000	0.656	0.827	0.747	0.765	0.656
2001	0.734	0.856	0.798	0.824	0.734
2002	0.750	0.884	0.834	0.859	0.750
2003	0.827	1.000	1.000	1.000	0.849
2004	0.908	0.978	0.946	0.970	0.908
2005	1.000	1.000	1.000	1.000	1.000
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	0.723

From Table 5-35, the polluted air sub-index has similar results with the efficiency score of method 1, except DMU 2003 and 2007. Despite the similarity, the sub-index of 2003 and 2007 indicates the data computation for both methods contains a discrepancy. The discrepancy between the efficiency scores and the sub-index in 2003 and 2007 is due to the perspective in viewing the desirable outputs. The ratio approach regards the desirable output as per unit of polluted air emitted. With this aggregated approach, an increase in the volume of polluted air would cause a change in the amount of desirable output.

The result also agrees with the finding in Chapter 4, that undesirable outputs can exert a negative or positive impact on the DMU’s performance. Therefore, under the polluted air sub-index with the undesirable output incorporated in the computation, the efficiency score of 2003 increases from 0.827 to 0.849 while 2007 decreases from 1.000 to 0.723.

The efficiency scores of method 2 to method 4 are generally higher than method 1 and polluted air sub-index. This is because method 2 to method 4 incorporates one more positive output into computation. With the phenomenon in confirmation with the finding in Section 4.2.1, an increase in the number of outputs may lead to an increase to the efficiency score as well.

5.7.2 Wastewater sub-index of Case Study 4

Table 5-36 shows the textile industry data and the amount of wastewater discharged. The first column identifies the 10 years as DMUs, while the second column lists the input for the study. Column 3 provides the desirable output and the fourth column indicates the undesirable output, which is the environmental quality to be assessed in this sub-index. Column 2 in Table 5-37 shows the ratios of the desirable output to the total volume of wastewater discharged, and the last column illustrates the results of the wastewater sub-index of the 10 DMUs, computed by the new eco-DEA Ratio Model.

Table 5-36 Data of the wastewater sub-index (Case Study 4)

DMU	Input	Desirable output	Undesirable output
	1	1	1
Year	**Labour (10 000 persons)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial wastewater discharge (10 000 tons)**
1998	4.48	44.78	4124.00
1999	3.95	53.11	4298.00
2000	4.07	66.85	4395.00
2001	3.64	66.27	5560.00
2002	3.56	76.73	4749.00
2003	3.23	100.76	4003.38
2004	2.94	134.01	5294.20
2005	2.67	169.58	5484.60
2006	2.83	212.20	6437.94
2007	3.88	261.98	5362.52

Source: Jiangsu Statistical Yearbook, various issues

Table 5-37 Output ratios and results of the wastewater sub-index (Case Study 4)

Year	Total textile value ratio ($x10^{-3}$)	Wastewater sub-index
1998	10.86	0.596
1999	12.36	0.676
2000	15.21	0.656
2001	11.92	0.734
2002	16.16	0.750
2003	25.17	0.827
2004	25.31	0.908
2005	30.92	1.000
2006	32.96	0.992
2007	48.85	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the wastewater sub-index. Therefore, the results titled wastewater sub-index in Table 5-37 and Table 5-38 are calculated by the Ratio Model.

There are two efficient DMUs identified by the wastewater sub-index which obtain a relative efficiency score of 1.000. They are the year 2005 and 2007. The remaining DMUs are considered to be inefficient, because the efficiency score is less than 1.000. From the wastewater sub-index, the environmental performance of Jiangsu chemical fibre production has been improving for the past 10 years. However, in 2006, the wastewater sub-index drops slightly, from 1.000 to 0.992. It is important that the computation of the parameters is significantly discriminative, so that the diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-38.

Table 5-38 Efficiency score of the four eco-DEA and the wastewater sub-index (Case Study 4)

Year	Method 1	Method 2	Method 3	Method 4	Wastewater Sub-index
1998	0.596	0.971	0.706	0.711	0.596
1999	0.676	0.931	0.782	0.790	0.676
2000	0.656	0.911	0.749	0.757	0.656
2001	0.734	0.826	0.734	0.734	0.734
2002	0.750	0.886	0.817	0.828	0.750
2003	0.827	1.000	1.000	1.000	0.827
2004	0.908	0.960	0.928	0.933	0.908
2005	1.000	1.000	1.000	1.000	1.000
2006	1.000	1.000	1.000	1.000	0.992
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-38, the wastewater sub-index has similar results with an efficiency score of method 1, except for DMU 2006. Despite the similarity, the sub-index of 2006 indicates the computation of the data for both methods contains a discrepancy. As the Ratio Model includes environmental quality, the data would show some differences that affect the results in both models.

The efficiency score of method 2 to method 4 are generally higher than method 1 and wastewater sub-index. This is because method 2 to method 4 incorporates one more positive output into the computation. With the phenomenon as discussed in the finding in Section 4.2.1, an increase in the number of outputs may lead to an increase in the efficiency score as well.

5.7.3 Solid waste sub-index of Case Study 4

Table 5-39 shows the data of the textile industry and the amount of solid waste generated. The first column identifies the 10 years as DMUs, while the second column lists the input for the study. Column 3 provides the desirable output and the fourth column indicates the undesirable output which is the environmental quality to be assessed in this sub-index. Column 2 in Table 5-40 shows the ratios of the desirable output to the total volume of solid waste produced, and the last column illustrates the results of the solid waste sub-index of the 10 DMUs computed by the new eco-DEA Ratio Model.

Table 5-39 Data of the solid waste sub-index (Case Study 4)

DMU	**Input**	**Desirable output**	**Undesirable output**
	1	**1**	**1**
Year	**Labour (10 000 persons)**	**Total industrial output value (100 million RMB) (at 1978 price)**	**Total volume of industrial solid waste produced (10,000 tons)**
1998	4.48	44.78	41.00
1999	3.95	53.11	47.00
2000	4.07	66.85	36.00
2001	3.64	66.27	34.05
2002	3.56	76.73	40.30
2003	3.23	100.76	42.42
2004	2.94	134.01	53.77
2005	2.67	169.58	67.96
2006	2.83	212.20	67.13
2007	3.88	261.98	79.83

Source: Jiangsu Statistical Yearbook, various issues

Table 5-40 Output ratios and results under solid waste sub-index (Case Study 4)

Year	**Total textile value ratio ($x10^{-1}$)**	**Solid waste sub-index**
1998	10.92	0.596
1999	11.30	0.676
2000	18.57	0.656
2001	19.46	0.734
2002	19.04	0.75
2003	23.75	0.827
2004	24.92	0.908
2005	24.95	1.000
2006	31.61	1.000
2007	32.82	1.000

Based on Figure 5-2, the results calculated by the Ratio Model under the Green Index framework is named as the solid waste sub-index. Therefore, the results titled solid waste sub-index in Table 5-40 and Table 5-41 are calculated by the Ratio Model.

There are three efficient DMUs identified by the solid waste sub-index which obtain a relative efficiency score of 1.000. They are the year 2005, 2006 and 2007. The remaining DMUs are considered to be inefficient because the efficiency score is less than 1.000. According to the solid waste sub-index, the environmental performance of Jiangsu chemical fibre production has been improving for the past 10 years. It is important that the computation of the parameters is significantly discriminative, so that diversity in the data can be well characterised by the DEA. To show the difference between the numerous approaches in incorporating undesirable output, the results are shown in Table 5-41.

Table 5-41 Efficiency score of the four eco-DEA and the solid waste sub-index (Case Study 4)

Year	**Method 1**	**Method 2**	**Method 3**	**Method 4**	**Solid waste Sub-index**
1998	0.596	0.830	0.734	0.737	0.596
1999	0.676	0.849	0.781	0.788	0.676
2000	0.656	0.949	0.867	0.871	0.656
2001	0.734	1.000	1.000	1.000	0.734
2002	0.750	0.959	0.931	0.936	0.750
2003	0.827	1.000	1.000	1.000	0.827
2004	0.908	1.000	0.992	1.000	0.908
2005	1.000	1.000	1.000	1.000	1.000
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	1.000

From Table 5-41, the solid waste sub-index has exactly the same results, with an efficiency score of method 1. Despite the similarity, the discrepancy under method 1 and the solid waste sub-index in the previous sections and examples indicate the data computation of the data for both methods is different. As the Ratio Model includes environmental quality, the data would show some differences that affect the results in both models.

The efficiency scores of method 2 to method 4 are generally higher than method 1 and the polluted air sub-index. This is because method 2 to method 4 incorporate 1 more positive output into computation. With the phenomenon as discussed in the finding in Section 4.2.1, an increase in the number of outputs may lead to an increase in the efficiency score as well.

5.7.4 The Green Index of Case Study 4

The overall Green Index can be obtained as the sum of the three environmental sub-indices as discussed in the previous sections. Table 5-42 describes the grading results of the 17 DMUs based on the Green Index.

Table 5-42 Efficiency score of the four eco-DEA and the Green Index (Case Study 4)

Year	Method 1	Method 2	Method 3	Method 4	Green Index
1998	1.788	2.734	2.155	2.166	1.788
1999	2.028	2.780	2.563	2.578	2.028
2000	1.968	2.687	2.363	2.393	1.968
2001	2.202	2.682	2.532	2.558	2.202
2002	2.250	2.729	2.582	2.623	2.250
2003	2.481	3.000	3.000	3.000	2.503
2004	2.724	2.938	2.866	2.903	2.724
2005	3.000	3.000	3.000	3.000	3.000
2006	3.000	3.000	3.000	3.000	2.992
2007	3.000	3.000	3.000	3.000	2.723

As evident from the three sub-indices of Case Study 4, it is concluded that methods 1-4 fail to characterise the environmental performance of the DMU. The Ratio Model aggregates the desirable and undesirable outputs in a ratio form so that the undesirable output is discriminative enough as a parameter to assess the DMU’s environmental performance. Thus, there is a significant difference between the overall performance indicators under the five approaches. The sum of efficiency scores under method 2 to method 4 are obviously higher than method 1 and the Green Index. For the results under method 1 and the Green Index, the difference in 2003 and 2007 shows the disparity between the two approaches.

The Green Index in Table 5-42 is the sum of the three pollutant sub-indices. Therefore, the result of the respective sub-index would directly affect the final Green Index. For example, the quick drop in 2007 under the Green Index is due to the low polluted air sub-index in the same year.

For the past 10 years, the environmental performance of Jiangsu chemical fibre production has been improving. In fact, the progressing environmental performance in the Jiangsu textile industry states that the laws and regulations implemented have had positive feedback. Jiangsu has been pioneering and developing its green manufacturing industry since the mid 1970s , therefore it is one of the more mature provinces in carrying out environmental management in its industrial activities (Jiangsu Huan Bao Chan Ye Zong Shu).

5.7.5 Improvement for the inefficient DMU of Case Study 4

In the DEA, the DMUs with less than 1.000 efficiency score are considered inefficient. DMUs with 1.000 are regarded as a benchmark for the inefficient DMUs. Therefore, in order to achieve an efficient performance, the inefficient DMUs can improve both their input and output to reach the frontier which is formed by the efficient DMUs. The efficiency frontier acts as a standard performance for the inefficient DMUs as reference. The targets for the inputs and outputs of the inefficient DMUs computed by the Ratio Model can be found in Appendix B.

5.8 Chapter Summary

This chapter illustrates Stage Two of the present study. As discussed in Chapter 2, the environmental performance indicator (EPI) for textile industry is underdeveloped. Therefore, the Green Index, which is a new EPI developed in this study, is introduced to evaluate the environmental performance of textile industry. In this chapter, the Green Index is applied in the China's textile industry. As China has a significant position in the world's textile industry, it is chosen to be the country to apply the Green Index in. The application of the Green Index is presented as four case studies which assess China's textile industry from different perspective i.e. the national level (China) and the provincial level (Jiangsu). The background and the rationale of the various factors studied in the case studies are verified and examined firstly in this chapter. Then, the four case studies are discussed thoroughly and accordingly. The Ratio Model, which is developed in Chapter 4 is employed to assess the environmental performance of each case study.

From the results of four case studies, it can be proved that the newly developed Ratio Model is more advanced in characterising undesirable output than other existing approaches. Table 5-43 summarises the results of the four case studies. With the Green Index, it is observed there is an overall improvement in the environmental performance of the Chinese textile industry. By comparing the four scenarios, Jiangsu has set a good example to illustrate a healthy and sustainable balance between industrial activities and the environment. Jiangsu's significant role in the production of textile products can exert a positive effect on the concept of environmental protection in the manufacturing sector.

Table 5-43 Summary of the results of the four case studies under the Green Index

Year	Case Study 1	Case Study 2	Case Study 3	Case Study 4
1991	2.406	3.000	-	-
1992	2.253	2.844	-	-
1993	2.298	2.805	-	-
1994	2.650	2.813	-	-
1995	2.201	2.191	-	-
1996	2.751	2.521	-	-
1997	2.579	1.904	-	-
1998	2.670	1.972	1.764	1.764
1999	2.998	2.080	1.926	1.926
2000	3.000	2.214	2.082	2.082
2001	2.944	2.246	2.301	2.301
2002	2.922	2.534	2.580	2.580
2003	2.958	3.000	2.889	2.889
2004	2.869	2.977	3.000	3.000
2005	2.779	2.860	3.000	3.000
2006	2.749	2.940	2.727	2.727
2007	2.719	2.950	3.000	3.000

CHAPTER 6 CONCLUSIONS

6.1 Introduction

The present study aims to develop a Green Index for the textile industry. This chapter outlines the research outcomes of the study. Section 6.2 summarises the research process and the major findings are presented in Section 6.3. The major findings are discussed in line with the objectives stated in Chapter 1. Followed by is the implication and significance of the present research as discussed in Section 6.4. Section 6.5 illustrates the research limitation and recommends the aspect for further research. Lastly, Section 6.6 is the conclusion of the chapter.

6.2 Research Summary

Environmental protection is vital to the sustainable growth of an industry. Green production is capable of helping the company not only in gaining credibility from the society but also recognition from the customers. Therefore, the textile industry, which has been criticised for polluting the environment, is striving to reduce the pollutants from its manufacturing activities. Among the countless approaches, management tools are popular in improving the environmental aspect of production in the textile industry. Environmental performance indicator (EPI) which is introduced by the International Organization for Standardization (ISO) is one of the commonly used environmental management tools.

However, these prior studies have encountered the research limitations as discussed in Section 2.4. The existing EPI frameworks are not consistent and standardised, they lack of a comprehensive view and suffer from weight subjectivity. In light of the research gap, the present study aims to develop a general framework to assess its environmental performance. With the increasing emphasis on creating an environmental friendly manufacturing process, there is a need for the textile industry to develop an EPI, which is labelled as the Green Index in the present study, to assist the stakeholders and policy makers in evaluating a plant’s or an industry’s environmental performance.

Data envelopment analysis (DEA) is introduced as a methodology to construct the Green Index because DEA is able to assess the environmental performance without prior knowledge of weights of the variables. The primary application of DEA is to measure the performance of similar units, which are named as decision making units (DMU), from the aspect of efficiency by comparing their inputs and outputs. With the results calculated by the DEA, one is able to compare and identify the relative efficiency of the DMUs. The increasing attention on the environment motivates the researchers to include undesirable outputs into the area of DEA and thus eco-DEA is developed. As the desirable and undesirable outputs are of different nature, they are incorporated in the eco-DEA with a dissimilar fashion.

The previous approaches of eco-DEA either ignore the presence of undesirable outputs or they are unable to properly characterise the undesirable outputs. To fill the research gap as discussed in Section 2.6, a new eco-DEA which is named as the Ratio Model, is therefore introduced in the present study. It is a more preferred method to acknowledge the green performance of the DMU. With the Ratio Model, the Green Index is applied to measure the environmental impact induced by the textile industry in China. This is the first attempt to apply eco-DEA in the textile field.

China is the world’s largest manufacturer of textile products, therefore the textile industry has always been the country’s main income source. Despite the economic advantage, the textile industry’s rapid development puts considerable pressure on China’s environment. It is important to maintain the sustainable development of the country without hampering its economic growth. Therefore, the Green Index developed in the present study is a tool to evaluate China’s textile industry, which accounts for both economic and environmental aspects.

From Figure 3.1 in Section 3.1, the study is divided into two stages. Stage One addresses the development of a new eco-DEA. There are two comparative studies conducted in Stage One. The first comparative study discusses the four existing approaches in modelling undesirable output. To carry out a DEA study, relevant data is collected in advance. The data collected is then processed by Microsoft Excel is executed by the software DEAP 2.1 to calculate the efficiency score for each DMU. From the comparative study, it is concluded that these approaches are insufficient to characterise the impact of undesirable output in the existing eco-DEA. Thus, a new approach, the Ratio Model, is introduced to deviate the computation of the undesirable output. Again, the second comparative study is conducted to verify and prove the new approach is a preferred method to model the undesirable output. With the Ratio Model developed, Stage Two applies the developed Green Index to assess the environmental performance of the Chinese textile industry. To give a more comprehensive picture, various perspectives are included in the four case studies which examined the environmental problems induced by the textile manufacturing industry at the national and provincial level. The inputs studied are labour and total energy consumption. The desirable outputs are yarn, cloth, chemical fibres and the total industrial output value of the respective textile products. The undesirable outputs are polluted air, wastewater and solid waste.

6.3 Major Findings of the Study

In order to achieve the research objectives, the study is divided into two stages. Firstly, a new eco-DEA is proposed. Next, a Green Index is developed to provide a framework to evaluate the textile industry’s environmental performance. This section summarises the whole study according to the four objectives as outlined in Chapter 1. Each of the objective is examined in order.

Objective 1: To review the impact of the textile industry on the environment

Regardless of the type of industry, the emission of pollutants is unavoidable during the manufacturing process. The textile industry is no exception to this statement. To achieve the first objective, a thorough literature review is conducted to examine the environmental impact brought by the textile industry. As yarn, cloth and chemical fibre are studied in the present study, the environmental performance of producing these textile products is explored and they are summarised as below.

For yarn, the spinning process causes a considerable amount of dusts and wastewater. In addition, the use of heavy machinery consumes a huge amount of energy. For cloth, the most serious source of pollution is the wet processing of cloth to acquire desirable properties. Water is the necessary mean for wet processing therefore the intensive use of chemicals, dyes and auxiliaries leads to severe water pollution problems. Apart of the negative environmental impact, the manufacturing of textile products also results in various health problems such as irritated skin, byssinosis or even mutagenicity. For chemical fibres, they are originated from the petroleum which is a non-renewable and non-biodegradable source. Thus, this causes environmental problems such as solid waste. Also, during the manufacturing of the chemical fibres, water and air pollution are also induced.

Objective 2: To investigate the tools in measuring environmental performance

After viewing the negative consequences that textile industry has on the environment, green management tools are introduced to alleviate, or possibly control the pollution problems. The concept of environmental management drives companies to re-evaluate and re-think their roles and responsibilities in protecting the nature. From the literature, environmental performance indicator (EPI) is one of the approaches that is able to identify the opportunities for sustainable growth. As defined by the International Organization for Standardization (ISO), EPI is defined as the specific expression that provides information about an organisation’s environmental performance. With the guidelines given by the ISO, four examples of EPIs are found in the literature and they are discussed accordingly in Chapter 2. However, the present EPIs for the textile industry have not only failed to consider the importance of inconsistency and flexibility, their objectivity has made them difficult to apply in the field. In order to strengthen the practice of environmental management, it is imperative for the textile industry to develop its own approach which is suitable for its own practices and technologies. A newly EPI framework, which is called the Green Index, is thus developed.

Objective 3: To develop a new eco-DEA for assessing environmental performance

DEA is introduced to construct the Green Index to assess the environmental performance of the textile industry. DEA has been widely adopted in various fields such as hospitals, schools and some financial organisations. By comparing the same set of inputs and outputs, the relative efficiency scores of the decision making units (DMUs) are then obtained. DEA accounts for the performance of DMU under different criteria, with its independence and subjective weightings included in the computation. As environmental issues are gaining momentum, the traditional DEA is not suitable to calculate the DMU eco-efficiency. It is because the principle of DEA tends to utilize a minimum amount of input to produce maximum output. However, the pollutants that are also referred to as undesirable outputs should not be maximised in the sense of environmental protection. Therefore, according to the literature, there are many new approaches developed in recent decades to incorporate undesirable outputs into the DEA. The problems realized from the literature on the prior studies of the four approaches of eco-DEA are divided into two categories: ignorance of undesirable output and improper description of undesirable output. The four identified methods, representing the different approaches of treating undesirable outputs in DEA, are as follows:

Method 1: Ignoring undesirable outputs in DEA;

Method 2: Treating undesirable outputs as inputs;

Method 3: Applying a nonlinear monotonic decreasing transformation, 1/b, to the undesirable outputs; and

Method 4: Using linear monotonic decreasing transformation to deal with undesirable outputs.

With 30 sets of input data, desirable output and undesirable output, a comparative study is conducted with four different eco-DEA to compare the efficiency scores obtained. Regardless of the various approaches of eco-DEA, each gives a similar result: efficiency scores tend to increase when undesirable outputs are accommodated. This observation addresses a new insight in the area of eco-efficiency. The reasoning behind the ecological extension of DEA is explored. The output variable, as restricted by the intrinsic nature of DEA linear programming, is assumed to be a positive value. Regardless of the form of transformation seen in the literature, as long as the final value of undesirable output incorporated in the DEA calculation remains positive, it would increase DMU efficiency accordingly. It is believed that undesirable outputs should bring about either positive or negative impacts to the DMU’s performance. Therefore, it is not appropriate for the undesirable output to solely favour the efficiency score. These findings offer several implications for theoretical development. A new eco-DEA, which is called the Ratio Model, is thus developed from the study. The Ratio Model considers the desirable and undesirable outputs simultaneously and incorporates them as a ratio. To verify the Ratio Model, another comparative study is conducted to confirm the advancement of the Ratio Model in characterising the undesirable outputs when compared with the four eco-DEA.

Objective 4: To apply the newly developed Green Index to evaluate the environmental performance of China's textile industry

As stated in Chapter 1, the present study aims to provide the textile industry with a Green Index to monitor its production progress and products in terms of undesirable outputs. With the newly developed Ratio Model, it is employed to form the Green Index which is applied to evaluate the environmental performance of China's textile industry. China is chosen to be the subject of the application of the Green Index because the textile industry's significant impact on China's economy and environmental issues is widely acknowledged. As both economy and environment are of equal importance to a country's stable development, this has left China in a dilemma. The Chinese Government must opt for a method to promote sustainable development in all types of industrial activities which would not impede the country's competitiveness and income at the same time. With the prominent role of the textile industry in China's economy, closing textile plants is not a viable environmental protection strategy as this would seriously affect the international textile trade. Therefore, the Green Index developed in this study is a helpful tool to assess the textile industry's performance which accounts for both economic and environmental aspects.

The Green Index assesses the textile industry's environmental performance based on three aspects of pollution - air, water and solid waste. The data was collected from the China Statistical Yearbook (The People's Republic of China State Statistical Bureau, Various issues) as well as the China Textile Industry Development Report (Zhongguo fang zhi gong ye xie hui, various issues) . The input variables are labour and energy consumption. The desirable output variables are the amount of yarn, cloth and chemical fibre produced and the total industrial output values of the respective textile products; while the undesirable output variables are quantity of wastewater, polluted air and solid waste discharged from textile industry activities. With data availability limitation on the environmental variables, the DMU chosen in this study is the annual environmental performance of China’s textile industry from 1991-2007 and the Jiangsu textile industry from 1998-2007. The Green Index is made up of three sub-indices, which examine environmental problems resulting from the three aspects of pollution previously mentioned.

With the four distinctive scenarios, the Green Index describes the environmental performance of the textile industry in China and Jiangsu on an annual basis. After comparing the diverging approaches of eco-DEA in evaluating these four cases, it is concluded that the newly developed Ratio Model can characterise the presence of undesirable outputs in the most appropriate way. The environmental performance of China’s textile industry, regardless of the production of yarn, cloth or chemical fibre has been fluctuating for the first 10 years and has been stable and improving for the last seven years. This change could be due to stringent government regulations implemented in the past decade. Jiangsu’s environmental performance has been improving for the past 10 years. Jiangsu has set a good example in allowing economic development to flourish through manufacturing activities, while protecting the environment at the same time.

In addition from the results of the four case studies, the finding in Chapter 4 has been further confirmed. The existing eco-DEA fail to describe the undesirable output in an appropriate way. With method 1 ignoring the undesirable output in computation, methods 2, 3 and 4 incorporate the undesirable output as a positive output/ input which in turn favour the efficiency score. As it is found that the undesirable output could have a positive or negative impact on the performance of the DMU, therefore, the newly developed Ratio Model is able to characterise the pollutants in an accurate and discriminative way.

6.4 Implications and Significance of the Present Study

Having developed a Green Index which provides a structured and scientific method to evaluate the environmental performance of China's textile industry, the present study contributes to the three aspects of academia, managerial practice and country policy making.

From the view of contribution to academia, the new developed Ratio Model provides an unprecedented approach in manipulating desirable and undesirable outputs into calculation. By the comparative study which is conducted in Chapter 4, it is beneficial to show the common problems encountered in incorporating the undesirable output in the models as well as to propose the relevant findings which illustrate the characteristics of the undesirable output appropriately. The comparative study points out that the existing approaches of eco-DEA tend to increase efficiency scores and also the undesirable output has a positive or negative effect on the efficiency score. This new perspective diverges the method in incorporating the undesirable output into the eco-DEA with an improved and comprehensive view. With the establishment of the new Ratio Model, the research gaps mentioned in Section 2.6 are answered as well.

From the view point of contribution to managerial practice, the Green Index is applied to individual textile plant as a complementary tool to achieve an environmental management system. In turn, this increases brand recognition from the marketplace and win widespread public approval. In addition, the empirical results also shed light on the undesirable outputs that affect performance efficiency, which can provide useful information for stakeholders or policy makers. Additionally, the Green Index assigns weights to the various factors studied, the prior weighting which distinguishes the relative importance of the inputs and outputs is not required. The adoption of the new method can give an unbiased evaluation to the environmental performance of the textile industry. Based on this new eco-DEA, the Green Index is thus developed to accommodate the unique aspects of the textile industry, as well as to improve the inadequacies of previous research. Also, it provides a consistent framework for the textile industry to evaluate the environmental performance of the manufacturing processes. Thus, the development of the Green Index fills the research gaps discussed in Section 2.4.

From the view point of contribution to policy makers, the Green Index provides a consistent and scientific approach for the Chinese Government to assess the annual performance of the country’s textile industry in order to formulate appropriate policy to regulate the sustainable development of the environment. Thus, China’s pollution problems can be improved without sacrificing economic development. A further advantage is that the health problems induced by the pollutants as discussed in Section 2.2.4 can be solved or minimised. The Green Index gives useful information as achievable guidance for government planners to evaluate the overall environmental performance of the industry. Another significance of the Green Index is in the versatility of its wide application. Although this study applies the index to China's textile industry, the entire study can be a reference or framework for other developing countries in regulating their textile industry.

6.5 Research Limitations and Recommendations for Future Work

The Green Index established in this study provides the textile industry a scientific, objective weighting of variables and a consistent framework which is constructed for the manufacturing process of various textile products. However, the present study has some limitations that lead to further research in the relevant area. This section explains the limitations and recommends the aspect for future study.

The Green Index is intended to be applied in an actual production mill and preliminary study is illustrated in Chapter 2. In fact, the purpose of the preliminary study is to familiarize with the technique necessary for sample collection as well as to understand the environmental management practice of the plant. However, there was a change in the managerial level of the visited company and the new manager considers the collected data as confidential. This limits the application of the Green Index in a real plant situation. Additionally, as this is a Teaching Company Scheme project, it is restricted to cooperate with the sponsoring company only but not other companies. Therefore, only one textile mill is visited for the preliminary study. It is recommended to apply the Green

Index at a factory level as the results of the Green Index can be associated with various variables such as raw materials and machinery. This can show whether the variable studied has an impact on the environmental performance of the plant. The Green Index can also evaluate the performance of the textile plants on a regular basis such as weekly, monthly, quarterly or annually for continuous assessment. The overall investigation into these factors helps the plants to strive for better solutions in green production.

The Green Index developed in the present study is made up of three sub-indices which are polluted air sub-index, wastewater sub-index and solid waste sub-index. The attainment of a score of 3.00 under the Green Index is an indication of an efficiently green DMU. To further distinguish the factors which contribute to the green performance of the DMU, a wider range of sub-indices can be considered to provide a comprehensive view on the assessment. The Green Index can evaluate the green performance of the DMU not only from the amount of the pollutants generated, it can also evaluate the DMU by each production process so as to identify which process is the most polluting. When the Green Index gives a more inclusive picture of the green performance of a DMU, the problem behind can be easily identified and the stakeholders of the DMU are able to seek for continuous improvement.

Due to time limitation, only one country is assessed in this study. To further the research, comparisons can be made between the textile industries of different countries by using the same assessment framework. It would be appealing to assess the environmental performance of diverse economies which are labour intensive as well as capital intensive. Also, the Green Index can be applied to compare the environmental performance of the textile industry of other developing countries, such as India and Bangladesh. Their regulations on governing the textile industry and the environmental impact can be used as a reference and guidelines for further investigation.

Another limitation of the present study is the employment of the professional DEA software such as DEAP 2.1. It might not be accessible to outsiders to use the instrument. Therefore, in order to facilitate a compatible form and user-friendly way to apply the Green Index, it is recommended that this entire indexing system is developed as a computer programme. The significance of this system is that government or private corporations can evaluate their environmental performance according to their practices and needs. The calculation time of the Green Index would also be shortened.

6.6 Chapter Summary

This chapter firstly presents the research summary which illustrates the outline of the whole study. Then, according to the four objectives indicated in Chapter 1, the major findings of the present study are addressed. Then, the implication and significance of the study is discussed, followed by the research limitations and recommendations for future work.

APPENDIX A

Table A1 Data on the adjustment of total industrial output value of Case Study 1

Year	Total industrial output value (100 million RMB) (current price)	Consumer Price Index (1978=100)	After normalisation of the price effect with 1978 as the base year
1991	1632.10	223.80	729.27
1992	1742.60	238.10	731.88
1993	3520.74	273.10	1289.18
1994	4949.93	339.00	1460.16
1995	4604.00	396.90	1159.99
1996	4722.29	429.90	1098.46
1997	4760.28	441.90	1077.23
1998	4376.27	438.40	998.24
1999	4529.82	432.20	1048.08
2000	4656.18	434.00	1072.85
2001	5358.55	437.00	1226.21
2002	6171.69	433.50	1423.69
2003	7730.92	438.70	1762.23
2004	9692.80	455.80	2126.55
2005	12517.74	464.00	2697.79
2006	15293.46	471.00	3247.02
2007	16900.88	493.60	3424.00

Table A2 Data on the adjustment of total industrial output value of Case Study 2

Year	Total industrial output value (100 million RMB) (current price)	Consumer Price Index (1978=100)	After normalisation of the price effect with 1978 as the base year
1991	229.00	223.80	102.32
1992	245.20	238.10	102.98
1993	453.80	273.10	166.17
1994	637.25	339.00	187.98
1995	809.94	396.90	204.07
1996	802.47	429.90	186.66
1997	861.98	441.90	195.06
1998	836.52	438.40	190.81
1999	975.28	432.20	225.65
2000	1236.57	434.00	284.92
2001	1232.29	437.00	281.99
2002	1105.12	433.50	254.93
2003	1391.67	438.70	317.23
2004	1927.24	455.80	422.82
2005	2559.62	464.00	551.64
2006	3148.97	471.00	668.57
2007	3713.85	493.60	752.40

Table A3 Data on the adjustment of total industrial output value of Case Study 3

Year	Total industrial output value (100 million RMB) (current price)	Consumer Price Index (1978=100)	After normalisation of the price effect with 1978 as the base year
1998	1039.79	438.40	237.18
1999	1104.23	432.20	255.49
2000	1237.96	434.00	285.24
2001	1350.47	437.00	309.03
2002	1539.75	433.50	355.19
2003	1829.26	438.70	416.97
2004	2280.14	455.80	500.25
2005	3027.39	464.00	652.45
2006	3665.57	471.00	778.25
2007	4313.94	493.60	873.97

Table A4 Data on the adjustment of total industrial output value of Case Study 4

Year	Total industrial output value (100 million RMB) (current price)	Consumer Price Index (1978=100)	After normalization of the price effect with 1978 as the base year
1998	196.30	438.40	44.78
1999	229.56	432.20	53.11
2000	290.12	434.00	66.85
2001	289.62	437.00	66.27
2002	332.62	433.50	76.73
2003	442.03	438.70	100.76
2004	610.83	455.80	134.01
2005	786.84	464.00	169.58
2006	999.44	471.00	212.20
2007	1293.12	493.60	261.98

APPENDIX B

Table B1 Performance target of polluted air sub-index in Case Study 1

DMU	Target input value		Target output ratio			Target output value		
	Labour (10 000 persons)	Energy (10 000 tn SCE)	Yarn	Cloth	Total industrial output value	Yarn (10 000 tons)	Cloth (100 million m)	Total industrial output value (100 million RMB)(at 1978 price)
1991	451.25	2497.00	41.66	17.56	6803.12	891.11	375.61	1455.19
1992	451.25	2497.00	41.66	17.56	6803.12	755.71	318.54	1455.19
1993	499.89	2501.72	39.64	17.33	7162.09	713.47	311.98	1531.97
1994	799.51	3410.81	37.82	15.27	8044.94	686.45	277.13	1720.81
1995	491.94	2500.95	39.97	17.37	7103.43	652.66	283.64	1519.42
1996	810.46	3332.29	37.31	15.23	8000.45	512.27	209.11	1711.30
1997	451.25	2497.00	41.66	17.56	6803.12	687.39	289.74	1455.19
1998	451.25	2497.00	41.66	17.56	6803.12	624.90	263.40	1455.19
1999	510.87	2502.79	39.18	17.28	7243.15	566.93	250.04	1549.31
2000	451.25	2497.00	41.66	17.56	6803.12	656.98	276.92	1455.19
2001	453.07	2552.05	41.86	17.58	6837.59	760.60	319.45	1462.56
2002	463.82	2876.90	43.04	17.70	7041.00	870.27	357.97	1506.07
2003	475.28	3223.40	44.30	17.84	7257.97	1075.58	433.06	1552.48
2004	519.16	4550.25	49.12	18.34	8088.81	1291.36	482.16	1730.20
2005	580.86	4978.35	48.03	16.04	8933.08	1450.51	484.41	1910.79
2006	604.84	5756.49	49.91	17.14	9298.45	1767.81	607.10	1988.94
2007	631.54	6207.57	51.83	16.92	8581.45	1926.00	628.75	1835.57

Table B2 Performance target of wastewater sub-index in Case Study 1

DMU	Target input value		Target output ratio			Target output value		
	Labour (10 000 persons)	Energy (10 000 tn SCE)	Yarn	Cloth	Total industrial output value	Yarn (10 000 tons)	Cloth (100 million m)	Total industrial output value (100 million RMB) (at 1978 price)
1991	451.25	2497.00	52.29	22.05	85.38	733.91	309.48	1198.33
1992	451.25	2497.00	52.29	22.05	85.38	724.13	305.36	1182.37
1993	515.85	2775.01	58.96	22.71	99.62	762.94	293.93	1289.18
1994	739.31	3197.70	58.85	23.70	119.72	717.70	289.02	1460.15
1995	515.96	2775.22	58.96	22.71	99.63	686.38	264.44	1159.94
1996	810.46	3332.29	58.81	24.01	126.12	512.24	209.13	1098.51
1997	474.18	2946.94	63.37	24.21	105.97	651.20	248.80	1089.06
1998	474.91	2592.00	54.19	21.88	90.64	596.79	240.96	998.20
1999	510.87	2502.79	46.77	20.62	86.45	567.04	250.00	1048.12
2000	451.25	2497.00	52.29	22.05	85.38	657.02	277.06	1072.79
2001	465.26	2679.32	58.98	22.49	95.07	760.69	290.06	1226.16
2002	476.09	2984.43	64.29	24.39	107.69	849.97	322.46	1423.75
2003	496.34	3468.96	69.63	25.03	124.75	983.62	353.58	1762.27
2004	519.16	4550.25	83.92	31.33	138.20	1291.32	482.09	2126.55
2005	580.86	4978.35	84.22	28.12	156.64	1450.54	484.32	2697.84
2006	604.84	5756.49	88.06	30.24	164.05	1743.01	598.55	3247.11
2007	631.54	6207.57	91.85	29.99	152.06	2068.18	675.28	3423.92

Table B3 Performance target of solid waste sub-index in Case Study 1

DMU	Target input value		Target output ratio			Target output value		
	Labour (10 000 persons)	Energy (10 000 tn SCE)	Yarn	Cloth	Total industrial output value	Yarn (10 000 tons)	Cloth (100 million m)	Total industrial output value (100 million RMB) (at 1978 price)
1991	451.25	2497.00	150.33	63.38	24548.15	909.50	383.45	1485.16
1992	451.25	2497.00	150.33	63.38	24548.15	959.11	404.36	1566.17
1993	451.25	2497.00	150.33	63.38	24548.15	823.81	347.32	1345.24
1994	451.50	2502.33	165.86	68.91	27343.75	885.69	367.98	1460.16
1995	451.25	2497.00	150.33	63.38	24548.15	768.19	323.87	1254.41
1996	451.44	2501.16	162.43	67.69	26726.58	667.60	278.21	1098.46
1997	451.25	2497.00	150.33	63.38	24548.15	762.17	321.34	1244.59
1998	451.25	2497.00	150.33	63.38	24548.15	653.94	275.70	1067.84
1999	451.26	2497.14	150.73	63.52	24620.83	641.66	270.42	1048.08
2000	451.25	2497.00	150.33	63.38	24548.15	657.00	277.00	1072.85
2001	451.25	2497.00	150.33	63.38	24548.15	771.19	325.14	1259.32
2002	451.54	2503.32	168.73	69.93	27860.85	862.23	357.36	1423.69
2003	496.34	3468.96	2980.55	1071.27	534010.29	983.58	353.52	1762.23
2004	451.25	2497.00	150.33	63.38	24548.15	1307.87	551.41	2135.69
2005	452.54	2524.76	231.16	92.17	39098.40	1595.01	635.94	2697.79
2006	453.31	2541.40	279.62	109.42	47820.60	1898.59	742.97	3247.02
2007	453.84	2552.92	313.17	121.37	53860.65	2068.17	801.53	3556.96

Table B4 Performance target of polluted air sub-index in Case Study 2

DMU	Target input value		Target output ratio		Target output value	
	Labour (10 000 persons)	Energy (10 000 tn SCE)	Chemical fibre	Total industrial output value	Chemical fibre	Total industrial output value (100 million RMB) (at 1978 price)
1991	30.75	855.60	102.87	55.10	191.03	102.32
1992	30.75	855.60	102.87	55.10	239.38	128.22
1993	32.08	920.42	166.04	73.23	376.74	166.16
1994	32.93	961.47	206.04	84.71	457.19	187.97
1995	32.60	945.52	190.50	80.25	484.43	204.08
1996	32.10	921.25	166.84	73.46	423.94	186.66
1997	31.61	903.60	162.12	67.05	471.61	195.05
1998	31.71	1054.26	176.29	69.05	510.01	199.76
1999	32.20	1071.03	202.63	76.21	599.99	225.66
2000	33.99	1033.01	274.51	103.61	754.91	284.93
2001	33.79	1322.25	299.32	100.32	841.39	282.00
2002	33.49	1673.27	320.78	95.75	991.21	295.87
2003	34.85	2199.87	433.61	116.46	1181.15	317.24
2004	38.67	1303.03	664.76	165.36	1699.79	422.83
2005	40.76	1342.00	576.85	191.14	1664.79	551.63
2006	41.12	1423.97	792.20	255.47	2516.03	811.37
2007	44.58	1553.97	963.97	300.48	3366.18	1049.28

Table B5 Performance target of wastewater sub-index in Case Study 2

DMU	**Target input value**		**Target output ratio**		**Target output value**	
	Labour (10 000 persons)	**Energy (10 000 tn SCE)**	**Chemical fibre**	**Total industrial output value**	**Chemical fibre**	**Total industrial output value (100 million RMB) (at 1978 price)**
1991	30.75	855.60	36.82	19.72	191.03	102.31
1992	30.75	855.60	36.82	19.72	219.73	117.68
1993	31.57	900.58	67.03	28.84	386.21	166.18
1994	32.23	936.49	91.14	36.12	474.28	187.97
1995	32.26	938.27	92.33	36.48	516.53	204.09
1996	32.19	934.37	89.71	35.69	469.21	186.67
1997	32.21	935.36	90.38	35.89	491.13	195.04
1998	32.13	1055.10	93.51	34.99	509.98	190.83
1999	33.03	980.79	120.88	45.10	604.84	225.67
2000	33.80	1022.81	149.10	53.62	792.21	284.90
2001	33.23	1254.97	140.95	47.24	841.40	282.00
2002	33.81	1689.16	183.71	52.01	991.19	280.59
2003	34.85	2199.87	241.81	64.94	1181.17	317.21
2004	38.67	1303.03	358.10	89.08	1699.79	422.84
2005	39.21	1319.16	348.08	113.70	1688.74	551.63
2006	41.12	1423.97	418.46	134.95	2073.18	668.58
2007	44.58	1553.97	493.04	153.69	2413.78	752.42

Table B6 Performance target of solid waste sub-index in Case Study 2

DMU	Target input value		Target output ratio		Target output value	
	Labour (10 000 persons)	Energy (10 000 tn SCE)	Chemical fibre	Total industrial output value	Chemical fibre	Total industrial output value (100 million RMB) (at 1978 price)
1991	30.75	855.60	10.85	5.81	190.96	102.26
1992	30.75	855.60	10.85	5.81	265.83	142.35
1993	30.86	892.68	14.57	6.73	359.95	166.23
1994	30.94	917.27	17.04	7.34	436.28	187.90
1995	30.99	935.41	18.86	7.79	494.21	204.10
1996	30.82	879.79	13.28	6.41	386.39	186.53
1997	30.87	893.45	14.65	6.75	471.73	217.32
1998	31.03	946.73	20.00	8.07	510.00	205.81
1999	31.06	956.49	20.98	8.31	600.03	237.75
2000	31.10	970.48	22.38	8.66	736.43	284.91
2001	31.14	983.58	23.70	8.99	841.35	318.97
2002	31.28	1028.00	28.16	10.09	991.23	355.06
2003	34.85	2199.87	145.82	39.16	1181.14	317.20
2004	32.02	1273.31	52.79	16.17	1699.84	520.77
2005	32.02	1271.58	52.62	16.13	1799.47	551.65
2006	32.22	1338.09	59.29	17.78	2229.45	668.53
2007	32.64	1476.34	73.18	21.21	2595.52	752.32

Table B7 Performance target of polluted air sub-index in Case Study 3

DMU	Target input value	Target output ratio	Target output value
	Labour (10 000 persons)	Total industrial output value	Total industrial output value (100 million RMB) (at 1978 price)
1998	29.41	11.91	356.23
1999	29.41	11.91	349.08
2000	29.41	11.91	349.08
2001	29.41	11.91	478.94
2002	29.41	11.91	549.24
2003	29.41	11.91	474.88
2004	29.41	11.91	500.26
2005	29.71	16.29	652.45
2006	30.37	18.19	778.25
2007	32.05	23.05	873.96

Table B8 Performance target of wastewater sub-index in Case Study 3

DMU	Target input value	Target output ratio	Target output value
	Labour (10 000 persons)	Total industrial output value	Total industrial output value (100 million RMB) (at 1978 price)
1998	29.41	11.86	259.73
1999	29.42	11.89	255.49
2000	29.41	11.86	291.48
2001	29.41	11.86	394.11
2002	29.41	11.86	406.39
2003	29.49	12.33	416.99
2004	29.41	11.86	500.24
2005	29.71	13.61	652.47
2006	31.79	16.07	778.27
2007	32.05	16.37	873.95

Table B9 Performance target of solid waste sub-index in Case Study 3

DMU	Target input value	Target output ratio	Target output value
	Labour (10 000 persons)	Total industrial output value	Total industrial output value (100 million RMB) (at 1978 price)
1998	29.41	3.20	278.57
1999	29.41	3.20	256.16
2000	29.43	3.28	285.27
2001	29.41	3.20	336.95
2002	29.41	3.20	408.90
2003	29.41	3.20	442.00
2004	29.41	3.20	500.18
2005	29.71	4.58	652.47
2006	30.28	4.99	778.18
2007	32.05	6.27	873.98

Table B10 Performance target of polluted air sub-index in Case Study 4

DMU	Target input value	Target output ratio	Target output value
	Labour (10 000 persons)	Total industrial output value	Total industrial output value (100 million RMB) (at 1978 price)
1998	2.67	32.88	88.78
1999	2.67	32.88	82.86
2000	2.67	32.88	103.90
2001	2.67	32.88	120.67
2002	2.67	32.88	112.12
2003	2.742	38.23	100.76
2004	2.67	32.88	142.56
2005	2.67	32.88	169.57
2006	2.83	44.71	212.19
2007	2.805	42.89	262.01

Table B11 Performance target of wastewater sub-index in Case Study 4

DMU	Target input value	Target output ratio	Target output value
	Labour (10 000 persons)	Total industrial output value	Total industrial output value (100 million RMB) (at 1978 price)
1998	2.67	30.92	127.51
1999	2.67	30.92	132.89
2000	2.67	30.92	135.89
2001	2.67	30.92	171.92
2002	2.67	30.92	146.84
2003	2.67	30.92	123.78
2004	2.67	30.92	163.70
2005	2.67	30.92	169.58
2006	2.808	32.96	212.19
2007	3.88	48.85	261.96

Table B12 Performance target of solid waste sub-index in Case Study 4

DMU	Target input value	Target output ratio	Target output value
	Labour (10 000 persons)	Total industrial output value	Total industrial output value (100 million RMB) (at 1978 price)
1998	2.67	24.95	102.30
1999	2.67	24.95	117.27
2000	2.67	24.95	89.82
2001	2.67	24.95	84.95
2002	2.67	24.95	100.55
2003	2.67	24.95	105.84
2004	2.67	24.95	134.16
2005	2.67	24.95	169.56
2006	2.83	31.61	212.20
2007	3.88	32.82	262.00

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