Developing Data Envelopment Analysis Model for Performance Evaluation of Green Supply Chain Management

Farzad Zaare Tajabadi

Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in

Industrial Engineering

Eastern Mediterranean University
July 2023
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

Prof. Dr. Ali Hakan Ulusoy
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy in Industrial Engineering.

Asst. Prof. Dr. Emine Atasoylu
Chair, Department of Industrial Engineering

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Doctor of Philosophy in Industrial Engineering.

Assoc. Prof. Dr. Sahand Daneshvar
Supervisor

Examining Committee

1. Prof. Dr. Kovács Gergely
2. Prof. Dr. Zoltán Lakner
3. Prof. Dr. Béla Vizvári
4. Assoc. Prof. Dr. Sahand Daneshvar
5. Asst. Prof. Dr. Kehinde Adewale Adesina

ABSTRACT

In recent times, there has been a growing concern regarding environmental issues. This has resulted in increased pressure on companies and producers from government regulations, while also striving to maintain customer satisfaction by addressing environmental concerns. Green Supply Chain Management (GSCM) has emerged as a means to enhance efficiency and reduce environmental impact for firms collaborating with clients and suppliers. GSCM encompasses various aspects such as green purchasing, design, manufacturing, distribution, packaging, marketing, and reverse logistics within supply chains, to improve environmental performance. The use of nonparametric models, specifically Data Envelopment Analysis (DEA), has been prevalent in assessing the efficiency and proficiency of supply chains as decision-making units (DMUs). However, the earliest research on efficiency fulfilment in GSCM has not thoroughly explored the combined effect of economic and environmental factors, such as service level, CO_2 emissions, and supply chain size (arcs), on the overall efficiency of the supply system. These principles are crucial as they can impact a manager's capability to accurately evaluate the performance of a green supply chain. Therefore, it is imperative to evaluate GSCM efficiency using DEA models while incorporating green principles to identify efficient DMUs and potential DMUs that can be improved with less cost and effort. This study aims to address this research gap by developing a benchmark approach to identify efficient DMUs and potentially efficient DMUs, which can be enhanced through minor adjustments. The study utilizes DEA standard models to determine benchmarks and potentially efficient DMUs and modifies their inputs to achieve an efficient status. Additionally, the impact of green elements on the efficiency of DMUs is assessed using Tobit regression analysis pre and post adjustment. Pragmatic outcomes obtained from the case study demonstrate the practicality of the proposed procedure in prioritizing potential DMUs for modification.

Keywords: Green supply chain management, Performance evaluation, Efficiency, Benchmarking, Data envelopment analysis, Tobit regression

ÖZ

Son zamanlarda, çevre sorunları ile ilgili artan bir endişe var. Bu, çevresel endişeleri ele alarak müşteri memnuniyetini sürdürmeye çabalarken, hükümet düzenlemelerinden şirketler ve üreticiler üzerinde artan baskıyla sonuçlandı. Yeşil Tedarik Zinciri Yönetimi (GSCM), müşteriler ve tedarikçilerle işbirliği yapan firmalar için verimliliği artırmanın ve çevresel etkiyi azaltmanın bir yolu olarak ortaya çıkmıştır. GSCM, çevresel performansı iyileştirmek için tedarik zincirlerinde yeşil satın alma, tasarım, üretim, dağıtım, paketleme, pazarlama ve tersine lojistik gibi çeşitli yönleri kapsar. Parametrik olmayan modellerin, özellikle Veri Zarflama Analizinin (DEA) kullanımı, karar verme birimleri (VMU'lar) olarak tedarik zincirlerinin etkinliğini ve yeterliliğini değerlendirmede yaygın olmuştur. Bununla birlikte, GSCM'de verimliliğin yerine getirilmesine ilişkin en eski araştırma, hizmet seviyesi, CO2 emisyonları ve tedarik zinciri boyutu (yaylar) gibi ekonomik ve çevresel faktörlerin tedarik sisteminin genel verimliliği üzerindeki birleşik etkisini tam olarak araştırmamıştır. Bu ilkeler, bir yöneticinin yeşil tedarik zincirinin performansını doğru bir şekilde değerlendirme yeteneğini etkileyebileceğinden çok önemlidir. Bu nedenle, verimli KVB'leri ve daha az maliyet ve çabayla iyileştirilebilecek potansiyel KVB'leri belirlemek için yeşil ilkeleri dahil ederken VZA modellerini kullanarak GSCM verimliliğini değerlendirmek zorunludur. Bu çalışma, verimli KVB'leri ve küçük ayarlamalarla geliştirilebilecek potansiyel olarak verimli KVB'leri belirlemek için bir kıyaslama yaklaşımı geliştirerek bu araştırma boşluğunu ele almayı amaçlamaktadır. Çalışma, ölçütleri ve potansiyel olarak verimli KVB'leri belirlemek için VZA standart modellerini kullanır ve verimli bir duruma ulaşmak için girdilerini değiştirir. Ek olarak, yeşil unsurların KVB'lerin verimliliği üzerindeki etkisi, düzeltme öncesi ve sonrası Tobit regresyon analizi kullanılarak değerlendirilir. Vaka çalışmasından elde edilen pragmatik sonuçlar, değişiklik için potansiyel KVB'lere öncelik verilmesinde önerilen prosedürün uygulanabilirliğini göstermektedir.

Anahtar Kelimeler: Yeşil tedarik zinciri yönetimi, Performans değerlendirmesi, Verimlilik, Kıyaslama, Veri zarflama analizi, Tobit regresyon

I dedicate this thesis to my dear parents, who have shown me unwavering love and provided constant support throughout my journey

ACKNOWLEDGMENT

I am writing to express my sincere gratitude to my thesis supervisor Assoc. Prof. Dr. Sahand Daneshvar for his guidance and support throughout my Ph.D. study and research. Your willingness to take the time to discuss my ideas, review my work, and offer constructive criticism has been invaluable to me.

I would also like to extend my heartfelt thanks to our department's staff member specially to our chairperson Asst. Prof. Dr. Emine Atasoylu for all the opportunities that I have been given. I would like to express my deepest gratitude to my respected advisor, Assoc. Prof. Dr. Adham Makkieh and my dear professors, Prof. Dr. Gökhan İzbırak and Prof. Dr. Béla Vizvári, who have provided me with a strong academic foundation and the tools to succeed in my research. Their encouragement and motivation have inspired me to pursue my academic goals.

To my loving parents, brother, and grandparents, thank you for your unwavering support, encouragement, and belief in me. I could not have made it this far without your love and guidance. I am forever grateful for your sacrifices and the opportunities that you have provided me.

Finally, I would like to express my gratitude to my friends for their unwavering support and encouragement. Their love and encouragement have been a source of strength and motivation for me throughout my academic journey.

Thank you all once again for everything you have done for me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

APICS	American Production and Inventory Control Society
ACGS	Average Cost of Goods Sold
AHP	Analytic Hierarchy Process
ANN	Artificial neural network
ANP	Analytic Network Process
CRS	Constant Return to Scale
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
GSCM	Green Supply Chain Management
LAC	Latin America and Caribbean
MADA	Multi-Attribute Decision Analysis
NSGA-II	Non-dominated Sorting Genetic Algorithm
NRGA	Non-dominated Ranked Genetic Algorithm
SCM	Supply Chain Management
SC	Supply Chain
SDEA	Stochastic Data Envelopment Analysis
VRS	Variable Return to Scale

Chapter 1

INTRODUCTION

With the increasing concerns about the environment in the recent decade, environmental pollution should be paid attention to in the processes besides industry development. The environmental and economic benefits of product remanufacturing and consumer environmental consciousness have pushed numerous manufacturing and retail enterprises to produce and sell green products (Mondal & Giri, 2022). All the solutions to this problem should be combined and reviewed in a comprehensive supply chain procedure framework. Supply chain management (SCM) is an important factor that is directly related to the company’s efficiency and competitive position. SCM entails planning product manufacture from raw materials to customer delivery (Andiappan et al., 2022). Supply chain management is essential to every company organization, and proper planning will assure economic, environmental, and social sustainability (Bui et al., 2021). Greening the supply chain is a new concept. Green supply chain management (GSCM), in particular, has seen considerable expansion in recent years (Rajeev et al., 2017). Green supply chains rely primarily on cutting costs, enhancing efficiency, and generating "green" or environmentally friendly products (Tseng et al., 2019). According to this concept, the purchaser uses his/her purchasing power to demand better environmental performance from the upstream supplier in the supply chain. This means that in most cases, the purchaser is a big company that has a facilitating role for its suppliers. These suppliers are usually companies of small or medium sizes and they help them to become environment-friendly organizations. In recent years, following the rapid industrialization of most of the developed economies, environmental losses have been paid a great deal of attention and all over the world, governments have begun to apply environmental protection rules. Although from a merely economic view and regardless of some side factors, industry and industrial activities, constituting a major share of national income and a large percentage of the present human force of the sociality, are considered as the main basis of development and growth of the countries. Moreover, as a major indicator of development, from a sustainability view, the benefits of such a development which is resulted from not regarding environmental aspects of exploitation of national resources and environmental protection is not justifiable in the long term; because from an environmental view, destructive consequences of industrial activities will finally lead to health damage, lack of working motivation, and above all, gradual or sudden decrease of life quality in societies and residential. This imposes further costs on society in addition to the apparent and tangible costs.

In latest years, nearly 70% of the world's leading firms have prioritized sustainability in their work plans (Herrmann et al., 2021). According to the reports of leading firms, the success of their sustainability activities is also dependent on collaboration with supply chain (SC) participants (de Sousa Jabbour, 2015; Jabbour et al., 2015). Green supply chain management (GSCM) entails incorporating environmental and economic goals into the supply chain's operating plan. This type of integration reduces carbon footprint while enhancing financial return and profitability (Sellitto et al., 2015). (Bowen et al., 2001) define GSCM as the “integration of the company’s purchase plan with the environmental activities in SCM, to improve the environmental performance of supplier and customers.” Concerns of product design, usage, reuse, disassembly, and final disposal are also included in GSCM (Sarkis, 2003), in addition to storage, transportation, supplier development to satisfy green purchasing criteria, and encouragement for the adoption of environmental certifications such as ISO 14000 (Sarkis, 2003; Sarkis et al., 2011). (Zhu & Sarkis, 2006) Consider GSCM to be the integration of environmental thinking with SC operations management, beginning with product design and progressing through raw material selection, manufacturing processes, transportation and delivery, and the end consumer arriving at the final destination after usage. (Large & Gimenez Thomsen, 2011) According to the definition, GSCM comprises the design process, raw material selection, green procurement, production, distribution, and reverse logistics.

Figure 1: Functions of GSCM

Therefore, regarding the emphasis on organizational efficiency to effectively and properly use the resources for achieving organizational goals, and also due to the requirements of national and international rules about environmental issues, proper compromise and compatibility between the two goals of economic growth and environmental protection, and integrating the two important issues of efficiency and environmental protection under the title “green efficiency program” can be of great importance.

This study poses the following research questions: How we can measure efficiency in green supply chains? How we can distinguish the potential DMUs among inefficient ones that can be efficient with less cost and effort according to benchmark DMUs? And how we can verify the effect of green factors on the decision-making unit’s efficiency values?

The following can consider as the contributions of the current study. Efficiency evaluation of the SCs as DMUs with a different product, production cost per unit, and chain size to introduce the efficient DMUs and consider them as a benchmark. Finding the potential DMUs (those that have the ability to become efficient) among the inefficient DMUs who can become efficient after modification according to the benchmarks. Finally, verify the effectiveness of three green factors such as service level, emissions (CO_2), and the size of the chains (arcs) on the efficiency of the whole system before and after modifications of the potential DMUs and compared the results. The expectation is the positive effect of service level (customer satisfaction) and arcs (as the size of the transportation factor) and the negative effect of CO_2 emission (environmental effect) on the efficiency value of DMUs. Moreover, the changes in the mentioned effects after improvement adjustments will help the decision-makers to identify the true performance of the green supply chains.

1.1 Thesis Structure

The thesis design is organized as follows: Chapter 2 contains a literature review of the previous relevant research in efficiency improvement and performance evaluation in supply chain and green supply chain management. Chapter 3 is introduced the methodology procedure and explains it in detail. In Chapter 4 a case study is considered and some analytical discussions are provided. The conclusion and result are performed in Chapter 5 with guidelines for future studies.

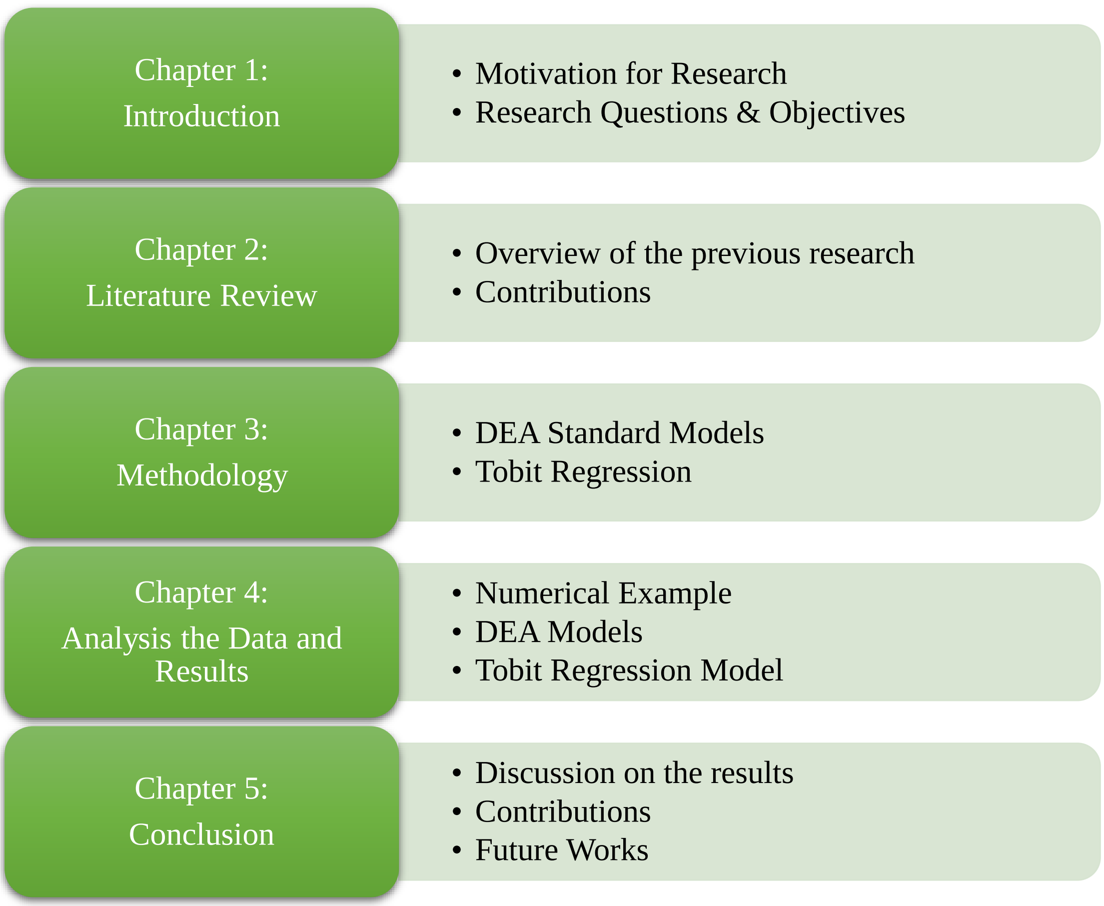

Figure 2: Thesis framework

Chapter 2

LITERATURE REVIEW

This chapter provides an overview of the previous research that has direct consequences on efficiency improvement and performance evaluation in supply chain and green supply chain management. Also, aims to study literature in the backgrounds on supply chain management, methods of solving multi-objective problems of supply chain network designing, green supply chain management, developed benchmark approach, and standard DEA models to find out the research gap, distinguish the recent approaches, methods, and models that are discussed for evaluating the efficiency of supply chain and green supply chain management.

2.1 Background of Supply Chain Management

In the 1990s, along with the improvement of production capacities, the managers of industries found that the raw materials received from different suppliers have a significant role in increasing organizational capabilities to meet the customers' needs. This also significantly affected the organization's concentration, supply bases, and resourcing strategies. Also, the managers found that only manufacturing a qualitative product is not enough, and in fact, supplying the products with the criterion considered by the customers (when, where, and how) and their desired quality and cost led to new challenges. In such conditions, as a conclusion of the mentioned changes, they found that they will not be enough to manage their organization for a long time. In managing the network, they shall be involved with the customers in managing the network of all the factories and companies that supplied their organization inputs directly or indirectly and also the network of companies engaged in delivery and after-sale services. With such an attitude, approaches of “supply chain” and “supply chain management” appeared.

Supply chain management (SCM) is considered one of the important management activities in most organizations. In general, all of the activities of an organization that associate the suppliers, factories, warehouses, retailers, and final consumers and require managing the goods, finance, and information are referred to as supply chain (SC) in the literature (Nahmias, 1993). Due to the complexity of mutual relationships between different components of SC, the supply chain is exposed to a wide range of risks, making decision-making a challenging problem for managers. Undoubtedly, one of the most important and difficult aspects of the supply chain structure of goods and services is making decisions about facility location for each layer of the chain. This is considered one of the strategic decisions; usually, its change is not justifiable in the short term or even midterm period (Ghosh et al., 2004). There are examples that there is uncertainty and risk in the reliability of chain facilities due to phenomena such as natural disasters, changes in capital holders, mistakes of the labour force, climatic conditions, etc. In October 2001, the prevalence of anthrax virus in the Washington branch of the US postal service led to the closure of the 633,000 square feet office (facility) and as a result, the loss of a major part of the capacity of the chain. Hurricane Katrina in 2005 resulted in the fact that after many years, parts of Central Louisiana are still faced with a shortage of materials due to the breakdown of some factories and warehouses (Sheffi, 2005). Quarrels of labour forces in September 2002 led to the closure of western ports of America, while the retailers intended to store a great deal of depot before the beginning of seasonal holidays. In this situation, production was stopped for a while in some factories. Therefore, when making strategic decisions, uncertainties of the real world should be considered, so that at the time of their occurrence, the system can continue functioning with the minimum loss.

2.1.1 Definition of Supply Chain

Different sources presented very comprehensive definitions of supply chains. For example, in the APICS dictionary the term “supply chain” is defined as follows:

A supply chain includes all the processes linking the suppliers and consumers to each other. Such processes begin with the initial; raw materials and end with the final consumer receiving the completed product. In addition, the term supply chain was mentioned in the American Production and Inventory Control Society (APICS) dictionary as follows: The functions inside and outside a company enable the value chain to produce products and deliver customer service.

In this definition, value chain means the functions inside a company adding value to the products or services sold by the organization to receive money.

In another definition, the supply chain was defined as follows:

A network of interconnected organizations through the upstream and downstream relations in different processes and activities produces value as a product or service for the final customer (Christopher, 1998). This definition indicates that a supply chain is a group of three or more organizations that are directly present in the flow of products or services to final customers. The integration of supply chain management seems necessary to ensure coordination in the supply chain.

However, some other definitions were presented from the supply chain dimensions of the supply chain. Here is a review of some of these definitions:

Supply chain management is a set of methods used for effectively integrating the suppliers, manufacturers, warehouses, and stores to produce the required products at a certain amount, place, and time to minimize the total chain costs and satisfy customer needs at a high-service level.

A supply chain refers to a set of activities coordinating the following goals (Johnson & Malucci, 1999):

- Having access to new materials
- Transferring and transforming the raw materials to certain products
- Creating the value added in these products
- Distributing these products to retailers and customers.
- Facilitating the exchange of information between different institutions in the business environment (including the suppliers, manufacturers, distributors, etc.).

In this definition, the supply chain includes two main processes:

- Materials management (internal logistics)
- Physical distribution and support (external logistics).

Materials management deals with the discharge and storage of raw materials, parts, and procurement. Specifically, materials management includes all steps of purchase, internal control, materials planning for production, circulating inventory control, warehouse, transportation, and final product distribution. On the other hand, physical distribution and support involve all external logistic activities in customer service delivery. These activities include taking orders, inventory settlement, warehousing, locating, external transportation, pricing, advertising, product locating, and life cycle support. As a result of combining materials management with physical distribution and support, a supply chain cannot be the linear chain of one-by-one business relations but a texture of multiple relations and networks.

(Harland, 1996) explained supply chain management as the business process management and internal relations of an organization with direct and indirect suppliers (first-rank, second-rank, etc.) and customers over the supply chain with supply chain institutions. He defined supply chain management as a tool for linking the chain of each supply and manufacturing process until the final consumer including the organizational boundaries. Based on this extensive definition, supply chain management includes all activities and institutions in the supply chain from raw materials extraction until the end of its useful life.

According to (Beamon, 1998), supply chain management is defined as the sets of common integrated processes between a variety of firms (e.g., suppliers, manufacturers, distributors, and sellers) working together to achieve the following goals:

- Achieving the raw materials
- Converting the raw materials into certain final products
- Delivering these final products to sellers and finally to customers.

Supply chain management was defined by (Simchi-Levi et al, 2003) as follows:
SCM is a set of approaches used for the efficient integration of suppliers, manufacturers, warehouses, and stores to minimize system costs and satisfy the needs of customers so that the products are produced and distributed at the right place and time. The above-mentioned definitions indicated that supply chain management

depends on all partners of the chain and considers the whole supply chain. The purpose of supply chain management is to increase clarity among the members and have their goals in line with each other. For this purpose, all chain elements should cooperate, otherwise, the chain will be disrupted.

2.2 Background of Research on Methods of Solving Multi-Objective Problems of Supply Chain Network Designing

In view of the fact that supply chain management is based on integrating suppliers, manufacturers, warehouses, and stores, supply chain management encompasses all activities of the company at various levels, from the strategic to the tactical and operational. All of these activities should be taken into account when designing the supply chain. To design a supply chain, decision-making should be conducted in five areas: production inventory, facilities, locating, transportation, and information. (Chopra and Meindl, 2001) referred to these five areas as functional leverages and stated that the required potentials of a supply chain can be created by managing these leverages. Efficient supply chain management requires an understanding of each leverage and its function. Each leverage has a direct effect on the supply chain and activates certain potentials in the chain. An appropriate combination of accountability and efficiency of each leverage increases the efficiency and reduces the operational and inventory costs in the supply chain.

There are few types of research in the literature on supply chain design with a multi-objective optimization approach. (Sabri & Beamon, 2000) used the ε limitation method for solving the model after designing an integrated three-purpose model for minimizing the cost, maximizing the service rate, and flexibility about the uncertainty of delivery time and demands for the product. (Chan et al., 2004) proposed a multi-objective genetic algorithm for demand-oriented distribution problems in the supply chain network. The goals of the mentioned problem included optimization of system costs, total delivery time, and an efficiency rate of the manufacturers' capacity. (Chen & Lee, 2004) designed a multi-period, multistage, and multiproduct scheduling model in a supply chain network about the uncertainty of demand and product price with the goal of fair distribution of profits among all the stakeholders, keeping the inventory and service rate at the optimum level, and stable decision making regarding the instability of demand. For solving the problem, they used the two-stage fuzzy decision-making method. By using limitation ε and branch and bound techniques, (Guillén et al., 2005) solved their two-purpose model (to maximize the profit in the determined period and increase the level of customer satisfaction) which belonged to the category of linear mixed-integer random planning.

Considering operational costs, service level, and resource efficiency as the goals of the study of production and distribution problems, (Chan et al., 2004) proposed a hybrid approach based on the combination of genetic algorithms by the hierarchical method (AHP).

2.3 Background of Green Supply Chain Management

In 1996, Michigan State University's industrial research association introduced green supply chain management. Environmental protection is achieved through the use of this new management model. From the perspective of the product life cycle, green supply chain management includes all the stages of raw materials, designing, manufacturing the product, selling the product, transportation, using the product, and recycling the product. Using green supply chain management and technology, the company can decrease the negative environmental effects and achieve the optimum use of resources and energy. Greening the supply chain is the process of considering the environmental criteria or observations throughout the supply chain. Green supply chain management integrates supply chain management with environmental requirements in all the stages of designing the product, choosing, and greening the supply chain, considering environmental criteria or observations throughout the supply chain. Green supply chain management integrates supply chain management with environmental requirements in all the stages of designing the product, choosing, and supplying the raw materials, manufacturing, and building, distribution and transportation processes, delivering to the customer, and after consumption, managing recycling for maximizing the efficiency of energy and resource consumption besides improving the function the whole supply chain (Sarkis, 2006). During the review of the environmental impacts of supply chain activities, the effects of products on the environment are examined from a holistic perspective (including the analysis of the life cycle of a product from its beginning to its end life. The ecological effects of every activity throughout the product life cycle of a product (the science of the creatures' habits and their interactions with the environment) are measured and considered in the design process, including product concept, design, raw material preparation, manufacturing and construction, montage, keeping, packaging, transporting, and subsequent use of the product (Zanjirani Farahani et al., 2009).

(Kuo et al., 2010) want to create a green supplier selection model that combines an artificial neural network (ANN) and two multi-attribute decision analysis (MADA) methods: data envelopment analysis (DEA) and analytic network process (ANP). (Hsu & Hu, 2009) introduced 19 environmental criteria in their article and classified them into five groups. They considered five groups purchase management, research and development management, process management, quality control of the input materials, and system management, and then, they chose the suppliers using the network analysis process technique.

In their study, (Chen et al., 2010) chose 18 criteria the most important of which include environmental criteria, environment management system, supplier's profitability, and close relationships of the supplier, and then, using fuzzy theory, the criteria were converted to definite numbers.

In a case study on the printed circuit board in Taiwan, (Chen et al., 2010) sought for implementing green supply chain management for selecting the supply. He developed two classes of environmental and non-environmental criteria in the studied company, determined the weights of the criteria based on qualitative and quantitative factors, and finally used the Gray analysis method for rating the suppliers. (Shaik & Abdul-Kader, 2011) used a framework of environmental, green, and organizational criteria for selecting the green supplier. He created a hierarchy for evaluating the criteria and sub-criteria of suppliers which led to the compilation of an appropriate liable strategy by the managers.

For a two-echelon supply chain, (Tajabadi & Kazemi, 2016) presented an NL-IP model aiming to minimize total costs, maximize demand served, and minimize transportation pollution. Two meta-heuristic algorithms, NSGA-II and NRGA, are developed to solve the problem, and the Taguchi method is used to set the parameters. (Forghani et al., 2022) modified classic stochastic data envelopment analysis (SDEA) model by manipulating weak efficient hyperplanes. The suggested model was applied to the environmental efficiency of sustainable development goals in Latin America and

Caribbean (LAC) countries resulting in better discrimination. A summary of the research on green supply chain management is presented in Table 1.

Table 1: Criteria of the green supply chain in the previous studies

Criterion	Component	Authors (year)
Green supply and purchase	Choosing the supplier regarding the environmental criteria, providing the materials in environment-friendly packs, having environmental certificates such as ISO 14000, holding seminars for informing the suppliers about environmental issues, supporting the suppliers in improving their environmental performance, and requiring the suppliers to observe environmental rules, and buying recyclable materials	(ElTayeb et al., 2010; Kuo et al., 2010; Olugu et al., 2010; Shen et al., 2013; Walker & Jones, 2012; Zhu et al., 2008; Zhu & Sarkis, 2007)
Green designing	Designing the products regarding the reduction of material or energy consumption, recyclability of the products, designing the product for reducing or avoiding the consumption of dangerous materials or inappropriate production processes, designing the products to reduce their environmental effects	Olugu et al., (2010); Eltayeb et al., (2010); Kuo et al., (2010); Diabat & Govidan, (2010); Zhu et al., (2007); Walker et al., (2008); Ninlawan et al., (2010)
Green production	A commitment of the senior and junior managers to observe the environment-related rule have qualified environmental management, have environmental certificates such as EUP, ROHS, and ODC, use materials with less harm to the environment, use devices with less pollution to the environment, control release of dangerous gases such as ammonia and CO_2, using appropriate methods for removing wastewater, having an appropriate environmental position to other manufacturers, low occurrence of environmental incidents, decreasing noise pollution,	Olugu et al., (2010); Zhu et al., (2008); Tseng & Chiu, (2010); Hsu & Hu, (2009); Kuo et al., (2010); Diabat & Govidan, (2010); Zhu et al., (2007); Walker et al., (2008); Ninlawan et al., (2010)

	holding environmental educational programs for the staff and the managers, focusing on reducing the wastes and optimizing the use of materials, using environment-friendly equipment and technology	
Green packing	Using recyclable packs and containers, using environment-friendly materials in packing the products, using labels for showing the level of accordance of the product with environmental standards, using labels for showing the recyclability of the product	Olugu et al., (2010); Zhu et al., (2008); Eltayeb et al., (2010); Kuo et al., (2010); Diabat & Govidan, (2010); Zhu et al., (2007); Walker et al., (2008); Ninlawan et al., (2010)
Green transportation and distribution	Marketing the products relies on environmental issues such as emphasizing environmental certificates, increasing the consumers' environmental awareness, choosing clean transportation methods, returning the products to the company for recycling, better competitive situation than other competitors, choosing the distribution networks and customers with an emphasis on environmental criteria	Olugu et al., (2010); Zhu et al., (2008); Eltayeb et al., (2010); Kuo et al., (2010); Diabat & Govidan, (2010); Zhu et al., (2007); Walker et al., (2008); Ninlawan et al., (2010)
Green production costs	The costs of eliminating dangerous and harmful materials, costs of producing environment-friendly products, costs of offering environment-friendly packs, costs of informing the staff about environmental products	Olugu et al., (2010); Eltayeb et al., (2010); Kuo et al., (2010); Zhu et al., (2007); Walker et al., (2008); Ninlawan et al., (2010

According to Table 1, this study emphasis on three criteria in green supply chain management such as green transportation, green production, and green production cost to reduce the emissions and cost of production. Also, considering some green factors' efficacy on the whole system's efficiency like service level to meet the customer satisfaction about the ordering green product cost and delivery, emission (CO_2) caused by vehicles through chain and arcs which indicates the size of the chain for transportation.

2.4 Background of Benchmarking in GSCM

Benchmarking likely had its origins in the textile mills of the 1800s (Bogan & English, 1994). Over time, it has experienced significant advancements, particularly concerning the emergence of quality management principles. The Xerox[1] Corporation began using benchmarking as an effective and practical management tool during the 1980s when the company was losing market share and experiencing significant pressure from competitors, particularly Japanese companies. It was Xerox's success that encouraged many other corporations to adopt this revolutionary approach to increase performance levels and production efficiency to gain a competitive advantage (Camp, 1989). Several studies have found that it improves performance (Yasin, 2002), eliminates trial and error, increases new product development efficiency (Hong et al., 2014), and results in improved customer satisfaction (Brah et al., 2000). In this regard, there are various definitions of benchmarking in the literature. Benchmarking is the process of searching for best practices and trying to emulate them (Shabani et al., 2012). Benchmarking has quickly become a standard practice among top companies. GSCM benchmarking is the practice of comparing a company's green goods, services, and procedures along the supply chain to the relevant indicators of successful enterprises or chains. As a result, GSCM benchmarking encompasses a wide variety of factors like processes, products, performances, and strategies.

[1] Xerox Corporation is a globally operating American multinational company that offers a wide range of paper-based solutions, services, and information technology products on a global scale

Data Envelopment Analysis (DEA) is a widespread and accepted tool for measuring efficiency and performance for many years. According to (Stewart, 2010), one of the standard outputs of DEA can be a benchmark for inefficient DMU which by slight implication can reach the desired point. In the standard DEA models mainly the inefficient DMUs reveal upon the previous data. So, it means that if we have selected efficient DMUs as a benchmark, they are suitable for now and maybe not inefficient in the future.

(da Costa et al., 2022) recognized sustainability indexes for benchmarking the performance and decreasing the environmental effects of the product life cycle with a benchmarking method. (Radovanov et al., 2020) operated a two-stage DEA model for benchmarking and improving the sustainability performance of tourism-driving services. A majority of sustainability research has examined the relationship between energy, environmental, and economic factors while focusing less on how social factors impact safety performance (Ang & Zhang, 2000; Zhou et al., 2008).

In essence, benchmarking is a strategy that aims to improve performance by studying and adopting the best practices of other organizations to assort the needs of the company. According to (Asher and Kanji, 1996), benchmarking helps companies focus and get closer to their marketplaces and consumers. According to (Boxwell Jr, 1994), the benchmarking process can be categorized into three approaches: training, management, and comprehensive. The training approach aims to enhance employees' understanding of competition, whereas the management approach focuses on addressing weaknesses and enhancing processes at the level of factory laborers. The overall approach involves creating an all-inclusive benchmarking process within the organization. Regardless of the approach used, all organizations share two goals: they are not satisfied with the current situation and want to boost their competitiveness. By way of explanation, benchmarking helps organizations think differently and look for the best attitude to achieve their objectives (Alosani et al., 2016).

(Rostamzadeh et al., 2021), identified eight major applications such as product planning, service sector, hotel industry, transportation, education, maintenance, distribution, and environmental factors. The highest recent development among all the applications has been applied in both the service sector and transportation. In addition, the results illustrate that DEA as a suitable efficiency evaluation and performance measurement has the highest potential for future benchmarking research, while the production specification between inputs and outputs has been tough to gain.

2.5 Background on the Application of DEA in SCM and GSCM

The concepts of DEA have been proposed by (Farrel, 1957) and (Charnes et al., 1978) paper "Measuring the efficiency of decision-making units" foremost employed linear programming for the experimental bound of the production technology estimation. thenceforth, many papers and articles have been published about DEA or the different areas that DEA can be used to address the issues. Data Envelopment Analysis (DEA) is an implementation for measuring the efficiency of decision-making units (DMU) with multiple inputs and outputs. The DEA is a linear technique and free parameter programming method. This method has been used in such a situation to compare the inputs and outputs of DMUs that represent production units with each other. Also, DEA is a suitable tool for measuring the performance and evaluation efficiency of manufacturers or units. The old and most popular statistical methods could evaluate by comparing the specifications of manufacturers due to the average characteristics of the manufacturing unit. Whenever, DEA as an extreme point method, compares the specification of each DMUs and evaluates them with only the best one. Moreover, developing the DEA method has begun with the measurement of productivity with input and output in the usual way and then introduced the method of estimating comparative efficiency with different inputs as a ratio of the weighted output to input. So, in the past decade, it has been used for many goals like in the economy, environmental issues, selecting the best supplier, and many more. According to (Lambert & Cooper, 2000), DMUs impart on several bases like transport, business, universities, hospitals, etc. Classic DEA considers the DMUs as a black box that their structures denied and performance evaluation of DMUs just related to the inputs and outputs. However, in most scenarios, DMUs have a network design like the output of the first stage will be the input for the next level.

(Färe & Grosskopf, 2000), introduced the overall efficiency measurement of new methods with DEA models. Although, overall efficiency can be considered as an average weighted regardless of the state of the efficiency for each stage. So, in recent years, many studies were done on DMUs that are considered efficient for each stage. DEA is counselled to assist in common benchmarking activities and to give management guidance (Donthu et al., 2005). According to several experiments, this method is an effective way of evaluating performance, benchmarking, and improving the company's performance. In consequence, since DEA is first suggested by (Charnes et al., 1978), it is widely used in benchmarking studies. DEA also positively impacts on defining functions and operating efficiency of different firms (Sarkis et al., 2011).

Evaluation of the efficiency of green supply chain management should consider the effect of environmental factors besides the profitability of the firms. These factors may lead to the failure of green supply chains in meeting the green principles and the expectation of customers who care about the environment. Hence, regular evaluation of the efficiency of green supply chains could impact the performance regarding environmental issues. When these factors are considered simultaneously, green supply chain management can be planned more efficiently to minimize the environmental effects and production costs. Thus, this work aims to present a new approach to evaluating the efficiency of green supply chains when some of them are inefficient and has the potential to become efficient through their benchmarks, and the environmental factors are considered. An important novelty in this approach is by benchmarking the efficient DMUs we can distinguish the potential DMUs and modify them to become efficient while they are following the green principles factors at the same time. In addition, the comparison of results before and after modification of potential DMUs through green factors and their effect on the whole system efficiency has been applied.

Chapter 3

METHODOLOGY

In this chapter, the standard Data Envelopment Analysis (DEA) models and Tobit regression model have been introduced with their brief historical origins about how they developed and used in the research. Also, the relation between the two methods and the way of approach has been shown by a methodology diagram at the end of this chapter with an explanation.

3.1 DEA Efficiency Analysis

3.1.1 Standard CCR Model

DEA is a method for evaluating efficiency that employs a non-parameter approach and has been widely applied in operations research and general management (Charnes et al., 1978). Productivity is a function of economic factors that determine output and input (Farrell, 1957). It is important to identify both desirable and undesirable outcomes in environmental evaluation (Sueyoshi & Goto, 2011). The following five efficiency measurements were identified by (Zhou et al., 2008) after analysing more than 100 energy and environment research papers: (1) radial efficiency, (2) non-radial efficiency, (3) slacks-based efficiency, (4) hyperbolic efficiency, and (5) directional distance function efficiency. We assume that each DMU_j has multiple inputs $x_{i,j}$ and multiple outputs $y_{k,j}$.

To institutionalize these assumptions, we have used the following notations:

DMU_j, by *j* = 1, 2, 3, . . ., *n*, defines the *j*-th DMU;

x_{ij}, by *i* = 1, 2, 3, . . ., *m* & *j* = 1, 2, 3, . . ., *n*, defines the *i*-th input of the *j*-th DMU;

y_{kj}, by *k* = 1, 2, 3, . . ., *s* & *j* = 1, 2, 3, . . ., *n*, defines the *k*-th output of the *j*-th DMU;

v_i, by *i* = 1, 2, 3, . . ., *m*, defines the weight of the *i*-th input; &

u_k, by *k* = 1, 2, 3, . . ., *s*, defines the weight of the *k*-th output.

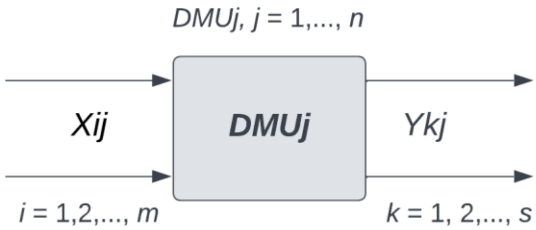

Figure 3: Inputs and Outputs of *j*-th DMU

The relative efficiency measure is defined as follows:

$$\text{Efficiency} = \frac{\sum_k u_k y_{k,j}}{\sum_i v_i x_{i,j}} \tag{1}$$

where *u* and *v* are weights. The efficiency is often scaled to range between [0, 1].

The weights have a flaw: assigning a standard value to them across all DMUs is quite arbitrary. The key notion underlying DEA is that we give each DMU_{j0} the ability to select its weights. It can do so by solving the following optimization issue. According to (Charnes et al., 1978), the efficiency score in the CCR model is 1 and inefficiency is 1/efficiency. So, Whenever the DMU’s score exceeds one, it is considered inefficient. For output-oriented DMUs, most packages provide a score ranging from 0 to 1. Maximize the efficiency of DMU_{j0} while keeping all other DMUs’ efficiencies less than or equal to 1 (Kalvelagen, 2004).

$$\text{Maximize } \theta_0 = \frac{\sum_k u_k y_{k,j0}}{\sum_i v_i x_{i,j0}}$$

$$\text{Subject to } \frac{\sum_k u_k y_{k,j}}{\sum_i v_i x_{i,j}} \leq 1 \ \forall j \tag{2}$$

$$u_k, v_i \geq 0$$

It is not an LP model. So, make a simple change to fix the denominator to a constant value of 1, which can be set as a constraint on the v_j weights as below:

$$\text{Maximize } \sum_k u_k y_{k,j0}$$

$$\text{Subject to } \sum_i v_i x_{i,j0} = 1 \tag{3}$$

$$\sum_k u_k y_{k,j} \leq \sum_i v_i x_{i,j} \ \ \forall j$$

$$u_k, v_i \geq 0$$

Note that the decision variables are *u* and *v* as weights. In some cases, the dual model is preferable for primal models with many rows and columns. The dual DEA model can be represented as:

$$\text{Minimize } z_0 = \theta_{j0}$$

$$\sum_j \lambda_j y_{k,j} \geq y_{k,j0}$$

$$\theta_{j0} x_{i,j0} \geq \sum_j \lambda_j \, x_{i,j} \tag{4}$$

$$\lambda_{\mathrm{j}} \geq 0$$

Model (4) will be used to compare the inefficient DMUs and efficient DMUs as the benchmark units. Cross-efficiency will determine the potential DMUs to become efficient after some adjustments in their inputs or outputs values.

The DEA model has been proposed in other forms. We discussed the CCR model above (Charnes et al., 1978) as one of the standard DEA models.

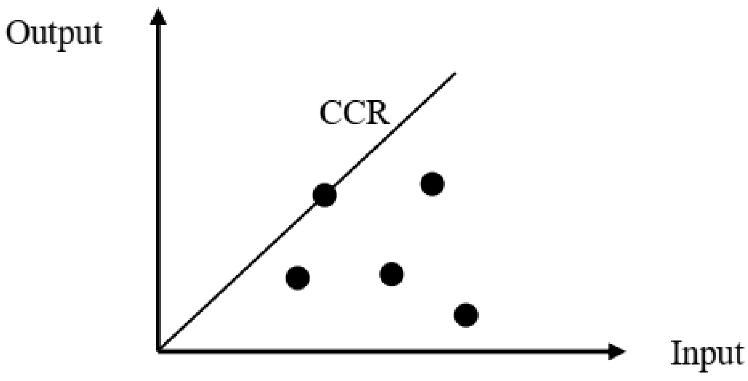

Figure 4: CCR frontier

3.1.2 Two-stage DEA Model

Two-stage in a DMU means the procedure is divided into two stages with intermediate values in between. Initially, inputs are used to make intermediate values, which are then used to make outputs. The intermediate values are used in the second stage to produce the final outputs. First-stage outputs are the only inputs to the second stage, which is a critical assumption. The following notations have been used to institutionalize these assumptions:

DMU_j, by *j* = 1, 2, 3, . . ., *n*, defines the *j*-th two-stage designed DMU;

x_{ij}, by *i* = 1, 2, 3, . . ., *m*, & *j* = 1, 2, 3, . . ., *n*, defines the *i*-th input of the *j*-th DMU in stage 1;

z_{dj}, by *d* = 1, 2, 3, . . ., *D*, & *j* = 1, 2, 3, . . ., *n*, defines the *d*-th output of the *j*-th DMU in stage 1 & the *d*-th input of the *j*-th DMU in stage 2;

y_{rj}, by *r* = 1, 2, 3, . . ., *s*, & *j* = 1, 2, 3, . . ., *n*, defines the *r*-th output of the *j*-th DMU in stage 2;

v_i, by *i* = 1, 2, 3, . . ., *m*, defines the *i*-th input factor in stage 1;

η_d^1, by *d* = 1, 2, 3, . . ., *D*, defines the *d*-th output factor in stage 1;

η_d^2, by *d* = 1, 2, 3, . . ., *D*, defines the *d*-th input factor in stage 2; and

u_r, by *r* = 1, 2, 3, . . ., *s*, defines the *r*-th output factor in stage 2.

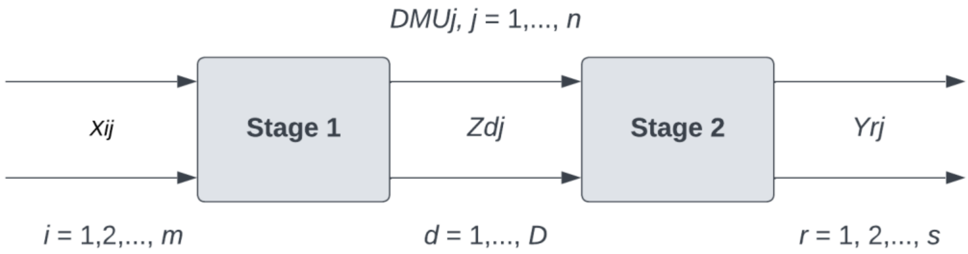

Figure 5: Two-stage DEA model

Figure 5 illustrates the first stage of evaluating each DMU starting with *m* inputs and producing *D* output units. Intermediary units are created from *D* output units and become inputs to the next level. Hence, the DMUs have to be evaluated in the second stage to determine their ability to convert *D* intermediate units into *r* final outputs.

In the first and second stages, the CRS efficiency of the *j*-th DMU, in each case *j* = 1, 2..., *n*, is as follows:

$$\theta_j^{1*} = \sum_{d=1}^{D} \eta_d^1 z_{dj} / \sum_{i=1}^{m} v_i x_{ij} \text{ and } \theta_j^{2*} = \sum_{r=1}^{s} u_r y_{rj} / \sum_{d=1}^{D} \eta_d^2 z_{dj}$$

The overall CRS efficiency of DMU_j is defined by (Kao and Hwang, 2008) as the result of the two individual efficiencies, namely $\theta_j^* = \theta_j^{1*} \times \theta_j^{2*}$. Since the two stages have a series relationship, they assumed that $\eta_d^1 = \eta_d^2 = \eta_d$ for *d* = 1…, *D*. As a result of their research, they developed a two-stage DEA model to measure the total performance of each DMU over some time:

$$\theta_0^* = \text{Maximize} \left[\frac{\sum_{d=1}^{D} \eta_d z_{d0}}{\sum_{i=1}^{m} v_i x_{i0}} \times \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{d=1}^{D} \eta_d z_{d0}} = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \right] \quad (5)$$

$$\text{Subject to } \frac{\sum_{d=1}^{D} \eta_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad j = 1, 2, \dots, n,$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} \eta_d z_{dj}} \leq 1, \qquad j = 1, 2, \dots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1, 2, \dots, D;\ i = 1, 2, \dots, m;\ \mathrm{r} = 1, 2\dots, s,$$

while DMU_0 indicates the DMU undergoing inspection. A linear program (LP) below can be generated for the result of the model (5) using (Charnes and Cooper's, 1962) transformation:

$$\theta_0^* = \text{Maximize} \sum_{r=1}^{s} u_r y_{r0} \tag{6}$$

$$\text{Subject to} \sum_{i=1}^{m} v_i x_{i0} = 1,$$

$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1\ldots, n,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_{i,} u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s.$$

After obtaining the total efficiency θ_0^*, the two individual efficiencies θ_0^{1*} and θ_0^{2*} values could be determined by solving one of the following LP models, and the other by using $\theta_0^2 = \theta_0^* / \theta_0^{1*}$ or $\theta_0^1 = \theta_0^* / \theta_0^{2*}$.

Using DEA in two stages, Kao and Hwang presented the following model for measuring DMUs' overall CRS efficiency:

$$\theta_0^{1*} = \text{Maximize} \sum_{d=1}^{D} \eta_d z_{dj} \tag{7}$$

$$\text{Subject to } \theta_0^* = \sum_{r=1}^{s} u_r y_{r0},$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1,$$

$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1\ldots, n,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s,$$

or

$$\theta_0^{2*} = \text{Maximize} \sum_{r=1}^{s} u_r y_{r0} \tag{8}$$

$$\text{Subject to} \sum_{d=1}^{D} \eta_d z_{dj} = 1,$$

$$\sum_{r=1}^{s} u_r y_{r0} - \theta_0^* \sum_{i=1}^{m} v_i x_{i0} = 0,$$

$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1\ldots, n,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s.$$

In (Chen et al., 2009) the overall efficiency is not defined as the product of the two individual efficiencies. The overall efficiency of a two-stage process is estimated as the weighted sum of its two individual efficiencies. The multiplicative and additive models can both be applied equally well to aggregate their components. Regarding the two-stage DEA model, the following recall was issued:

$$\theta_0^* = \text{Max}\left[w_1 \cdot \frac{\sum_{d=1}^{D} \eta_d z_{d0}}{\sum_{i=1}^{m} v_i x_{i0}} + w_2 \cdot \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{d=1}^{D} \eta_d z_{d0}}\right] \tag{9}$$

$$\text{Subject to } \frac{\sum_{d=1}^{D} \eta_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad j = 1\ldots, n,$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} \eta_d z_{dj}} \leq 1, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s.$$

Where w_1 and w_2 are user-specified weights satisfying $w_1 + w_2 = 1$. Rather than being decision variables, these weights represent functions of decisions, reflecting their relative contributions of the performances of DMU_0 to its overall outcome in two stages. By setting:

$$w_1 = \frac{\sum_{i=1}^{m} v_i x_{i0}}{\sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0}} \quad \text{and} \tag{10}$$

$$w_2 = \frac{\sum_{d=1}^{D} \eta_d z_{d0}}{\sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0}},$$

The objective function of (9), which is presumed to reverberate the relative sizes of the two stages, can then be rewritten as follows:

$$\theta_0 = \left(\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{r=1}^{s} u_r y_{r0}\right) / \left(\sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0}\right)$$

Thus, the aliquot programming model (9) can be interpreted as the linear programming model (LP) below:

$$\theta_0^* = \text{Maximize } \sum_{d=1}^{D} \eta_d z_{d0} + \sum_{r=1}^{s} u_r y_{r0} \tag{11}$$

$$\begin{aligned} & Subject\ to \sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0} = 1, \\ & \quad \sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1\ldots, n, \\ & \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \le 0, \qquad j = 1\ldots, n, \\ & \quad \eta_d, v_i, u_r \ge 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s. \end{aligned}$$

Following the determination of the optimal objective value of (11) at the end of the process, the efficiency of the two levels could be analysed in an identical way to (Kao and Hwang's, 2008) study. For instance, θ_0^{1*} could be defined by solving the following linear programming (LP) model:

$$\theta_0^{1*} = \text{Maximize } \sum_{d=1}^{D} \eta_d z_{d0} \tag{12}$$

$$\begin{aligned} & \text{Subject to } \sum_{i=1}^{m} v_i x_{i0} = 1, \\ & \quad (1-\theta_0^*) \sum_{d=1}^{D} \eta_d z_{d0} + \sum_{r=1}^{s} u_r y_{r0} = \theta_0^*, \\ & \quad \sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1\ldots, n, \\ & \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \le 0, \qquad j = 1\ldots, n, \\ & \quad \eta_d, v_i, u_r \ge 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s. \end{aligned}$$

θ_0^2 could be figured out by $\theta_0^2 = (\theta_0^* - w_1^* \theta_0^{1*})/w_2^*$, where w_1^* and w_2^* are the weights gained from the model (10) by way of (9). θ_0^{2*} could also be defined by solving the following linear programming (LP) model:

$$\theta_0^{2*} = \text{Maximize } \sum_{r=1}^{s} u_r y_{r0} \tag{13}$$

$$\begin{aligned} & \text{Subject to } \sum_{d=1}^{D} \eta_d z_{d0} = 1, \\ & \quad \theta_0^* \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{r0} = 1 - \theta_0^*, \\ & \quad \sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1\ldots, n, \end{aligned}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s.$$

θ_0^1 could be obtained by $\theta_0^1 = (\theta_0^* - w_2^* \theta_0^{2*})/w_1^*$.

(Wang and Chin's, 2010) generalized the two-stage DEA model of (Chen et al., 2009) which could be used to compute both CRS and VRS efficiency score. To reflect the relative importance of each stage in the process, they assigned a weight to each one. By letting $\lambda_1 > 0$ and $\lambda_2 > 0$ to set of comparative significance weights of both stages like $\lambda_1 + \lambda_2 = 1$. Henceforth, the total output and input of DMU_j can be gained as $\lambda_1 \sum_{d=1}^{D} \eta_d z_{dj} + \lambda_2 \sum_{r=1}^{s} u_r y_{rj}$ and $\lambda_1 \sum_{i=1}^{m} v_i x_{ij} + \lambda_2 \sum_{d=1}^{D} \eta_d y_{dj,}$ it is necessary to calculate both the first stage efficiency as well as the second stage efficiency to calculate the CRS efficiency of the entire two-stage process.

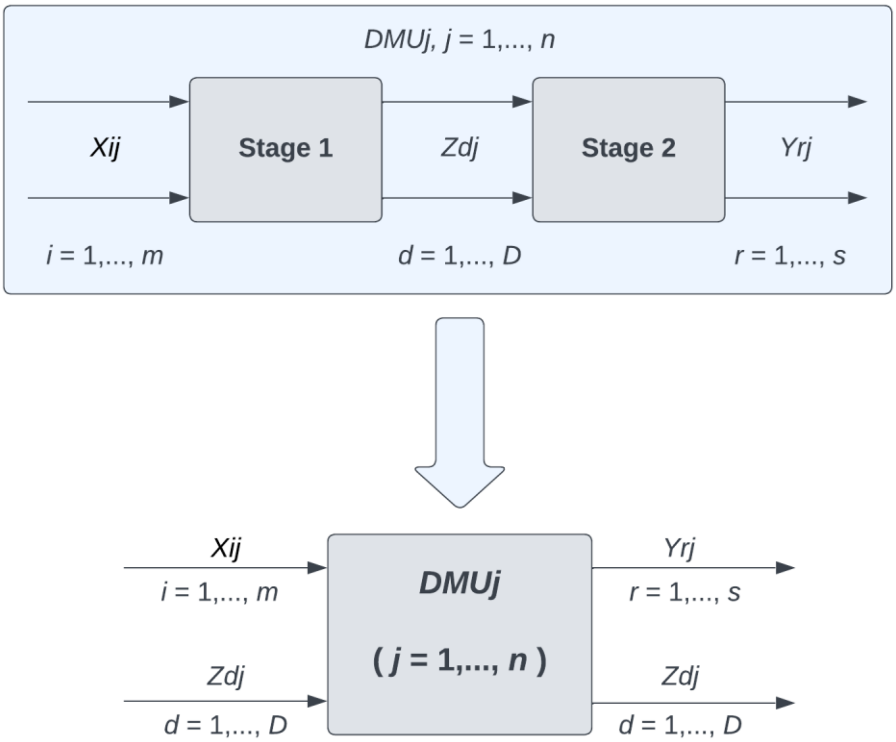

Figure 6: Conversion of two-stage procedure to single process

The total efficiency of DMU_0 can be estimated by either of the following models:

$$\theta_0^* = \text{Max } \lambda_1 \sum_{d=1}^{D} \eta_d z_{d0} + \lambda_2 \sum_{r=1}^{s} u_r y_{r0} \tag{14}$$

$$\text{Subject to } \lambda_1 \sum_{i=1}^{m} v_i x_{i0} + \lambda_2 \sum_{d=1}^{D} \eta_d z_{d0} = 1,$$

$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1\ldots, n,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s$$

and

$$\theta_0^* = \text{Maximize } \lambda_1 \left(\sum_{d=1}^{D} \eta_d z_{d0} + \sigma^1\right) + \lambda_2 \left(\sum_{r=1}^{s} u_r y_{r0} + \sigma^2\right) \tag{15}$$

$$\text{Subject to } \lambda_1 \sum_{i=1}^{m} v_i x_{i0} + \lambda_2 \sum_{d=1}^{D} \eta_d z_{d0} = 1,$$

$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} + \sigma^1 \leq 0, \qquad j = 1\ldots, n,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} + \sigma^2 \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s$$

$$\sigma^1 \text{ \& } \sigma^2 \text{ free variables}$$

While the overall efficiency θ_0^* is gained, θ_0^{1*} to obtain, one would need to solve the following linear programming (LP) models for different assumptions regarding returns to scale:

$$\theta_0^{1*} = \text{Maximize } \sum_{d=1}^{D} \eta_d z_{d0} \tag{16}$$

$$\text{Subject to } \sum_{i=1}^{m} v_i x_{i0} = 1,$$

$$(\lambda_1 - \lambda_2 \theta_0^*) \sum_{d=1}^{D} \eta_d z_{d0} + \lambda_2 \sum_{r=1}^{s} u_r y_{r0} = \lambda_1 \theta_0^*,$$

$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1\ldots, n,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \qquad j = 1\ldots, n,$$

$$\eta_d, v_i, u_r \geq 0, \qquad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s$$

or

$$\theta_0^{1*} = \text{Maximize } \sum_{d=1}^{D} \eta_d z_{d0} + \sigma^1 \tag{17}$$

Subject to $\sum_{i=1}^{m} v_i x_{i0} = 1,$

$$(\lambda_1 - \lambda_2\theta_0^*)\sum_{d=1}^{D} \eta_d z_{d0} + \lambda_1\sigma^1 + \lambda_2\sum_{r=1}^{s} u_r y_{r0} + \lambda_2\sigma^2 = \lambda_1\theta_0^*,$$

$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} + \sigma^1 \leq 0, \quad j = 1\ldots, n,$

$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} + \sigma^2 \leq 0, \quad j = 1\ldots, n,$

$\eta_d, v_i, u_r \geq 0, \quad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s$

σ^1 & σ^2 free variables

Likewise, θ_0^{2*} could be defined by solving one of the following linear programming (LP) models for different return-to-scale assumptions:

$$\theta_0^{2*} = \text{Maximize} \sum_{r=1}^{s} u_r y_{r0} \tag{18}$$

Subject to $\sum_{d=1}^{D} \eta_d z_{d0} = 1,$

$\lambda_2 \sum_{r=1}^{s} u_r y_{r0} - \lambda_1\theta_0^* \sum_{i=1}^{m} v_i x_{i0} = \lambda_2\theta_0^* - \lambda_1,$

$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1\ldots, n,$

$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leq 0, \quad j = 1\ldots, n,$

$\eta_d, v_i, u_r \geq 0, \quad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s$

or

$$\theta_0^{2*} = \text{Maximize} \sum_{r=1}^{s} u_r y_{r0} + \sigma^2 \tag{19}$$

Subject to $\sum_{d=1}^{D} \eta_d z_{d0} = 1,$

$$\lambda_2 \sum_{r=1}^{s} u_r y_{r0} + \lambda_2\sigma^2 - \lambda_1\theta_0^* \sum_{i=1}^{m} v_i x_{i0} + \lambda_1\sigma^1 = \lambda_2\theta_0^* - \lambda_1,$$

$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} + \sigma^1 \leq 0, \quad j = 1\ldots, n,$

$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} + \sigma^2 \leq 0, \quad j = 1\ldots, n,$

$\eta_d, v_i, u_r \geq 0, \quad d = 1\ldots, D; \quad i = 1\ldots, m; \quad r = 1\ldots, s$

σ^1 & σ^2 free variables

In (Kao and Hwang, 2008), the assumption that $\eta_d^1 = \eta_d^2 = \eta_d$ is vital to transform the two-stage DEA model into a linear programming (LP) problem and computing the efficiency scores of DMUs. Veritably, with a lack of this assumption it's clear that is not possible to cancel the factors $\sum_{d=1}^{D} \eta_d^1 z_{d0}$ and $\sum_{d=1}^{D} \eta_d^2 z_{d0}$ in the objective function $\theta_0^* = \theta_0^{1*} \times \theta_0^{2*}$ of model (6). Aside from that, assuming that $\eta_d^1 = \eta_d^2 = \eta_d$ also connects two levels of the chain to transform it into a particular process rather than two autonomous one-stage processes evaluated by two non-aligned CCR models. Accordingly, (Chen et al., 2009) and (Wang and Chin, 2010) also assigned the same weight to mediator outputs when they are considered intermediate inputs.

3.2 Tobit Regression Analysis

(Tobin, 1958) established the Tobit regression model, which is a statistical model based on linear assumptions that are employed when information on the dependent variable is unavailable for every perception due to censoring. (Holden, 2004), has tested the normality assumptions in the Tobit model. A significant portion of the information has been altered due to the skewness of the continuous dependent variable to one side. As a result, by altering, the regression is enabled. The population's conventional Tobit regression model is specified as:

$$y^* = x\text{ß} + u, \quad \text{u} \sim N\,(0, \sigma^2) \tag{20}$$

$$y = max\,(0, y^*)$$

y^* is a vector of the dependent variable

x is a vector of the independent variable

β is a vector coefficient measured by Tobit regression analysis

u is a vector of fault with regard to normal distribution.

The relationship between dependent and independent variables has been investigated using the Tobin regression model.

As part of this study, we analysed how some of the green principles' factors can affect the whole supply chain efficiency. The two factors that we are focusing on are environmental and economic. The three selected sub-factors are:

1- Service Level: it's the percentage of the orders from customers that need to be satisfied and the time they need to wait to receive the service or product.
2- Emission (CO_2): the average of each truck emission produced per day in kilograms.
3- Arcs: the total number of arcs in each chain (size of the chain for transportation factor).

In this test, we considered the efficiency of each supply chain as a dependent variable and the three mentioned sub-factors like service level, emission, and arcs were considered independent variables to see their effects on the supply chain efficiency. Therefore, the following is used for Tobit regression analysis.

$$efficiency = \beta_1(Service\ Level) + \beta_2(Emission) + \beta_3(Arcs) + u \quad (21)$$

The Tobit test will be provided a better understanding of the changes in efficiency based on some factors of green principles.

3.3 Methodology Description

To present the novelty of this research and better describe the process of introducing the approach, a sequence of steps is illustrated in Figure 7 below.

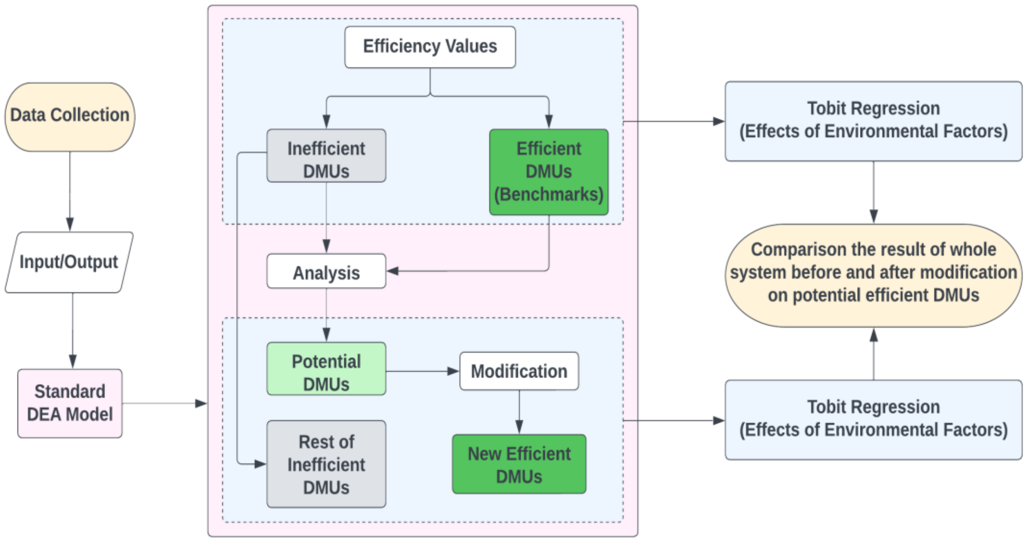

Figure 7: Methodology summary diagram

As Figure 7 illustrates, in the first step data collection from an official source which has been mentioned in the references at the end of the thesis, and then, specifying the inputs and outputs have been done. The second step is efficiency determination, this will determine both efficient and inefficient DMUs by applying standard DEA models. The third step is benchmarking, Inefficient DMUs are analysed using the efficient DMUs as a benchmark. This will produce potential DMUs (those that compare favourably well with the efficient DMUs) and strictly inefficient DMUs (those that failed to compare with those on the frontier). In the last step After modification, the inefficient DMUs became efficient, and then, measuring the effects of environmental factors on the whole system and comparison between the result before and after the modification of inefficient DMUs have done by Tobit regression analysis.

The mentioned methodology and approach have been applied to data in the numerical examples and will explain fully in detail in the next chapter.

Chapter 4

ANALYSIS OF DATA AND RESULTS

In this chapter, the main theoretical contributions that have been made in this thesis will present by a numerical example with real-world data and the results will be discussed. This chapter has two main parts, the first part represents the application of standard DEA models to find the initial efficient DMUs and with a developed benchmark approach attempt to increase the number of efficient DMUs. In the second part Tobit regression model has been applied to verify the effect of environmental factors on the whole system before and after the modification of inefficient DMUs.

4.1 Numerical Example

There are 38 supply chains from different companies that differ in size, material, and final product for applying the CCR and two-stage model to find which of them can consider efficient DMUs (see Appendix A). Then according to those who were selected as efficient, the cross-efficiency upon the benchmarks was applied to find out which inefficient DMUs can become efficient. First of all, categorizing the data and specifying the chains with their structure according to their final product profit. For this purpose, in the CCR model inputs including distribution, manufacture, supplier, retailer, and transportation and output as an average cost of goods sold (ACGS) for each chain and for two-stage ACGS as an input and sales profit as an output has been considered. Table 2 shows the minimum, maximum, average, and variance of the cost metrics for each stage and their percentage from the total ACGS.

Table 2: Summary of collected data for 38 under-evaluation DMUs

	Dist.	Manuf.	Part.	Retail.	Transp.	Av. CGS
Min	0.0001%	0.1%	23.3%	0.0001%	0.1%	$3.12
Max	64.2%	100.0%	99.1%	6.0%	62.8%	$150,816.00
Av	8.9%	29.5%	70.6%	1.8%	6.7%	$8,706.01
Var	0.025675	0.082809	0.043919	0.0003146	0.021063	-

(Willems, 2008)

4.2 DEA Models

The two-stage and CCR input-oriented model as one of the standard DEA models is applied to the extracted data to find out which one of the DMUs is efficient. Table 3, show the results of the two-stage under the CRS assumption by model (6), while Table 4 and 5 shows the result from model (14) with different weights for each stage, and Table 6 illustrates the results of the CCR model (3) to find out the efficient DMUs respectively. Model selection made based on constant returns to scale assumption of under-evaluation DMUs. This means that any radial increase in the input vector will have resulted in a proportional radial increase in the output vector. The model (6) was running according to each ACGS chain because even the financial part is an essential part of each chain and management besides greening the supply chain. Below shows the results for the efficiency of 38 firms upon CRS assumption by the model (6).

Table 3: Efficiency of 38 firms upon CRS assumption

DMU	Overall efficiency $\boldsymbol{\theta_0^*}$	First-stage efficiency $\boldsymbol{\theta_0^{1*}}$	Second-stage efficiency $\boldsymbol{\theta_0^{2*}}$
1	1.0000	0.0228	0.9000
2	1.0000	1.0000	1.0000
3	0.3875	0.3227	0.1010
4	0.2587	0.1176	0.0028
5	0.0578	0.0036	0.0008
6	0.0287	0.0287	0.0000
7	1.0000	1.0000	1.0000
8	0.0025	0.0012	0.0016
9	0.0194	0.0100	0.0002

10	1.0000	1.0000	0.0352
11	1.0000	1.0000	1.0000
12	0.0007	0.0007	0.0002
13	1.0000	1.0000	0.0022
14	0.2972	0.2972	0.0001
15	0.0106	0.0026	0.0001
16	0.0813	0.0812	0.0022
17	0.0003	0.0003	0.0002
18	0.0012	0.0012	0.0006
19	0.0321	0.0298	0.0009
20	0.0046	0.0046	0.0031
21	0.0065	0.0057	0.0001
22	0.0297	0.0244	0.0000
23	0.0425	0.0210	0.0007
24	1.0000	1.0000	0.0065
25	1.0000	1.0000	0.0155
26	1.0000	1.0000	0.0775
27	0.0213	0.0196	0.0005
28	0.0052	0.0052	0.0010
29	0.0001	0.0001	0.0000
30	0.0002	0.0002	0.0000
31	1.0000	1.0000	0.2314
32	0.0008	0.0008	0.0000
33	0.0001	0.0001	0.0000
34	0.0630	0.0630	0.0009
35	0.0000	0.0000	0.0000
36	0.2542	0.0614	0.0036
37	0.2475	0.0211	0.0035
38	0.0115	0.0086	0.0048

Table 3 above illustrates the two-stage results, DMUs 1, 2, 7, 10, 11, 13, 24, 25, 26, and 31 are overall efficient while DMUs 2, 7, and 11 are efficient in each stage and the rest of the DMUs are not efficient in one or two of their stages. To check the alternative results, the model (14) has been applied two times by imposing different weights for stages and the results have been provided in Tables 4 and 5 respectively. By testing the model with different weights of course we will receive somehow different results but, some DMUs are always efficient overall or at least one of their stages while the others cannot be considered as efficient DMUs generally. Now by applying model (14) the results with different weights for stages will be discussed.

Below shows the results for the efficiency of 38 firms upon CRS assumption for a certain set of stages weight with $\lambda_1 = 2/5$ and $\lambda_2 = 3/5$.

Table 4: Efficiency of 38 firms upon CRS assumption for a certain set of stages weight ($\lambda_1 = 2/5$, $\lambda_2 = 3/5$)

DMU	**Overall efficiency** $\boldsymbol{\theta_0^*}$	**First-stage efficiency** $\boldsymbol{\theta_0^{1*}}$	**Second-stage efficiency** $\boldsymbol{\theta_0^{2*}}$
1	0.9409	1.0000	0.9409
2	0.9786	0.9621	0.9417
3	1.0000	0.9926	0.9926
4	0.9304	0.9543	0.8871
5	0.9452	0.9441	0.8922
6	0.9083	0.9975	0.9058
7	0.9559	0.9868	0.9433
8	0.9697	0.9869	0.9569
9	0.9058	1.0000	0.9058
10	0.9814	0.9981	0.9796
11	0.9426	0.9982	0.9407
12	0.9927	0.9980	0.9907
13	0.9378	0.9853	0.9241
14	0.9647	0.9717	0.9362
15	0.9739	0.9738	0.9477
16	0.9533	0.9853	0.9393
17	0.9758	0.9923	0.9683
18	0.9979	0.9842	0.9823
19	0.9599	0.9927	0.9528
20	0.9691	0.9869	0.9552
21	0.9766	0.9867	0.9636
22	0.9356	0.9785	0.9146
23	0.9836	0.9991	0.9830
24	0.9906	0.9911	0.9821
25	0.9732	0.9879	0.9604
26	0.9814	0.9845	0.9665
27	0.9565	0.9835	0.9405
28	0.9675	0.9926	0.9609
29	0.9734	0.9924	0.9655
30	0.9628	0.9835	0.9475
31	0.9785	0.9856	0.9648
32	0.9615	0.9916	0.9531
33	0.9763	0.9836	0.9602
34	0.9538	0.9953	0.9491
35	0.9757	0.9852	0.9611
36	0.9680	0.9899	0.9587
37	0.9717	0.9791	0.9499
38	0.9865	0.9989	0.9789

As we can see in Table 4 with mentioned weights for stages the results get closer to having more efficient DMUs but, still need improvements. The only overall efficient DMU is 3 and, the rest does not efficient in their overall stage, but some DMUs like 1 and 9 are efficient in their first stage and not efficient in their second and overall stages. It seems that with the mentioned above weights for each stage there are less amount of efficient DMUs while they are nearly to become efficient by slight improvements.

After that, the efficiency of 38 firms under the CRS assumption has been tested for a certain collection of equal stage weights by the model (14) with $\lambda_1 = 1/2$ and $\lambda_2 = 1/2$. Below shows the result of the test. Although, having more efficient DMUs are expected at this time because of equal weights for each stage.

Table 5: Efficiency of 38 firms upon CRS assumption for a certain set of stages weight ($\lambda_1 = 1/2$, $\lambda_2 = 1/2$)

DMU	Overall efficiency $\boldsymbol{\theta_0^*}$	First-stage efficiency $\boldsymbol{\theta_0^{1*}}$	Second-stage efficiency $\boldsymbol{\theta_0^{2*}}$
1	0.9409	1.0000	0.9409
2	0.9786	0.9621	0.9417
3	1.0000	0.9926	0.9926
4	0.9304	0.9543	0.8871
5	0.9452	0.9441	0.8922
6	1.0000	1.0000	1.0000
7	0.9486	0.9811	0.9310
8	1.0000	0.9866	0.9866
9	1.0000	0.9572	0.9572
10	0.9523	0.9848	0.9375
11	0.9744	1.0000	0.9744
12	0.9425	1.0000	0.9425
13	1.0000	1.0000	1.0000
14	0.9652	1.0000	0.9652
15	0.9838	1.0000	0.9838
16	0.9562	1.0000	0.9562
17	0.9877	1.0000	0.9877
18	1.0000	0.9982	0.9982
19	0.9725	1.0000	0.9725
20	0.9796	0.9667	0.9468
21	0.9779	1.0000	0.9779

22	0.9915	1.0000	0.9915
23	0.9437	0.9875	0.9323
24	0.9757	1.0000	0.9757
25	0.9714	1.0000	0.9714
26	0.9849	1.0000	0.9849
27	1.0000	0.9867	0.9867
28	0.9649	0.9696	0.9341
29	0.9892	0.9946	0.9839
30	0.9516	1.0000	0.9516
31	0.9687	1.0000	0.9687
32	0.9667	0.9655	0.9336
33	0.9791	1.0000	0.9791
34	1.0000	0.9817	0.9817
35	0.9694	1.0000	0.9694
36	0.9989	1.0000	0.9989
37	0.9846	1.0000	0.9846
38	1.0000	1.0000	1.0000

According to Table 5 results, DMUs 3, 6, 8, 9, 13, 18, 27, 34, and 38 are overall efficient while DMUs 6, 13, and 38 are efficient in their all stages and the rest of the DMUs are efficient in one or two stages. By the mentioned weights for each stage in this test, there are more efficient DMUs than previous results according to our expectations. Also, some of the DMUs have the potential to become efficient with a slight improvement in one or two of their stages. Moreover, the CCR model (3) has been applied to 38 firms and the result was compared with previous results.

As obvious from the results of the CCR model (3) in Table 6 below, there are nine efficient DMUs. The efficient DMUs are 13, 14, 24, 28, 31, 33, 34, 36, and 38. They are selected as benchmarks for cross-efficiency verification. So, the optimal weights of each efficient DMU are used to compute the relative efficiency value (equation (1)) for each inefficient DMU.

Table 6: CCR model results

DMU	Efficiency	DMU	Efficiency
01	54.49	20	35.4
02	62.12	21	54.87
03	41.97	22	48.3
04	79.14	23	60.95
05	38.94	24	100
06	66.9	25	65.58
07	37.26	26	37.66
08	39.22	27	57.56
09	52.48	28	100
10	86.21	29	36.84
11	39.05	30	61.84
12	68.1	31	100
13	100	32	69.19
14	100	33	100
15	57.1	34	100
16	85.57	35	36.43
17	78.84	36	100
18	27.32	37	34.04
19	59.05	38	100

Table 7 contains the cross-efficiency values for each inefficient DMU concerning the benchmark DMUs. The eleventh column of this table shows that each one of the inefficient DMUs can be efficient, concerning the optimal weights of the benchmark DMUs (the number of 100 in each row). A DMU can consider a potentially efficient DMU when its efficiency value is near 100 and/or its relevant efficiency value is 100 more than four times in cross-efficiency verification. Moreover, as a supportive factor for the above criteria, the summation of cross-efficiency values in each line compute for inefficient DMUs as the last column of Table 7, shows which one of the inefficient DMUs where more efficient according to the benchmark DMUs weights. Therefore, the eleventh and twelfth columns have been investigated to find the potential DMUs.

Due to mentioned criteria, six DMUs can be considered as potentially efficient DMUs. These six DMUs are 4, 5, 10, 16, 17, and 27.

Table 7: Result of cross-efficiency verification

DMU	13	14	24	28	31	33	34	36	38		Eff	Total
01	100	2.23	18.67	100	34.57	1.27	100	100	20.35	4	54.49	477.09
02	100	100	22.65	27.97	43.58	9.7	18.1	74.4	100	3	62.12	496.4
03	100	8.21	100	55.3	7.17	100	70.66	29.75	100	4	41.97	571.09
04	100	13.95	100	86.45	56.48	15.95	67.97	100	100	4	79.14	640.8
05	74.24	3.31	100	100	100	3.26	100	100	28.17	5	38.94	608.98
06	100	10.73	64.52	44.83	9.07	100	41.72	34.93	100	3	66.9	505.8
07	100	7.39	100	61.35	6.53	33.95	100	27.87	100	4	37.26	537.09
08	100	8.21	100	55.3	7.17	100	70.66	29.75	100	4	39.22	571.09
09	78.25	14.27	100	89.8	100	14.79	70.8	100	100	4	52.48	667.91
10	100	11.06	100	100	24.2	12.35	100	70.68	100	5	86.21	618.29
11	100	100	22.65	27.97	43.58	9.7	18.1	74.4	100	3	39.05	496.4
12	100	8.5	100	55.54	7.58	100	67.97	31.05	100	4	68.1	570.64
15	78.25	14.27	100	89.8	100	14.79	70.8	100	100	4	57.1	667.91
16	100	13.95	100	86.45	56.48	15.95	67.97	100	100	4	85.57	640.8
17	100	13.95	100	86.45	56.48	15.95	67.97	100	100	4	78.84	640.8
18	100	13.95	100	86.45	56.48	15.95	67.97	100	100	4	27.32	640.8
19	100	7.39	100	61.35	6.53	33.95	100	27.87	100	4	59.05	537.09
20	100	7.39	100	61.35	6.53	33.95	100	27.87	100	4	35.4	537.09
21	100	3.48	100	100	50.07	3.48	100	100	29.91	3	54.87	586.94
22	100	100	31.75	30.23	61.41	41.34	19.65	81.67	100	3	48.3	566.05
23	100	2.23	18.67	100	34.57	1.27	100	100	20.35	4	60.95	477.09
25	78.25	14.27	100	89.8	100	14.79	70.8	100	100	3	65.58	667.91
26	100	2.23	18.67	100	34.57	1.27	100	100	20.35	4	37.66	477.09
27	74.24	3.31	100	100	100	3.26	100	100	28.17	5	57.56	608.98
29	100	10.4	20.42	100	37.86	2.48	75.34	100	100	4	36.84	546.5
30	100	100	30.61	28.79	40.64	54.91	18.91	71.43	100	3	61.84	545.29

32	100	8.21	100	55.3	7.17	100	70.66	29.75	100	3	69.19	571.09
35	100	7.39	100	61.35	6.53	33.95	100	27.87	100	4	36.43	537.09
37	100	100	30.61	28.79	40.64	54.91	18.91	71.43	100	3	34.04	545.29
Total	23	4	18	8	4	5	11	14	24			

The potentially efficient DMUs could be able to become efficient with small adjustments in the value of their inputs. The target results of the CCR model provide the necessary changes in the inputs of the potential DMUs to make them efficient. Table 8 contains the target results of the input-oriented CCR model.

Table 8: Targets result of CCR model for potential DMUs

DMU	Input 1 (%)	Input 2 (%)	Input 3 (%)	Input 4 (%)	Input 5 (%)
4	-89.4	-20.86	-20.86	0	0
5	-61.06	-610.6	-61.06	-61.06	0
10	0	-13.79	-13.79	0	0
16	-97	-14.43	-14.43	0	0
17	-94.16	-21.16	-21.16	-21.16	-21.16
27	-42.44	-42.44	-42.44	-42.44	0

If an inefficient potential DMU keeps its output at the same level and decreases its inputs as given in Table 8 it can perform efficiently. For example, DMU 10 with a 13.79% decrease in the value of inputs 2 and 3 (manufacturer and supplier) can be able to become efficient.

4.3 Tobit Regression Model

In this part, after recognizing the potential DMUs and finding out each of them should improve in which inputs and how much to become efficient. Then Tobit Regression was used to verify the effects of the green factors that we considered before as service level, emission (CO_2), and arcs which express the size of the chain, on the efficiency before and after the modification of potential DMUs to see which one and how much can affect the total efficiency of the whole supply chain. The result of Tobit regression before recognising the potential DMUs is shown in Table 9 below:

Table 9: Result of Tobit regression (for the whole DMUs before modification of potential DMUs)

Efficiency	**Coefficient**	**Std. err.**	**t**	**p>∣t∣**	**[95% conf.**	**interval]**
Service level	3.058122	2.432441	1.26	0.217	-1.879996	7.99624
Emission (CO_2)	-0.1192653	0.2147632	-0.56	0.582	-0.5552578	0.3167272
Arcs	0.4362361	0.2238707	1.95	0.059	-0.0182455	0.8907178
_cons	-2.297785	2.335146	-0.98	0.332	-7.038383	2.442814
var(e.Efficiency)	0.0477093	0.0109453			0.0299458	0.07601

As we can see here from the efficiency column, the Service level has the most positive effect to improve the efficiency of the DMUs and emission has the most negative effect on the DMUs' efficiency. On the other hand, the number of arcs in the supply chain network has a slightly positive effect to make a DMU more efficient. The numbers in the coefficient column show the changes in the efficiency value of DMUs with respect one-unit change on each green factor. For example, if CO_2 emission increases by a unit, the total efficiency value will decrease by 0.1193%, or if the service level increase by one unit the total efficiency value by approximately increases 3%. Moreover, the effect of one-unit increases in under-evaluation green factors on total efficiency value is 0.0477. There is an inverse reaction to green factors when the total efficiency value of the supply chain system is increased. Therefore, after necessary adjustments on input values of potential DMUs and by nature increasing the total efficiency value, there will be some changes in the effect of the green factors on the efficiency of the whole system. To see this, the first Tobit test ran for selected six potential DMUs to see the changes and effects of green factors on their efficiency. The result is shown in Table 10 below:

Table 10: Result of Tobit regression (for six potential DMUs)

Efficiency	Coefficient	Std. err.	t	p>|t|	[95% conf.	interval]
Service level	9.254766	6.93133	1.34	0.274	-12.80382	31.31335
Emission (CO_2)	2.07091	0.7734005	2.68	0.075	-0.3903959	4.532215
Arcs	3.377883	3.981558	0.85	0.459	-9.29321	16.04898
_cons	-8.676349	6.86242	-1.26	0.295	-30.51563	13.16294
var(e.Efficiency)	0.0125101	0.0072227			0.001992	0.0785645

This table illustrates the significant positive effect of service level, CO_2 emission, and arcs on the selected DMUs' efficiency values. It shows that efficiency improvement on these DMUs will be caused an improvement in their network and relations between the stages and customer satisfaction of their service level dramatically. But from the other side, this will have a positive undesirable effect on CO_2 emission.

The next Tobit test is done for all of the DMUs after adjustment on inputs of the potential DMUs and improving their efficiency. The results are summarized in Table 11. For the new set of supply chains still like in Table 9, service level and CO_2 have more positive and negative effects on the total efficiency level of the system respectively. On the other hand, the arcs have a slightly less positive effect. Moreover, the variety of the total efficiency value of the DMUs regarding the green factors is an increase from 0.047 to 0.058. This means that the efficiency scores of DMUs are now more sensitive to green factors.

Table 11: Result of Tobit regression (for the whole DMUs after modification of potential DMUs)

Efficiency	Coefficient	Std. err.	t	p>|t|	[95% conf.	interval]
Service level	5.13511	2.683682	1.91	0.064	-0.3130544	10.58327
Emission (CO_2)	-0.1338235	0.2369456	-0.56	0.576	-0.6148486	0.3472016
Arcs	0.2947164	0.2469937	1.19	0.241	-0.2067075	0.7961404
_cons	-4.233967	2.576338	-1.64	0.109	-9.464211	0.996276
var(e.Efficiency)	0.0580738	0.0133231			0.0364513	0.0925227

To verify which one of the potential DMUs has the best situation to invest in for improvement and become efficient besides ranking them based on their efficiency values, priority verification is done again by the Tobit test. The efficiency verity of each one of the potential DMUs is measured regarding the benchmark DMUs separately and the results are shown in Table 12.

Table 12: Result of Tobit regression for each potential DMU with Efficient DMUs

Rank	DMU	var(e.Efficiency)	Std. err.	Efficiency
1	10	0.0008452	0.000378	86.21
2	16	0.0011205	0.0005011	85.57
3	4	0.0016289	0.0007284	79.14
4	17	0.003404	0.0015223	78.84
5	27	0.0145833	0.0065218	57.56
6	5	0.0277673	0.0124179	38.94

The third column of the above table shows the effect of the green factors on the efficiency value of each one of the potential DMUs. Based on these numbers and their standard deviation of them DMU10 has the best situation for efficiency improvement. As seen in Table 12, the mentioned ranking method is matching the priority given by the efficiency values of the DMUs.

So, DMU 10 is the best candidate among the six potential DMUs for investing in improving and adjusting to becoming efficient. In this case, because of the fewer effects of green factors principles, it can be efficient and more robust compared to the other potential DMUs.

Chapter 5

CONCLUSION

This chapter outlines the theoretical contributions that have been made and shown in this thesis, the numerical example results with comparison and the conclusions that were reached in this study will be fully explained with details for each part. Also, suggestions for potential future studies based on the research done in this thesis are discussed.

This study attempts to develop general standard DEA models with the help of a benchmark approach that can distinguish the efficient (Supply Chains) DMUs from the under-evaluated DMUs, according to green supply chain management principles.

In the first step, the two-stage and CCR model has been applied to 38 DMUs which represent the companies' chain, and the results from the model (6) have shown in Table 3 under the CRS assumption that 10 DMUs were overall efficient while three DMUs were efficient in all stages and the rest of them were inefficient in one or two stages. In Tables 4 and 5, the results from the model (14) have been illustrated by imposing different weights for each stage under CRS assumption for 38 firms respectively. Upon the results with weights $\lambda_1 = 2/5$ and $\lambda_2 = 3/5$ there is only one overall efficient DMU and two others which efficient in their first stage, the rest are not efficient, and its shows that with the mentioned weights for each stage, there is less amount of efficient DMUs. Then, by changing the weights for each stage to $\lambda_1 = 1/2$ and $\lambda_2 =$

$1/2$ there has been an expectation to have more efficient DMUs to equal weights for the stages.

This time the results have shown that nine DMUs are efficient in their overall stage and three DMUs are efficient in their first and second stage too so, the rest of them are inefficient. Based on our expectation the number of efficient DMUs has been increased by implying equal weights for each chain. Also, according to Table 6 results from the CCR model (3) application, there were nine DMUs which are efficient initially. The outcomes from previous results revealed that some DMUs are robust and efficient under CRS assumption even with different weights and, others can become efficient or inefficient with different weights for each stage while some DMUs cannot consider efficient in any case.

Moreover, the initial efficient DMUs considered as a benchmark for the second step by applying cross-efficiency upon the elected ones to find out which DMUs from non-selected efficient have the potential to become efficient. According to the results, six DMUs can be efficient with a slight improvement in one or some inputs according to the target results of the CCR model (Table 7). After that, the Tobit regression model has been applied to investigate the effects of some green principal factors like service level, emissions (CO_2), and arcs to measure their effects on supply chain efficiency before modification of potential DMUs (Table 9).

In general, the service level has the most positive effect on efficiency. By contrast, the emission has the most negative impact on the efficiency of the supply chains. Also, the number of arcs for each chain which is the network size has a slight positive effect on the supply chain efficiency. But when the Tobit regression model is applied to the six potential DMUs, all three green factors had a positive effect on their efficiency improvement, even emission as an undesirable effect on the efficiency. After the modification of six potential DMUs as efficient, now there are 15 efficient DMUs in whole supply chains between 38 firms.

In the end, the Tobit regression model is used to find out the effect of total efficient DMUs on the whole supply chain's efficiency after modification of potential DMUs. Table 11, illustrates that the general idea about the green factors' effect on the total efficiency of the supply chains was correct but we should be aware of improving the efficiency of supply chains to hold the green principles factor efficiency robust. Also, the mentioned six potential DMUs compared with each other to recognize which of them has more value and a better situation to invest for improving its efficiency on it. It is found that DMU 10 according to the efficiency and standard deviation number is the best candidate among the potential DMUs to invest for its efficiency improvement (Table 12).

As it was expected, service level (customer satisfaction) and arcs (as the size of the transportation factor) had a positive effect and CO_2 emission (environmental effect) had a negative effect on the efficiency value of whole DMUs. But for potentially efficient DMUs, the effect of mentioned green factors was positive. This means that there is a benefit in the green aspect to improve the potential DMUs and make them efficient. Moreover, after necessary adjustment on potential DMUs, the Tobit regression results show that the sensitivity of the whole system is increased regarding the under-consideration of green factors. This indicates on importance of priority to modify the potential DMUs according to their ranks which are provided by the efficiency values and Tobit test results.

For future studies, researchers can use stochastic data in time for each stage can be used in the supply chain to find an efficient supply chain in the first phase, and in the second phase, more green principles can be considered to see their effect on the whole supply chain efficiency and verify the difference between with or without applying the green factors on calculation. Also, other models like stochastic DEA (SDEA), can be applied regarding the nature of data.

REFERENCES

Andiappan, V., Foo, D. C. Y., & Tan, R. R. (2022). Automated targeting for green supply chain planning considering inventory storage losses, production and set-up time. *Journal of Industrial and Production Engineering*, *39*(5), 341–352. https://doi.org/10.1080/21681015.2021.1991015

Ang, B.W.; Zhang, F.Q. (2000). A survey of index decomposition analysis in energy and environmental studies. *Energy*, 25, 1149–1176. https://doi.org/10.1016/s0360-5442(00)00039-6

Alosani, M. S., Al-Dhaafri, H. S., & Yusoff, R. Z. B. (2016). Mechanism of benchmarking and its impact on organizational performance. *International Journal of Business and Management*, 11(10), 172. https://doi.org/10.5539/ijbm.v11n10p172

Asher, M., & Kanji, G. K. (1996). *100 methods for total quality management*. Sage Publication.

Bowen, F.E.; Cousins, P.D.; Lamming, R.C.; Farukt, A.C. (2001). The role of supply management capabilities in green supply. *Prod. Oper. Manag*, 10, 174–189. https://doi.org/10.1111/j.1937-5956.2001.tb00077.x

Bui, T. D., Tsai, F. M., Tseng, M. L., Tan, R. R., Yu, K. D. S., & Lim, M. K. (2021). Sustainable supply chain management towards disruption and organizational ambidexterity: A data driven analysis. In *Sustainable Production and*

Consumption (Vol. 26, pp. 373–410). Elsevier B.V. https://doi.org/10.1016/j.spc.2020.09.017

Bogan, C. E., & English, M. J. (1994). Benchmarking for best practice: winning through innovative adaption. McGraw-Hill.

Boxwell Jr, R. J. (1994). Benchmarking for competitive advantage. McGraw-Hill.

Brah, S. A., Lin Ong, A., & Madhu Rao, B. (2000). Understanding the benchmarking process in Singapore. *International Journal of Quality & Reliability Management*, 17(3), 259-275. https://doi.org/10.1108/02656710010306157

Beamon, B. M. (1998). Supply chain design and analysis: Models and methods. *International Journal of Production Economics*, 55(3), 281–294. https://doi.org/10.1016/S0925-5273(98)00079-6

Camp, R. C. (1989). *Benchmarking: The search for industry best practice that lead to superior performance*. ASQ Quality Press.

Chan, F.T.; Chung, S. (2004). A multi-criterion genetic algorithm for order distribution in a demand driven supply chain. *Int. J. Comput. Integr. Manuf*, 17, 339–351. https://doi.org/10.1080/09511920310001617022

Chan, F.T.S.; Chung, S.H.; Wadhwa, S. (2004). A heuristic methodology for order distribution in a demand driven collaborative supply chain. *Int. J. Prod. Res*, 42, 1–19. https://doi.org/10.1080/00207540310001103293

Charnes, A., & Cooper, W. W. (1962). Programming with linear fractional functionals. Naval Research Logistics Quarterly, 9(3–4), 181–186. https://doi.org/10.1002/NAV.3800090303

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. In *Company European Journal of Operational Research* (Vol. 2).

Chen, C. C., Tseng, M. L., Lin, Y. H., & Lin, Z. S. (2010). Implementation of green supply chain management in uncertainty. *IEEM2010 - IEEE International Conference on Industrial Engineering and Engineering Management*, 260–264. https://doi.org/10.1109/IEEM.2010.5674461

Chen, C. L., & Lee, W. C. (2004). Multi-objective optimization of multi-echelon supply chain networks with uncertain product demands and prices. *Computers and Chemical Engineering*, *28*(6–7), 1131–1144. https://doi.org/10.1016/j.compchemeng.2003.09.014

Chen, Y., Cook, W. D., Li, N., & Zhu, J. (2009). Additive efficiency decomposition in two-stage DEA. *European Journal of Operational Research*, 196(3), 1170–1176. https://doi.org/10.1016/j.ejor.2008.05.011

Christopher, M. (1998). Logistics and supply chain management strategies for reducing cost and improving service. Financial Times, London Prentice-Hall

Chopra, S. and Meindl, P. (2001) Supply chain management strategy, planning, and operation. Prentice-Hall, Upper Saddle River, NJ.

da Costa, L. G., Ferreira, J. C. E., Kumar, V., & Garza-Reyes, J. A. (2022). Benchmarking of sustainability to assess practices and performances of the management of the end of life cycle of electronic products: a study of Brazilian manufacturing companies. *Clean Technologies and Environmental Policy, 24*(4), 1173–1189. https://doi.org/10.1007/s10098-020-01947-3

de Sousa Jabbour, A. B. L. (2015). Understanding the genesis of green supply chain management: Lessons from leading Brazilian companies. *Journal of Cleaner Production, 87*(1), 385–390. https://doi.org/10.1016/j.jclepro.2014.09.034

Donthu, N., Hershberger, E. K., & Osmonbekov, T. (2005). Benchmarking marketing productivity using data envelopment analysis. *Journal of Business Research*, *58*(11), 1474–1482. https://doi.org/10.1016/J.JBUSRES.2004.05.007

Diabat, A., & Govindan, K. (2011). An analysis of the drivers affecting the implementation of green supply chain management. *Resour. Conserv. Recycl*, 55(6), 659–667. https://doi.org/10.1016/j.resconrec.2010.12.002

ElTayeb, T. K., Zailani, S., & Jayaraman, K. (2010). The examination on the drivers for green purchasing adoption among EMS 14001 certified companies in Malaysia. *Journal of Manufacturing Technology Management*, *21*(2), 206–225. https://doi.org/10.1108/17410381011014378

Färe, R., & Grosskopf, S. (2000). Network DEA. *Socio-Economic Planning Sciences*, *34*(1), 35–49. https://doi.org/10.1016/S0038-0121(99)00012-9

Farrell, M. J. (1957). The measurement of productive efficiency. In *Source: Journal of the Royal Statistical Society. Series A (General)* (Vol. 120, Issue 3). https://www.jstor.org/stable/2343100

Forghani, D., Ibrahim, M. D., & Daneshvar, S. (2022). Improving weak efficiency frontier in a variable returns to scale stochastic data envelopment analysis model. *RAIRO - Operations Research*, *56*(4), 2159–2179. https://doi.org/10.1051/ro/2022100

Ghosh, S., Murthy, N., Park, B. J., & Park, B. J. (2004). Integrating product platform development with supply chain configuration in a global environment. https://ink.library.smu.edu.sg/lkcsb_research/2087

Guillén, G., Mele, F. D., Bagajewicz, M. J., Espuña, A., & Puigjaner, L. (2005). Multiobjective supply chain design under uncertainty. *Chemical Engineering Science*, *60*(6), 1535–1553. https://doi.org/10.1016/j.ces.2004.10.023

Herrmann, F. F., Barbosa-Povoa, A. P., Butturi, M. A., Marinelli, S., & Sellitto, M. A. (2021). Green supply chain management: Conceptual framework and models for analysis. *Sustainability (Switzerland)*, *13*(15). https://doi.org/10.3390/su13158127

Hsu, C. W., & Hu, A. H. (2009). Applying hazardous substance management to supplier selection using analytic network process. *Journal of Cleaner Production*, *17*(2), 255–264. https://doi.org/10.1016/j.jclepro.2008.05.004

Hong, S.-M., Paterson, G., Mumovic, D., & Steadman, P. (2014). Improved benchmarking comparability for energy consumption in schools. *Building Research & Information*, 42(1), 47-61. https://doi.org/10.1080/09613218.2013.814746

Harland, C. M. (1996). Supply chain management: Relationships, chains and networks. *British Journal of Management*, 7(SPEC. ISS.), S63–S80. https://doi.org/10.1111/J.1467-8551.1996.TB00148.X

Holden, D. (2004). Testing the normality assumption in the Tobit model. *Journal of Applied Statistics*. 31:521-532, 2004

Jabbour, A. B. L. de S., Jabbour, C. J. C., Latan, H., Teixeira, A. A., & de Oliveira, J. H. C. (2015). Reprint of "Quality management, environmental management maturity, green supply chain practices and green performance of Brazilian companies with ISO 14001 certification: Direct and indirect effects." *Transportation Research Part E: Logistics and Transportation Review*, *74*, 139–151. https://doi.org/10.1016/j.tre.2014.12.011

Johnson, G. M. and L. Malucci. (1999). Shift to supply chain reflects more strategic approach, APICS-The performance advantage, Oct., pp. 28-31

Kalvelagen, E. (2004). Efficiency solving DEA model with GAMS. http://amsterdamoptimization.com/models/dea/dea.gms

Kuo, R. J., Wang, Y. C., & Tien, F. C. (2010). Integration of artificial neural network and MADA methods for green supplier selection. *Journal of Cleaner Production*, *18*(12), 1161–1170. https://doi.org/10.1016/j.jclepro.2010.03.020

Kao, C., & Hwang, S. N. (2008). Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *European Journal of Operational Research*, 185(1), 418–429. https://doi.org/10.1016/j.ejor.2006.11.041

Large, R. O., & Gimenez Thomsen, C. (2011). Drivers of green supply management performance: Evidence from Germany. *Journal of Purchasing and Supply Management*, *17*(3), 176–184. https://doi.org/10.1016/j.pursup.2011.04.006

Lambert, D. M., & Cooper, M. C. 2000. Issues in supply chain management. *Industrial Marketing Management*, 29(1), 65–83. https://doi.org/10.1016/S0019-8501(99)00113-3

Mondal, C., & Giri, B. C. (2022). Investigating strategies of a green closed-loop supply chain for substitutable products under government subsidy. *Journal of Industrial and Production Engineering*, *39*(4), 253–276. https://doi.org/10.1080/21681015.2021.1974962

Nahmias, S. (1993). Production and operations analysis, Richard D. Irwin. Inc., Homewood, Illinois.

Ninlawan C, Seksan P., Tassapol K. & Pilada W. (2010). The implementation of green supply chain management practices in electronics industry. In World Congress on Engineering 2012. July 4-6, 2012. London, UK. (Vol. 2182, pp. 1563-1568). International Association of Engineers.

Olugu, E. U., Wong, K. Y., & Shaharoun, A. M. (2010). A comprehensive approach in assessing the performance of an automobile closed-loop supply chain. *Sustainability*, *2*(4), 871–889. https://doi.org/10.3390/su2040871

Radovanov, B., Dudic, B., Gregus, M., Horvat, A. M., & Karovic, V. (2020). Using a two-stage DEA model to measure tourism potentials of EU countries and Western Balkan countries: An approach to sustainable development. *Sustainability (Switzerland)*, *12*(12). https://doi.org/10.3390/SU12124903

Rajeev, A., Pati, R. K., Padhi, S. S., & Govindan, K. (2017). Evolution of sustainability in supply chain management: A literature review. In *Journal of Cleaner Production* (Vol. 162, pp. 299–314). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2017.05.026

Rostamzadeh, R., Akbarian, O., Banaitis, A., & Soltani, Z. (2021). Application of dea in benchmarking: A systematic literature review from 2003–2020. Technological and Economic Development of Economy, 27(1), 175–222. https://doi.org/10.3846/tede.2021.13406

Sabri, E. H., & Beamon, B. M. (2000). A multi-objective approach to simultaneous strategic and operational planning in supply chain design. *Omega*, *28*(5), 581–598. https://doi.org/10.1016/S0305-0483(99)00080-8

Sarkis, J. (2003). A strategic decision framework for green supply chain management. *Journal of Cleaner Production*, *11*(4), 397–409. https://doi.org/10.1016/S0959-6526(02)00062-8

Sarkis, J. (2006). The adoption of environmental and risk management practices: Relationships to environmental performance. *Annals of Operations Research*, *145*(1), 367–381. https://doi.org/10.1007/s10479-006-0040-9

Sarkis, J., Zhu, Q., & Lai, K. H. (2011). An organizational theoretic review of green supply chain management literature. *International Journal of Production Economics*, *130*(1), 1–15. https://doi.org/10.1016/J.IJPE.2010.11.010

Sellitto, M. A., Bittencourt, S. A., & Reckziegel, B. I. (2015). Evaluating the implementation of GSCM in industrial supply chains: Two cases in the automotive industry. *Chemical Engineering Transactions*, *43*, 1315–1320. https://doi.org/10.3303/CET1543220

Shabani, A., Saen, R. F., & Torabipour, S. M. R. (2012). A new benchmarking approach in Cold Chain. *Applied Mathematical Modelling*, *36*(1), 212–224. https://doi.org/10.1016/j.apm.2011.05.051

Shaik, M., & Abdul-Kader, W. (2011). Green supplier selection generic framework: A multi-attribute utility theory approach. *International Journal of Sustainable Engineering*, *4*(1), 37–56. https://doi.org/10.1080/19397038.2010.542836

Sheffi, Y. (2005). Fixing government after Katrina. https://web.mit.edu/sheffi/www/documents/genmedia.FixingGovAfterKatrina.pdf

Shen, L., Olfat, L., Govindan, K., Khodaverdi, R., & Diabat, A. (2013). A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences. *Resources, Conservation and Recycling*, *74*, 170–179. https://doi.org/10.1016/j.resconrec.2012.09.006

Stewart, T. J. (2010). Goal directed benchmarking for organizational efficiency. *Omega*, *38*(6), 534–539. https://doi.org/10.1016/j.omega.2010.01.004

Sueyoshi, T., & Goto, M. (2011). Methodological comparison between two unified (operational and environmental) efficiency measurements for environmental assessment. *European Journal of Operational Research*, *210*(3), 684–693. https://doi.org/10.1016/j.ejor.2010.10.030

Simchi-Levi, D., Kaminsky, S., & Simchi-Levi, E. (2003). Designing & Managing the Supply Chain Concepts, Strategies and Cases.

Tajabadi, F. Z., & Kazemi, A. (2016). To develop an integrated model for green supply chain. *Journal of Fundamental and Applied Sciences*, *8*(3), 1340. https://doi.org/10.4314/jfas.v8i3s.158

Tseng, M. L., Islam, M. S., Karia, N., Fauzi, F. A., & Afrin, S. (2019). A literature review on green supply chain management: Trends and future challenges. In *Resources, Conservation and Recycling* (Vol. 141, pp. 145–162). Elsevier B.V. https://doi.org/10.1016/j.resconrec.2018.10.009

Tseng, M. L., & Chiu, A. S. F. (2013). Evaluating firm's green supply chain management in linguistic preferences. *J. Clean. Prod*, 40, 22–31. https://doi.org/10.1016/J.JCLEPRO.2010.08.007

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica*, 26(1), 24. https://doi.org/10.2307/1907382

Walker, H., & Jones, N. (2012). Sustainable supply chain management across the UK private sector. *Supply Chain Management*, *17*(1), 15–28. https://doi.org/10.1108/13598541211212177

Walker, H., di Sisto, L., & McBain, D. Drivers and barriers to environmental supply chain management practices: Lessons from the public and private sectors. *Journal of Purchasing and Supply Management*. 2008, 14(1), 69–85. https://doi.org/10.1016/j.pursup.2008.01.007

Wang, Y. M., & Chin, K. S. (2010). Some alternative DEA models for two-stage process. *Expert Systems with Applications*, 37(12), 8799–8808. https://doi.org/10.1016/j.eswa.2010.06.024

Willems, S.P. (2008). Real-world multi-echelon supply chains used for inventory optimization. *Manufacturing and Service Operations Management*, 10(1), 19–23. https://doi.org/10.1287/MSOM.1070.0176.

Yasin, M. M. (2002). The theory and practice of benchmarking: Then and now. *Benchmarking: An International Journal*, 9(3), 217-243. https://doi.org/10.1108/14635770210428992

Zanjirani Farahani, R.; Asgari, N.; Davarzani, H. (2009). Supply chain and logistics in national, international and governmental environment: Concepts and models; Springer: Berlin/Heidelberg, Germany.

Zhou, P.; Ang, B.; Poh, K. (2008). Measuring environmental performance under different environmental DEA technologies. *Energy Econ*, 30, 1–14. https://doi.org/10.1016/j.eneco.2006.05.001

Zhou, P.; Ang, B.; Poh, K. (2008). A survey of data envelopment analysis in energy and environmental studies. *Eur. J. Oper. Res*, 189, 1–18. https://doi.org/10.1016/j.ejor.2007.04.042

Zhu, Q., & Sarkis, J. (2006). An inter-sectoral comparison of green supply chain management in China: Drivers and practices. *Journal of Cleaner Production*, *14*(5), 472–486. https://doi.org/10.1016/j.jclepro.2005.01.003

Zhu, Q., & Sarkis, J. (2007). The moderating effects of institutional pressures on emergent green supply chain practices and performance. *International Journal of Production Research*, *45*(18–19), 4333–4355. https://doi.org/10.1080/00207540701440345

Zhu, Q., Sarkis, J., & Lai, K. hung. (2007). Green supply chain management: pressures, practices and performance within the Chinese automobile industry. *J. Clean. Prod*, 15(11–12), 1041–1052. https://doi.org/10.1016/J.JCLEPRO.2006.05.021

Zhu, Q., Sarkis, J., & Lai, K. hung. (2008). Confirmation of a measurement model for green supply chain management practices implementation. *International Journal of Production Economics*, *111*(2), 261–273. https://doi.org/10.1016/j.ijpe.2006.11.029

APPENDICES

Appendix A: Firms Characteristics and Information

Figure A1 below illustrates the industry's chain with its size and the average cost of goods sold per unit of production. Although, the characteristics of the 38-supply chain that we encompass in the study with their number of arcs (size of the chain) and ACGS are shown in Table A1.

Table A1. General Classification of the Data Set

Chain Name	SIC Description	Total Arcs (Size of the Chain)	Average Cost of Goods Sold Per Unit
1	Industrial Organic Chemicals, Not Elsewhere Classified	10	$71.88
2	Semiconductors and Related Devices	13	$136.07
3	Computer Peripheral Equipment, Not Elsewhere Classified	18	$3,820.00
4	Games, Toys, and Children's Vehicles, Except Dolls and Bicycles	39	$212.67
5	Food Preparations, Not Elsewhere Classified	31	$31.46
6	Cutlery	28	$3.42
7	Construction Machinery and Equipment	78	$150,816.00
8	Electromedical and Electrotherapeutic Apparatus	48	$120.72
9	Cereal Breakfast Foods	52	$22.84
10	Electrical Appliances, Television and Radio Sets	176	$5,477.00
11	Construction Machinery and Equipment	108	$142,853.00
12	Cereal Breakfast Foods	107	$29.61
13	Semiconductors and Related Devices	452	$134.50
14	Arrangement of Transportation of Freight and Cargo	119	$18.11
15	Soap and Other Detergents, Except Specialty Cleaners	164	$9.17
16	Electromedical and Electrotherapeutic Apparatus	224	$342.88
17	Computer Peripheral Equipment, Not Elsewhere Classified	211	$33.16
18	Computer Peripheral Equipment, Not Elsewhere Classified	224	$91.68
19	Computer Peripheral Equipment, Not Elsewhere Classified	263	$135.40

20	Computer Peripheral Equipment, Not Elsewhere Classified	169	$448.02
21	Perfumes, Cosmetics, and Other Toilet Preparations	359	$17.81
22	Pharmaceutical Preparations	253	$3.23
23	Paints, Varnishes, Lacquers, Enamels, and Allied Products	524	$110.54
24	Power-Driven Hand tools	1245	$949.26
25	Farm Machinery and Equipment	853	$2,319.00
26	Aircraft Engines and Engine Parts	605	$11,681.14
27	Electromedical and Electrotherapeutic Apparatus	941	$72.80
28	Computer Storage Devices	2262	$149.71
29	Primary Batteries, Dry and Wet	753	$8.17
30	Arrangement of Transportation of Freight and Cargo	632	$6.73
31	Farm Machinery and Equipment	908	$9,609.00
32	Perfumes, Cosmetics, and Other Toilet Preparations	1685	$3.12
33	Perfumes, Cosmetics, and Other Toilet Preparations	1009	$6.29
34	Telephone and Telegraph Apparatus	4063	$130.79
35	Electromedical and Electrotherapeutic Apparatus	1857	$6.54
36	Farm Machinery and Equipment	4812	$422.44
37	Industrial Organic Chemicals, Not Elsewhere Classified	2069	$231.75
38	Aircraft Engines and Engine Parts	16225	$292.52

(Willems, 2008)

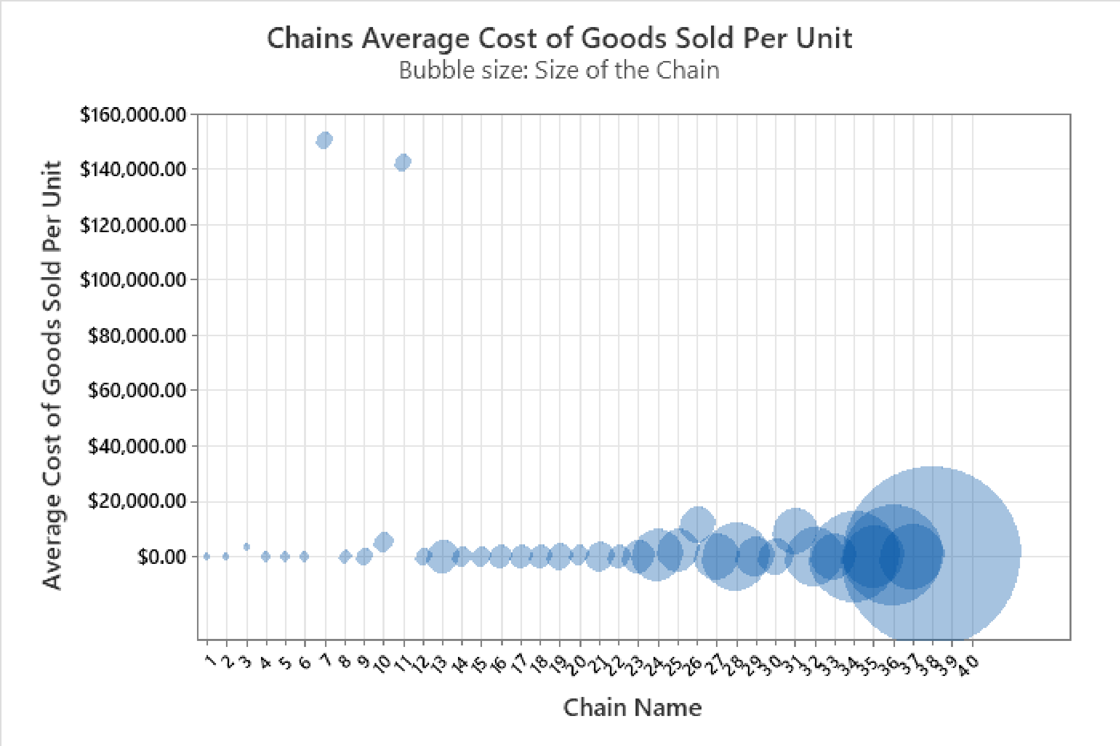

Figure A1. Summarizes each industry chain ACGS and Size

Appendix B: GAMS Code for CRS Assumption and Two-stage Models

```
sets i         "DMU's"  /Chain1*Chain38/
     j         'inputs and outputs' /Dist, Manuf, Part, Retail, Trans, ServiceLevel, Emisson, Arc, COGS/
     inp(j)  'inputs'  /Dist, Manuf, Part, Retail, Trans, ServiceLevel, Emisson, Arc/
     outp(j) 'outputs' /COGS/;

parameter
   x0(inp)    'inputs of DMU j0'
   y0(outp)   'outputs of DMU j0'
   x(inp,i)   'inputs of DMU i'
   y(outp,i)  'outputs of DMU i'
;

positive variables
   v(inp)   'input weights'
   u(outp)  'output weights'
;

variable
   eff 'efficiency'
;

equations
   objective   'objective function: maximize efficiency'
   normalize   'normalize input weights'
   limit(i)    "limit other DMU's efficiency";

objective..  eff =e= sum(outp, u(outp)*y0(outp));

normalize..  sum(inp, v(inp)*x0(inp)) =e= 1;

limit(i)..   sum(outp, u(outp)*y(outp,i)) =l= sum(inp, v(inp)*x(inp,i));


model dea /objective, normalize, limit/;


alias (i,iter);

x(inp,i) = data(i,inp);
y(outp,i) = data(i,outp);

parameter efficiency(i) 'efficiency of each DMU';

loop(iter,

   x0(inp) = x(inp, iter);
   y0(outp) = y(outp, iter);

   solve dea using lp maximizing eff;
   abort$(dea.modelstat<>1) "LP was not optimal";

   efficiency(iter) = eff.l;
);


display efficiency;

*
* create sorted output
```

```
*
set r /rnk1*rnk1000/;
parameter rank(i);
alias (i,ii);
rank(i) = sum(ii$(efficiency(ii)>=efficiency(i)), 1);
parameter efficiency2(r,i);
efficiency2(r,i)=efficiency(i)$(rank(i)=ord(r));
option efficiency2:4:0:1;
display efficiency2;

```

```
Set
   i          'units'
   is(i)      'selected unit'
   j          'inputs and outputs'
   ji(j)      'inputs'
   jo(j)      'outputs';

Parameter
   data(i,j) 'unit input  output'
   vlo        'v lower bound'
   ulo        'u lower bound'
   norm       'normalizing constant'
   lambda1
   lambda2;
   lambda1=1/2;
   lambda2=1/2;
Variable
   v(ji)      'input weights'
   u(jo)      'output weights'
   eta1(ji)   'input weights'
   eta2(jo)   'output weights'
   eff        'efficiency'
   var        'dual convexity'
   lam(i)     'dual weights'
   vs(ji)     'input duals'
   us(jo)     'output duals'
   z;

Positive Variable u, v, vs, us, lam, eta1, eta2;

Equation
   const1
   const2(j)
   const3(j)
   defe(i)     'efficiency definition - weighted output'
   denom(i)    'weighted input'
   lime(i)     'output / input < 1'
   dii(i,ji)   'input duals'
   dio(i,jo)   'output dual'
   defvar      'variable return to scale'
   dobj        'dual objective'
   objective   'overall efficiency';

* primal model
objective..   eff =e= lambda1*sum(ji, eta1(ji)*data(is,ji))+lambda2*sum(jo, u»
(jo)*data(is,jo));
const1.. lambda1*sum(ji, v(ji)*data(is,ji))+lambda2*sum(jo, eta(jo)*data(is,j»
i))=e=1;
const2.. sum(jo, eta(jo)*data(is,ji))-sum(ji, v(ji)*data(is,ji))=l=0;
const3.. sum(jo, u(jo)*data(is,jo))-sum(jo, eta(jo)*data(is,ji))=l=0;
denom(is)..   sum(ji, v(ji)*data(is,ji)) =e= norm;

lime(i)..     sum(jo, u(jo)*data(i,jo)) =l= sum(ji, v(ji)*data(i,ji)) + var;

* dual model
dii(is,ji).. sum(i, lam(i)*data(i,ji)) + vs(ji) =e= z*data(is,ji);

dio(is,jo).. sum(i, lam(i)*data(i,jo)) - us(jo) =e= data(is,jo);

defvar..      sum(i, lam(i)) =e= 1;

```

```
dobj..       eff =e= norm*z - vlo*sum(ji, vs(ji)) - ulo*sum(jo, us(jo));

Model
   wang 'two-stage' /objective, const1, const2, const3/
   deap  'primal'       / defe, denom, lime         /
   deadc 'dual with CRS' / dobj, dii,   dio          /
   deadv 'dual with VRS' / dobj, dii,   dio, defvar  /;

Set
   i     'units'               / Chain1*chain38                        /
   j     'inputs and outputs' / Dist_, Manuf_, Part_, Retail_, Trans_, COGS /
   ji(j) 'inputs'              / Dist_, Manuf_, Part_, Retail_, Trans_        /
   jo(j) 'outputs'             /           COGS/;


$eolCom //
option limCol   = 0         // no column listing
       limRow   = 0         // no row listing
       solveOpt = replace;  // don't keep old var and equ values

var.fx = 0;       // to run CRS with the primal model
*var.lo = -inf;   // to run VRS with the primal model
*var.up = +inf;   // to run VRS with the primal model
vlo  = 1e-4;
ulo  = 1e-4;
norm = 100;

v.lo(ji) = vlo;
u.lo(jo) = ulo;

*deadc.solPrint = %solPrint.quiet%;
*deadv.solPrint = %solPrint.quiet%;
*deap.solPrint  = %solPrint.quiet%;

Set ii(i) 'set of units to analyze' /Chain13, Chain14, Chain24, Chain28, Chain31, Chain33, Chain34, Chain36, Chain38  /;

*ii(i) = yes;      // use to run all depots
is(i) = no;

Parameter rep 'summary report';

loop(ii,
   is(ii) = yes;

   solve deap us lp max eff;
   rep(i,ii) =  sum(jo, u.l(jo)*data(i,jo))/sum(ji, v.l(ji)*data(i,ji));
   rep('MStat-p',ii) = deap.modelStat;

   solve deadc us lp min eff;
   rep('MStat-d',ii)   = deadc.modelStat;
   rep('obj-check',ii) = deadc.objVal - deap.objVal;
   is(ii) = no;
);

rep(i,'Min') = smin(ii, rep(i,ii));
rep(i,'Max') = smax(ii, rep(i,ii));
rep(i,'Avg') =  sum(ii, rep(i,ii))/card(ii);


display rep;

```

```
Set
   i          'units'
   is(i)      'selected unit'
   j          'inputs and outputs'
   ji(j)      'inputs'
   jo(j)      'outputs';

Parameter
   data(i,j) 'unit input  output'
   vlo       'v lower bound'
   ulo       'u lower bound'
   norm      'normalizing constant'
   lambda1
   lambda2;
   lambda1=1/2;
   lambda2=1/2;

Variable
   v(ji)      'input weights'
   u(jo)      'output weights'
   eta1(ji)   'input weights'
   eta2(jo)   'output weights'
   eff        'efficiency'
   var        'dual convexity'
   lam(i)     'dual weights'
   vs(ji)     'input duals'
   us(jo)     'output duals'
   z;

Positive Variable u, v, vs, us, lam, eta1, eta2;

Equation
   const1
   const2(j)
   const3(j)
   defe(i)     'efficiency definition - weighted output'
   denom(i)    'weighted input'
   lime(is)     'output / input < 1'
   dii(is,ji)   'input duals'
   dio(is,jo)   'output dual'
   defvar      'variable return to scale'
   dobj        'dual objective'
   objective   'overall efficiency';

Model
   wang 'two-stage' /objective, const1, const2, const3/
   deap  'primal'        / defe, denom, lime         /
   deadc 'dual with CRS' / dobj, dii,   dio          /
   ;
* primal model
objective..   eff =e= lambda1*sum(ji, eta1(ji)*data(is,ji))+lambda2*sum(jo, u(jo)*data(is,jo));
const1.. lambda1*sum(ji, v(ji)*data(is,ji))+lambda2*sum(jo, eta2(jo)*data(is,ji))=e=1;
const2(j).. sum(jo, eta2(jo)*data(is,j)) - sum(ji, v(ji)*data(is,j))=l=0;
const3(j).. sum(jo, u(jo)*data(is,j)) - sum(jo, eta1(jo)*data(is,j))=l=0;
denom(is)..  sum(ji, v(ji)*data(is,ji)) =e= norm;
lime(i).. sum(jo, u(jo)*data(i,jo)) =l= sum(ji, v(ji)*data(i,ji)) + var;
```