Thesis for the Degree of Doctor of Philosophy

Energy Consumption Analysis of International Container Terminals

-An Efficiency Analysis Using DEA-

by

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(국제 컨테이너 터미널 에너지 소비분석

-DEA 기법을 통한 효율성 측정-)

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-DEA 기법을 통한 효율성 측정-

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요약

세계의 대부분 현대화 된 컨테이너 터미널의 등장으로 실제적으로 많은 항만이 그들의 Throughput 을 올리며 소위 화물 처리능력에서 특별히 새로운 기록을 달성할 수 있도록 하였다. 하지만 고도화된 기계화와 다양한 기계와 설비의 도입이 항만 산업계에는 과다한 에너지 소비를 증가시켰다.

예를 들면 지속성 성장의 한계, 자원의 감소, 유해 물질 배출과 같은 수 많은 바람직하지 못한 측면효과도 발생시켰다. 항만산업은 이러한 바람직하지 못한 컨테이너화에 따른 효과를 극복해야 되는 도전에 직면함에 따라 항만운영자들은 글로벌 전략과 공중보건, 환경적 충격 그리고 지속성과 같은 점을 감안한 정책을 도입해야 할 상황에 처하게 되었다.

환경과 지속 성장이란 측면에서 노력은 에너지 소비의 절감노력은 중요한 요소로 등장하게 되었다. 사실 항만운영자들은 그의 정책을 지원하는 정확한 자료가 없다면 에너지 소비 감소정책을 계획하는데 주저할 수 밖에 없는 것이다. 따라서 항만의 에너지 효율성의 측정은 효율적인 에너지 개발과 관련된 정책을 지원하는 단단한 기반을 제공하는 중요한 요소의 한 가지가 되고 있다.

본 연구는 컨테이너 터미널에서 에너지 효율성을 측정하는 대안을 제시하는데 있다. 상이한 10 개국에 위치한 자동화 그리고 전통적인 터미널 처리 설비를 갖고 있는 18 개 터미널의 자료를 가지고 분석을 하였다.

자료에 대한 접근방식은 1957 년 Farrel 에 의해 소개된 비모수 효율측정 방법인 DEA(Data Envelopment Analysis)를 사용해서 분석하였다. 측정대상을 효율과 비효율로 2 분하여 나누고, 비효율 터미널의 에너지 효율성이 최적에 도달할 때까지 감소시켜야 할 잠재적인 에너지 소비량을 계산하였다. 아울러 동류집단의 개선 참고치를 파악하여 각 비효율 터미널의 최적 개선방안을 제시하였다.

Energy Consumption Analysis of International Container Terminals
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Abstract

The emergence of modern container terminals in most of ports all over the world has indeed helped many ports to increase their throughputs, and reach extraordinary new records in term of cargo handling volume. However, the high mechanization and the introduction of a wide range of machinery and equipment to the port industry increased dramatically the consumption of energy in the sector, and lead to numerous undesirable side effects; (i.a. 'sustainability issues, and depletion of natural resources', and 'harmful emissions'). To face the challenge of getting over the undesirable effects of containerization in the port industry, decision makers must adopt global strategies and policies that consider the public health, environmental impacts, and sustainability.

In the line of efforts to face environmental and sustainability issues, energy consumption has been emerging as an important matter. In fact decision makers are reluctant to act while planning energy use reduction policies, if there is no consistent data and accurate information to support the policy position they may take. Therefore,

measuring the energy efficiency of ports becomes one of the crucial elements that may provide solid basis to develop effective energy related policies.

This work aims to propose an alternative method to measure the energy use efficiency in container Terminals. The study includes a sample of eighteen units composed from both automated and traditional terminals located in ten different countries. The Approach is based on Data Envelopment Analysis (DEA), a non-parametric efficiency measurement method introduced by Farrell in 1957. The objective is to dichotomize the data set into efficient and inefficient units, compute the potential amount of energy consumption likely to be reducible by inefficient container terminals, to reach an optimal level of energy efficiency, find an improvement reference peer group, and investigate the best improvement path for each inefficient unit.

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Chapter I : Introduction

I.1. Research Background and Problem Statement

During the last 20 years the international trade knew an increasing growth, with an annual average of 5.3% (World Trade Organization, 2013) that goes in tandem with a considerably increasing seaborne trade, driven particularly by the rise of China's domestic demand as well as an increasing intra-Asian and South-South trade.

With the increase in seaborne trade (estimated at 4.4 % in 2013), about 9.6 billion tons of goods were handled in ports worldwide (Review of Maritime Transport, 2013), in 2013 containerized goods shared about 16.5% of the total shipped volume, while in 2007 the value of containerized good was equivalent to more than half of the total value of the seaborne trade (Review of Maritime transport, 2013).

Due to the rapid growth of containerization and the globalization of the market, container ports sector knows a fierce competition, where each port seeks to increase its productivity and operational efficiency, through the use of latest technologies, and the acquisition of more performing equipment.

Indeed, the emergence of a large number of modern container terminals helped many ports to increase their throughputs, enlarge their handled cargo volume, and obtain a bigger regional and international market share; however, the high level of mechanization, and the introduction of a wide range of machinery and equipment to the port industry, increased dramatically the ports' consumption in energy, and resulted into numerous undesirable side effects, and negative repercussions on the public health and the environment.

Governments are increasingly focusing on, and pressuring for, more climate sound strategies. However, their policies and actions focus rather on emissions as a symptom of industrial activities, than on causes, of which energy consumption is an important factor. Therefore a detailed understanding of energy consumption in the port industry is a necessary step to engage in strategies and policies toward a more sustainable performance and more environment friendly practices.

I.2. Research Motivation and Objectives

Traditionally, energy efficiency has not been a critical factor in the port industry due to the relative low weight of the energy cost over the total expenditures of container ports and terminals. However, in recent years this perception is changing due to different factors, like the increase in energy prices, the adoption of strong environmental regulations limiting the allowed levels of industrial emissions, and the civil society's awareness regarding sustainability and environmental impact of industrial activities.

By this work we aims to use Data Envelopment Analysis (DEA) as an alternative method to measure the energy use efficiency (energy efficiency) in the port industry, the focus will be on container terminals. The objective is to evaluate the energy use efficiency performed by a set of eighteen container terminals from ten different countries, and investigate the potential increase in their energy efficiency. The data set includes both traditional and automated container terminals.

I.3. Method

The method consists of five steps, briefly explained below.

I.3.1. Data Collection

The quality of the collected data will in a big part determine; the robustness of the model, the accuracy of the analyses, and thus the quality of the eventual decision. 60% of data have been collected on site via direct interview with terminals managers, 30% were collected by e-mails sent directly to the terminals managers, and 10% of the data are second hand data.

I.3.2. Designation of the Model's Variables:

To identify the energy usage profile, and assign each energy consumption to the proper port operation. There are two main questions to answer; first “What are the sources of energy in the terminal”? Second “What are the main factors directly involved in the port's energy use”? One word of caution is that the set of factors should be limited in size, and accordingly, only the main factors which significantly affect the port's energy consumption should be included in the data set. Too many indices with a limited number of data points will result in losing discriminatory power. The recommended maximum number of input and output indices for DEA will be detailed in Chapter V.

I.3.3. Model Selection

According to the property of the indices, and the decision purpose, we can select the most appropriate DEA model to our approach.

Model types might change based on our expected calculation of the projection (CCR, ADD), or problem/ variable characteristics (such as input oriented, or output oriented models). Steps 2 and 3 must be treated very carefully as the property of the indices would have a strong influence on the model's robustness.

I.3.4. Running the DEA Model

There are several software packages for DEA calculations such as; Frontier Analyst, DEA Frontier, Excel DEA Solver, etc. in this study, we used DEA Online Software (DEAOS).

I.3.5. Analysis' Result Discussion

The results obtained after running the software are analyzed, to determine the efficient and inefficient DMUs, and to evaluate the improvement path of each inefficient DMU according to its appropriate benchmarks.

I.4. Research Scope

Due to the multiple activities involved in the port industry, Port takes the form of a complex organization of a large variety of agents (port authorities, terminal operators , consignees, etc.), with various activities and tasks (preservation of the infrastructure, docking, handling of merchandise, administration, nautical assistance, etc.), for this reason the study of ports as a whole homogenous entity is not recommended, it is preferable to centre the analysis on a concrete activity, on a specific type of cargo, and limited number of units (Tongzong, 2001).

This work covers only container terminals, the sample to analyze comprises a total number of 18 units, including terminals from different regions in the world to ensure a good representation of the international container terminal industry.

I.5. Reasons to Use DEA

Unlike typical statistical methods, characterized as a central tendency approach that evaluate producers relative to an average producer, DEA compares each producer (Decision Making Unite) with only the "best" producers. DEA is not always the right tool for a problem, but is appropriate in certain cases and if it is used wisely DEA can be a powerful tool. A few of the characteristics that make it powerful are:

1) DEA can handle multiple input and multiple output models.
2) It doesn't require an assumption of a functional form relating inputs to outputs.
3) DMUs are directly compared against a peer or combination of peers.
4) Inputs and outputs can have very different units. For example; X_1 could be in units of Number, while X_2 could be in units of tons or dollars without requiring a priori tradeoff between the two.

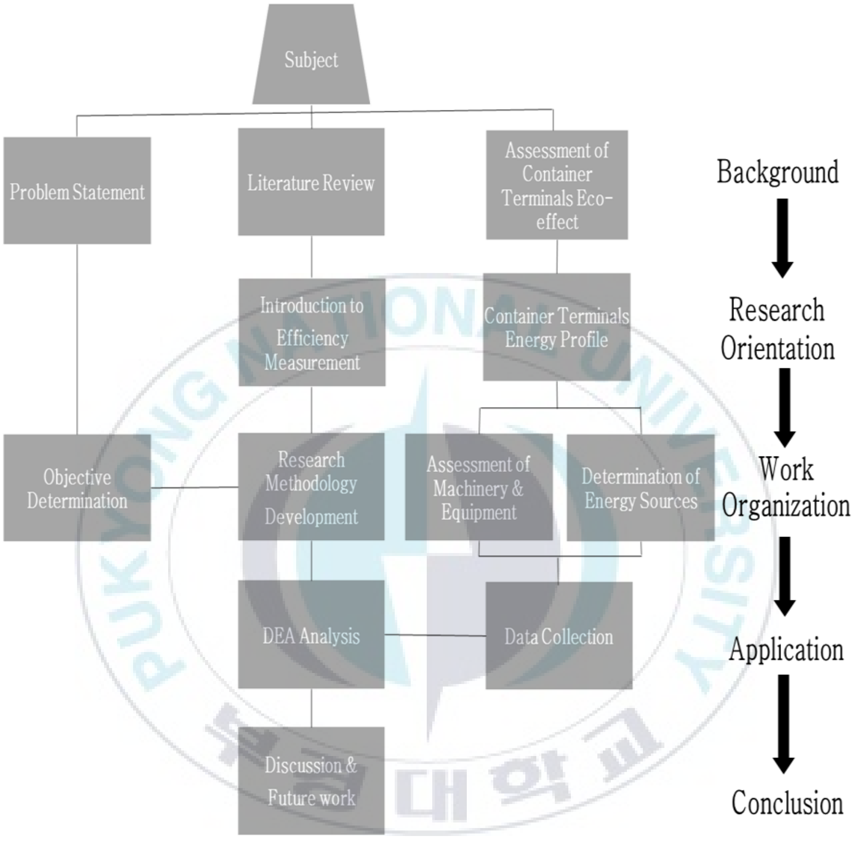
I.6. Organization of Chapters and Research Structure

The structure of the research depicted in <Figure I.1>, indicates the five steps that compose the framework of this study, the first step establish the background and foundation of the study, the second step marks the research method orientation, third and fourth steps summarize the research methodology, and the fifth step includes results discussion and conclusion.

The thesis structure is as following:

Chapter II, reviews efficiency measurement using DEA, and previous related works. Chapter III, aims to conduct a brief presentation of the port industry's impact on the environment. Chapter IV, introduces the typical equipment used by container terminals and details their energy consumption profile. Chapter V, is composed of three major parts; the first part presents the basic principle of the DEA method applied to this study and its theoretical aspect, the second part contains a detailed presentation of data points and variables, and explains the process that determines the sample's size and the variables selection; in the third part, data analysis is ran to get the final results, and finally Chapter VI, discusses the conclusion and suggests future complementary research works.

Figure I.1: Research Structure



Chapter II : Literature Review

II.1. Theoretical Framework

II.1.1. Efficiency Measurement

The origin of the modern discussion of efficiency measurement dates back to (Farrell, 1957), who identified two different ways in which productive units could be inefficient, the productive unit; can use more inputs than technically required to obtain a given level of output, or use a sub-optimal input combination given the input prices and their marginal productivities.

The first type of inefficiency is termed technical inefficiency while the second one is known as allocative inefficiency. Both theoretical and empirical measures of efficiency are based on ratios of observed output levels to the maximum that could have been obtained, given the inputs utilized. This maximum constitutes the efficient frontier which will be the benchmark for measuring the relative efficiency of the observations. Numerous techniques have been developed over the past decades to tackle the empirical problem of estimating the unknown and unobservable efficient frontier, these may be classified using several taxonomies. The two most widely used catalog methods into parametric or non-parametric, and into stochastic or deterministic. The parametric approach assumes a specific functional form for the relationship between the inputs and the outputs as well as for the inefficiency term incorporated in the deviation of the observed values from the frontier.

The non-parametric approach calculates the frontier directly from the data without imposing specific functional restrictions (Herrera and Pang, 2008.) The first approach is based on econometric methods, while the second one uses mathematical programming techniques. The deterministic approach considers all deviations from the frontier explained by inefficiency, while the stochastic focus considers those deviations combining inefficiency and random noises outside the control of the decision maker.

II.1.2. Alternative Techniques to Measure Efficiency

1. Ordinary Least Squares (OLS)

An estimation and regression method that fits an 'average line' through the data, Its strong points are; first, It is consistent with the underlying economic theory that offers a potential explanation for cost or production structures, and distinguishes between different variables' roles which affects output; second, there is an ample range of standard statistical tests available to assist the analysis. Its weakness is that all firms are considered as rational, i.e., there is no inefficiency, and thus all deviations from the frontier are attributed to random noise, this assumption is not always true in reality. Therefore, the estimation bears this built-in inaccuracy.

2. Corrected Ordinary Least Squares (COLS)

A parametric approach to evaluate productive efficiency, It belongs to the regime of regression methods, but differs from the OLS estimation method.

Its strong points are; first, it reveals information about the production technique, and it distinguishes between different variables' roles in affecting output as all parametric methods do; second, the adjustment from the average line to the 'frontier' allows for the measurement of relative efficiency.

Its weaknesses are; first, as all parametric methods it requires a priori specification of the production or cost function; second, it is not possible to measure errors, and other statistical noise (Greene W., 1993); and third, it is sensitive to outliers, since the 'best' performer along any dimension serves as the anchor for how much the 'average' line needs to be corrected in order to become the frontier.

3. Data Envelopment Analysis (DEA)

A mathematical programming approach to estimate productive efficiency, The strength of this method is that no a priori structural assumption is placed on the production process, the drawback is that it does not take into account the measurement error and other statistical noises, it is therefore not possible to test the statistical significance of the efficiency index for a specific observation. The choice of approach must be based on the objective of the research and the available data.

II.2. Review of Previous Researches on Energy Efficiency

Traditionally, energy efficiency has not been a critical factor on the port industry, and solicited a limited number of academic works due to the relative low energy cost over the total port's expenditures. However, in the recent years this perception is changing due to some emerging factors, such as the increase in energy prices, the adoption of strong environmental regulations, and the society awareness regarding sustainability and environmental impact of industrial activities.

As stated by Zhou and Ang (2008) and Zhou et al. (2008), DEA has gained in popularity in energy efficiency analysis. Initiated by Farrell (1957) and Developed by Charnes et al. (1978), DEA involves the use of linear programming methods to construct a non-parametric frontier. The best practices located on the efficiency frontier form the benchmarks, against which the potential energy saving for units not located on the frontier can be calculated. Therefore, by comparing the practices of different ports and terminals, we can identify the potential amount of energy reduction.

Various papers with different backgrounds deal with the topic of energy efficiency using a DEA framework, but those tackling the problem in the port industry tend to be scarce. Nassiri and Singh (2009), and Heidari et al. (2012) determined the amount and efficiency of energy consumption for paddy and horticultural greenhouses production in Iran using radial DEA methods, these two studies calculated the embodied energy of inputs based on a life cycle energy analysis, the weak point of this approach is that the conversion coefficients are not accurate, and their respective values vary considerably with the different calculation methods. Lee (2008) combined a multiple linear regression method with DEA, to examine the efficiency of energy management in governmental buildings in Taiwan, Onut, and Soner (2006) used a DEA approach to assess energy efficiency for the Antalya Region hotels in Turkey, Wu et al. (2010) used a DEA model with undesirable output, to assess Industrial energy efficiency with CO_2 emissions of Chinese firms.

As mentioned previously, in the port industry the use of DEA to analyze energy efficiency tends to be limited, while the few existing works focus mostly on emissions as a symptom of the port activity, and omit the causes of which energy consumption is a major factor. Shin and Jeong (2013) performed a comparative analysis of container terminals in Busan and Kwanyang ports, using an output oriented DEA window analysis with undesirable output to measure their respective environmental efficiency, CO_2 emissions was selected as an undesirable output, Chang (2013) used a Slacks-Based Measure DEA model to assess the environmental efficiency of Korean ports, considering CO_2 emissions as undesirable output, Chang (2013) had a more interesting approach considering the amount of energy consumption in the port, as well as its CO_2 emissions, however the only consideration of CO_2 emissions limited the energy consumption at fossil fuels, while fossil fuels are not the only energy source in a port as CO_2 is not its only undesirable externality.

In this study we use DEA to analyze the energy efficiency of a set of container terminals located in different regions in the world. To assess the Technical energy efficiency of each unit in the Data set, determine the origin of the overall inefficiency, and full ranking container terminals in term of best practices in energy use.

Chapter III : The Environmental Impact of Container Terminals

Container terminals' environmentally harmful emissions can be divided into two categories, direct emissions and indirect emissions. Direct emissions are those related to activities which the port is directly in control of, such as emissions to the air, noises from the port's non-road vehicles and working machinery, etc., whereas indirect emissions are those related to the transport to and from the port, whether by road, rail, or sea and inland waterways, in which case the port has very limited possibilities to influence.

III.1. Indirect Impact

III.1.1. Vessels Traffic Emissions

1. Air Pollution

Vessels calling container terminals produce the biggest share of air pollution from ports <Figure III.2>, they emit to the atmosphere a big amount of contaminants, toxic agents, and greenhouse gases (GHG), such as:

_ Dioxide of carbon (CO_2), resulted from the combustion of fossil fuels, it has a global impact on the biosphere and the climate (global warming).

_ Oxides of nitrogen (NO_x), generated by high temperature combustions, it can causes irritation of the eyes, inflammation of lung tissue, and emphysema, and it contribute in the formation of secondary pollutants that cause even more serious health problems.

_ Sulfur dioxide (SO_2), originated from the sulfur contained in fossil fuels, SO_2 is a toxic gas that may causes irritation of the eyes and respiratory passages, aggravates symptoms of respiratory diseases, and creates acid rains that may damage crops and buildings.

_ Carbon monoxide (CO), hydrocarbons (HC) and volatile organic compounds (VOCs), generated from partial combustions, cause the acidification of the soil and ozone formation at the lower layers of the atmosphere.

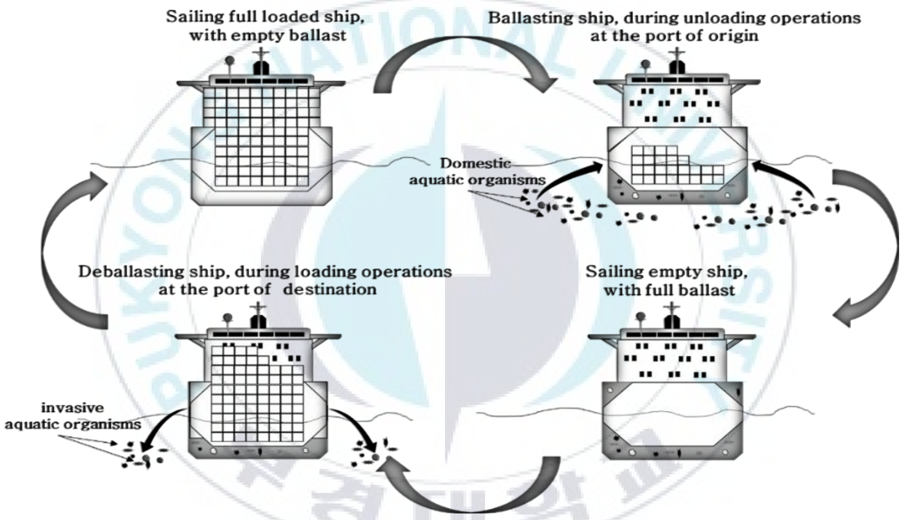
_ Diesel particulate matters that makes up diesel exhaust. It has a gas phase and a particle phase. The gas phase is composed of many of the urban hazardous air pollutants, such as acetaldehyde, formaldehyde and polycyclic aromatic hydrocarbons, etc., the particle phase is of greatest health concern; especially particles that are in the categories of fine, and ultra-fine particles. They are composed of elemental carbon with adsorbed compounds, such as organic compounds, sulfate, nitrate, metals and other trace elements.

2. Water pollution

Emissions to water stem from ships mainly by leakage of toxic agents from antifouling paint of ship hulls, release of harmful alien species and organisms with ballast water during ship loading operations <Figure

III.1>, spill during bunker operations, leakage from bilge water that often mixes with oil leaking from engine and machinery spaces or from engine maintenance activities, and Discharges of untreated or inadequately treated sewage that causes bacterial and viral contamination of fisheries and shellfish beds, etc..

Figure III.1: Ballast Water Cycle



Source: Self Developed

3. Noise Pollution

Noise emissions from ships arise during the port approach, berthing/unberthing maneuvering in the port area, and from the auxiliary engines and ventilating systems when at berth. The ship engines contribute mainly to the low frequency noise that difficult to quench and can be transported over long distances.

III.1.2. Inland Transport Emissions

Inland transportation can be divided into three main categories; roads, railways, and inland waterways (canals, rivers, lakes, etc.).

1. Air Pollution

The principal sources of air pollution are road transport trucks, and inland waterways vessels, such as barges. While railways have a little influence, and are considered as one of the least environmentally damaging modes of inland transportation. The type of air emissions related to inland transportation are similar to those mentioned for vessels traffic, with the consideration of the respective differences in concentration and volume of the various toxic elements and pollutants emitted.

2. Water Pollution

Inland water pollution is caused exclusively by inland waterways transportation. Impacts are proportional to the traffic density, depend on the type of vessels carrying the cargo, and on maintenance activities required to keep channels navigable. The water pollution origin can be; fuel and oil spillage, accidents and disposal of waste, wastewater and sewage from vessels, and pollution from shore or bankside activities, such as; vessel maintenance, or fuel and goods storage.

3. Noise Pollution

Trucks are a significant inland source of noises, the inland waterways impact depends on; the size of the waterway, the density of its traffic, and type of vessels sailing through it. While the noise nuisance posed by rail is generally considered to be less than that posed by the two other modes, this is in large measure because a railway noise is intermittent, whereas highway noise for example ends to be relatively constant.

III.2. Direct Impact

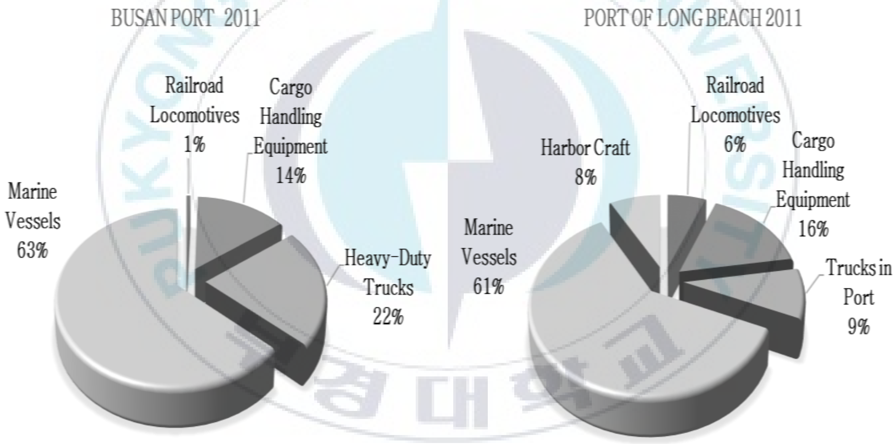
III.2.1. Air Pollution

Consumption of energy in container terminal results in; direct emissions of toxic gases, GHGs, and other externalities from diesel fuel combustion, and indirect emissions from public grids and power plants, where electricity to supply container terminals is generated. These emissions that are a direct result of the energy consumption, have a dramatic impact on the climate and health; they cause the global warming, destroy the natural environment, and represent harmful risks for the population's health.

According to a study made on the port of Busan in Republic of Korea, and air emissions inventory of the port of Long Beach <Figure III.2>, cargo handling equipment and machinery are responsible of about respectively 14% and 16%, of total air emissions in the port area (Shin & Cheong, 2011, Port of Long Beach, 2011).

Another study made by the Swedish environmental research institute on Goteborg Port, reveals that direct emissions to the air within the port area arise mainly from non-road vehicles and working machinery of the port, with a breakdown of 90% of the NOX, CO and exhaust PM emissions, and 75% of the CO2 and VOC emissions (Swedish Environmental Research Institute, 2007).

Figure III.2: Examples of Air Emissions Distribution



Source: Shin & Cheong, 2011, Air Emissions Inventory of Port of Long Beach. 2011

III.2.2. Water pollution

Emissions to the water within the port area arise from the yard's surface water released directly to the harbor basin. Risks of water pollution from the container yard are essentially due to:

Risks of chronic pollution due to yard tractors and other cargo handling vehicles parking at the yard, resulting into grease and engines oil leakage, emissions of heavy metals from car bodies, particles from tires, etc…

Accidental pollution risks due to handling and stacking of containers containing dangerous cargo.

III.2.3. Dredging

Dredging operations are often made to maintain the depth of the harbor basin. During the dredging a temporary turbidity and dispersion of pollutants may occurs. These pollutants may be of a local origin, or transported from remote locations and accumulated over a long period of time leading to exceedances of contaminants concentrations. However, the extent of dredging to maintain the required depths of the harbor basin does not have a major environmental impact compared to other factors.

III.2.4. Noise Pollution

Noise generated by the container terminal's platform arises in general from non-road vehicles and cargo handling machinery, e.g., reach stackers, trailers, tractors, etc…

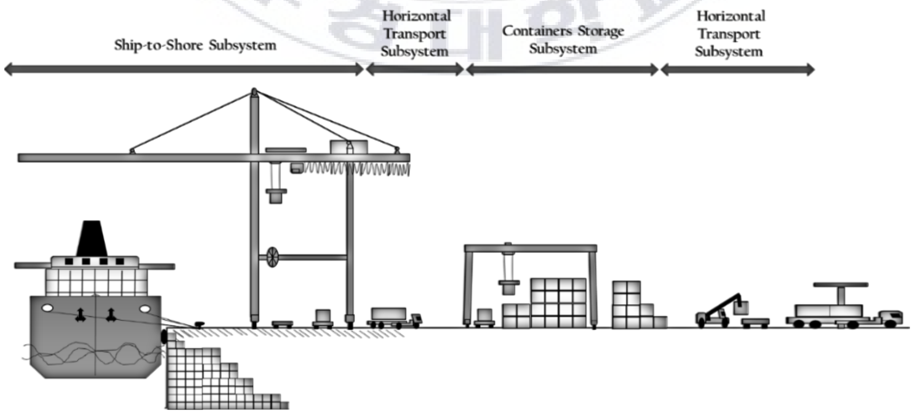
The increase in the port activities leads to increase the overall number of units and the overall number of operation hours of these units, resulting into a higher noise emissions.

Chapter IV : Container Terminals and Energy Consumption

IV.1. an Over View of Operation Subsystems of Container Terminals

Container terminals are complex systems that can function efficiently only when their layouts are designed in such a way to allow a smooth cargo handling process. Container terminals' layouts vary from one terminal to the other. Nevertheless, most terminals have a comparable arrangement of their subsystems and facilities <Figure IV.1>. The basic concept of a container terminal consist of three major operational subsystems:

Figure IV.1: Basic Concept of a Container terminal



Source: Self Developed

IV.1.1. Ship-to-Shore Subsystem

Located at the quay wall edge, it is the subsystem in charge of loading/unloading containers from ships to the shore and vice-versa, composed of rail mounted portainers (quay container gantry crane) it is the direct interface that ensures the transfer of containers, from the sea transportation mode to land transportation modes.

IV.1.2. Horizontal Transportation Subsystem

It ensures the cargo transportation between containers stacking area and the loading/unloading and delivery/reception areas, Cargo transportation can be ensured using a number of vehicles varying in carrying capacity, flexibility, propulsion modes and velocity, automation, etc…, the use of horizontal transportation vehicles depends on the operational model and the cargo handling concept of the container terminal. It is composed of two parts, quay side and gate side.

The quay side horizontal transportation follows the ship-to-shore subsystem, it is in charge of cargo transfer along the quay's apron to the storage area. While the gate side horizontal transportation ensures the movement of containers between the storage area and the gate. The gate acts as an interface for the container terminal with other modes of transportation, such as rails, road, and inland waterways.

IV.1.3. Containers Storage Subsystem

The center piece of the container storage subsystem is the storage yard, where containers are stacked according to several blocks composed of bays, rows, and tiers. Blocks are composed according to the attributes of the containers, there are blocks of containers planned for vessel loading, or of containers planned for hinterland departure, and other blocks are used as storage areas for empty containers, damaged containers, container carrying dangerous goods, and reefers.

IV.2. Container Terminals Machinery and Equipment

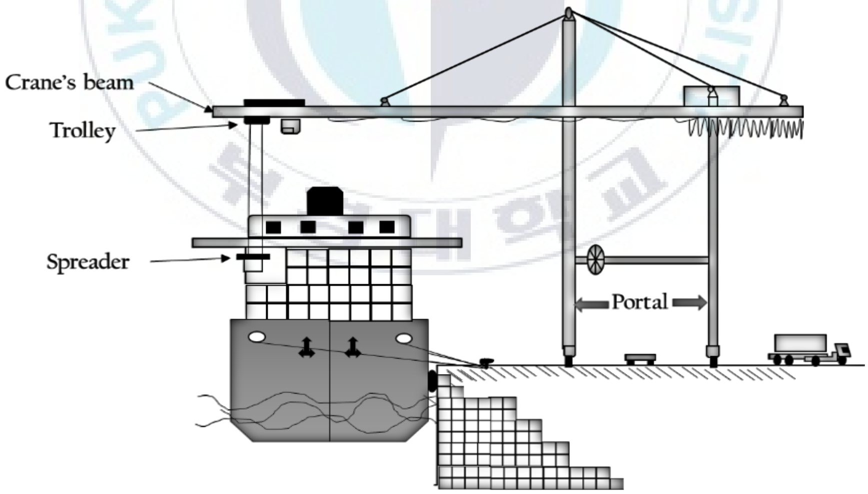
Cargo handling equipment in container terminals can be divided into two categories; quayside equipment in charge of ship-to-shore subsystem operations, and yard equipment that is used for both Horizontal transportation and containers stacking.

IV.2.1. Quay Side Equipment

Quay container gantry cranes (called also portainers, or Sip-To-Shore cranes) are the main equipment used to load and unload containers from vessels to the dock and vis-versa <Figure IV.2>. Most of modern container terminals use electric operated rail mounted quay cranes, the use of rubber tired gantry cranes is not infrequent, because they are less performing in term of productivity and containers handling capacity, even though they have a better flexibility in term of motion.

To perform the movements necessary for loading/unloading operations, quay cranes have three major moving components; portal, trolley, and spreader <Figure IV.2>. The portal is the frame of the gantry crane that ensures the crane's movement alongside the quay wall. The trolley is mounted on the crane's beam, where it can moves along allowing the containers' transfer between the ship and the shore. The spreader is connected to the trolley by means of winches and cables, it is the only crane component that physically contacts the container, by means of a system of pins that allows to secure containers, and safely lock them during cargo handling operations.

Figure IV.2: Ship-To-Shore Crane and its Moving Components



Source: Self Developed

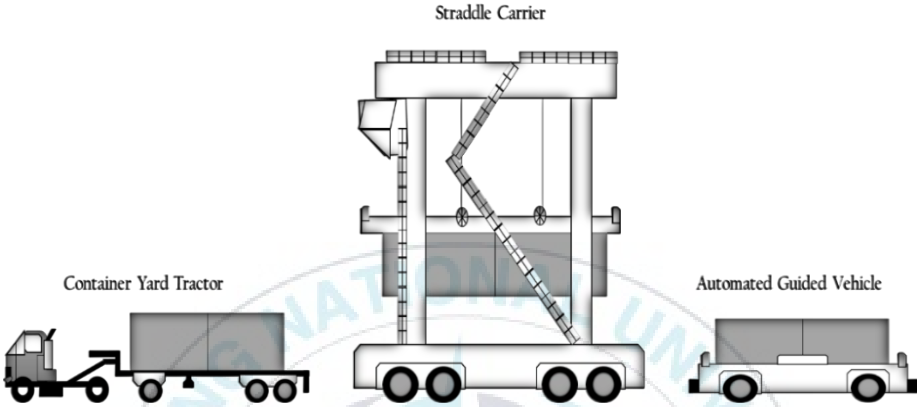
IV.2.2. Yard Equipment

Container yard equipment represents the machinery used for the horizontal transportation, container stacking, and gate side loading/unloading operations, it is composed of a range of different vehicles and cranes. Container yard handling equipment inventoried in this study consisted of; transfer cranes, reach stackers, yard tractors, forklifts, empty container handlers, and straddle carriers, categorized into transfer equipment and stacking equipment. In addition to reefer plugs used to supply refrigerated containers by electricity.

1. Transfer Equipment

All vehicles used for the horizontal transport between containers stacking yard and loading/unloading areas on both quay and gate sides. They may vary from container terminal to another. However, we can classify them into three main categories following their specific characteristics; the two first categories are straddle carriers and yard tractors that are manually operated diesel driven vehicles, the third category is automated-guided vehicles (AGV), these are electric remote controlled vehicles less frequently used than the two other categories <Figure IV.3>. While straddle carries are capable to auto-load and stack containers, AGVs and yard tractors need the assistance of containers stacking vehicles.

Figure IV.3: Container transfer Vehicles



Source: Self Developed

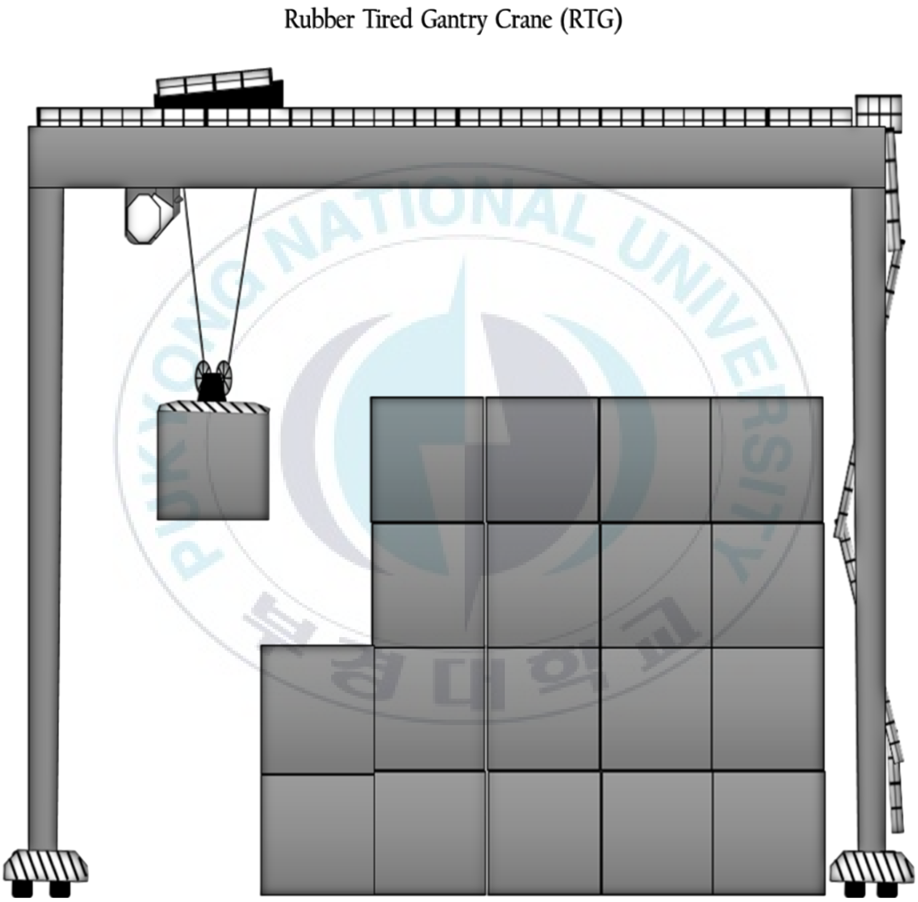
2. Stacking Equipment

Containers stacking machinery varies in size, mode of propulsion, stacking height, and lifting capacity. Their main tasks are; to store containers at the terminal's yard in blocks, using a system of bay-raw-tier according to numerical coordinates related to length, width, and height, and to ensure containers loading/unloading operations on/off the horizontal transport vehicles. The most frequently used stacking vehicles are; reach stackers, empty/loaded containers handlers <Figure IV.4>, straddle carriers (seen previously), and yard transfer cranes that can be rail mounted (RMG) or rubber tired (RTG), <Figure IV.5>.

Figure IV.4: Container Yard Stacking Vehicles

Source: Self Developed

Figure IV.5: Container Yard Transfer Crane



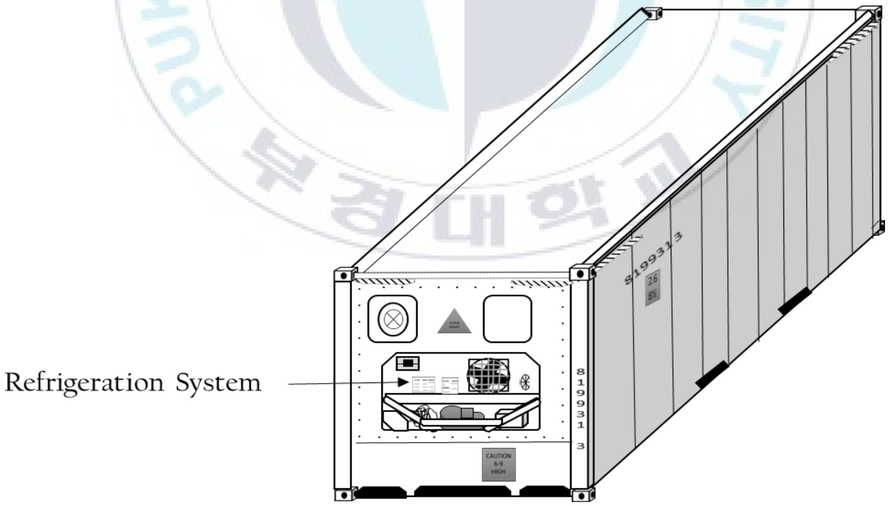
Source: Self Developed

3. Reefer Plugs

Preservation of temperature sensitive goods involves the use of reefers or refrigerated containers <Figure IV.6>. This type of containers is equipped with an integral refrigeration unit, however, the energy autonomy of the refrigerating unit is limited, and reefers have to rely on external energy supply from reefer plugs (electrical power points) at a land based site.

The layout of container terminals includes an area equipped with electrical power points, to ensure the energy supply for reefers during their yard storage time.

Figure IV.6: Refrigerated Container (Reefer)



Source: Self Developed

IV.3. Container Terminals Energy Consumption Pattern

To elaborate an energy consumption map of a container terminal there are three main questions to answer; what kind of energy is consumed? Where is the energy consumed? And how much energy is consumed?

In container terminals energy consumption profile varies from one subsystem to another, but it also differs among machinery and equipment in the same subsystem. The first step to do is to determine the type of each energy source supplying the terminal, then classify the terminal's machinery and equipment following their respective technical specifications, finally the type of energy and its consumption amount for each type of consumer is evaluated. That would provide key information to understand the actual energy consumption pattern of a container terminal.

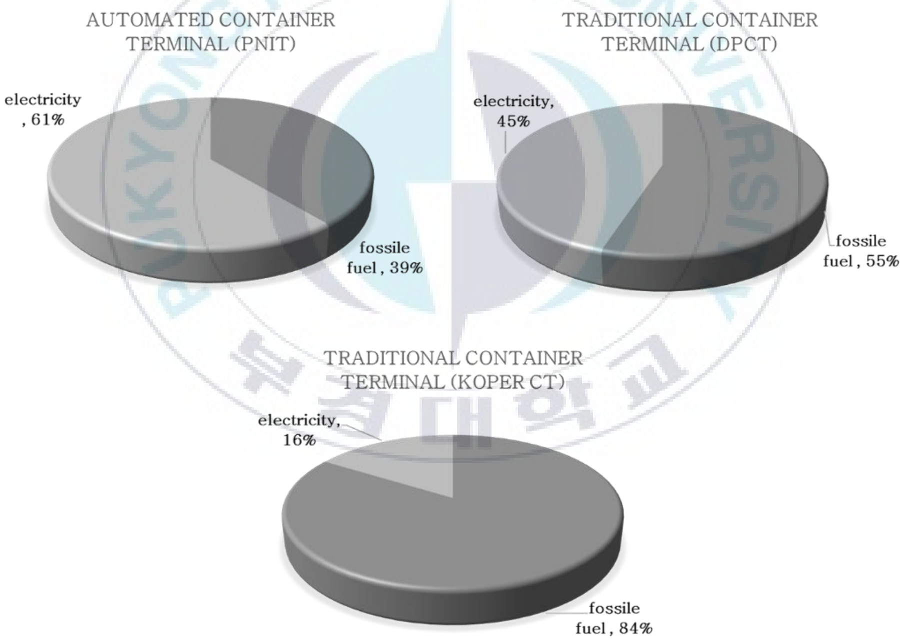
To make an energy consumption disaggregation the cases of some container terminals from our sample have been investigated. Selected terminals can be fairly considered as representative of our data set, thus the results obtained can be easily extrapolated to the whole observation points.

IV.3.1. Determination of Types of Energy Sources

The first thing to consider is the summary of the annual energy consumption for major energy aspects for the container terminal. <Figure IV.7> shows that the major energy sources for each of three different container terminals, selected from our data set are electricity and fossil fuel (diesel in particular), with the specification that automated container terminals tend to consume relatively more electricity than traditional ones, while traditional container terminals tend to consume relatively more fossil fuel than automated ones.

We can conclude that, the main energy sources used by container terminals to run and operate their equipment and facilities, are electricity and diesel oil.

Figure IV.7: Examples of Energy Consumption Profile



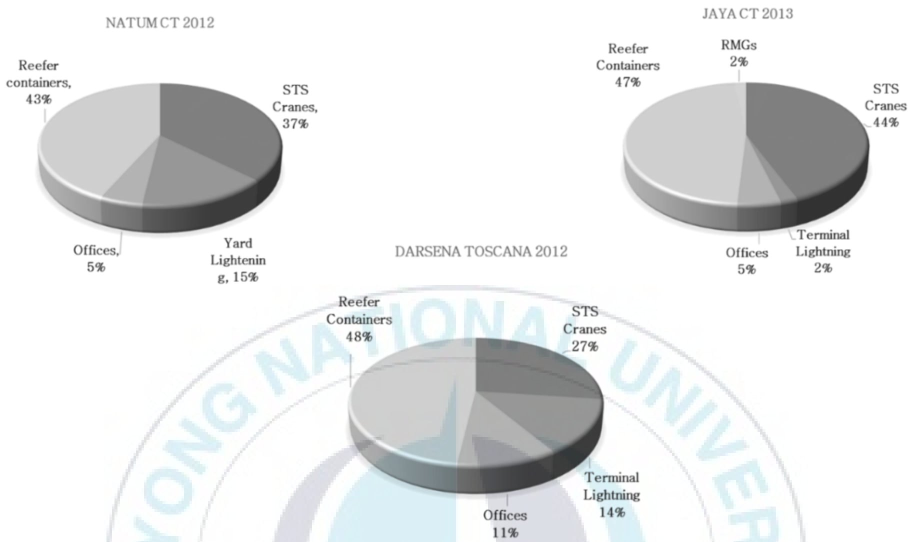
Source: Self Developed, based on the collected data

IV.3.2. Energy Consumption by Type of Equipment

Now we can analyze the energy consumption related to each consumer. The consumed energy is disaggregated by aspect and quantity consumed, according to each type of energy consumer from the whole subsystems of the container terminal. <Figure IV.8> summarizes the type of machinery and facilities that use electricity as source of energy, and their respective consumption rates in three different terminals from our data set. We can notice that, even though the relative percentage of energy consumed by each element varies from one terminal to another, the type of electricity consumers represent big similarities.

We conclude that, the main equipment and facilities that are operated using electrical energy are; ship-to-shore cranes, reefer containers, RMGs, terminal's lightning, and offices. We notice that the biggest share of electricity consumption goes always to reefer containers, and STS cranes.

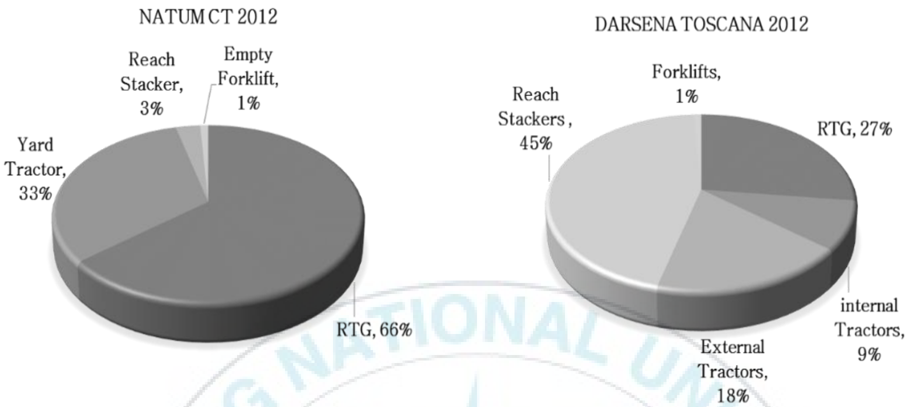
Figure IV.8: Examples of Electricity Consumption Distribution



Source: Self Developed based on the collected data & Green Cranes "Report on Container Terminals Energy Profile, Feb 2013"

<Figure IV.9> summarizes the equipment operated using diesel as energy source by two different container terminals of our data set. The chart shows that the main fossil fuel consumers in the container terminals are; reach stackers, yard tractors, forklifts, and RTGs.

Figure IV.9: Examples of Diesel Consumption Distribution



Source: Green Cranes "Report on Container Terminals Energy Profile Feb 2013"

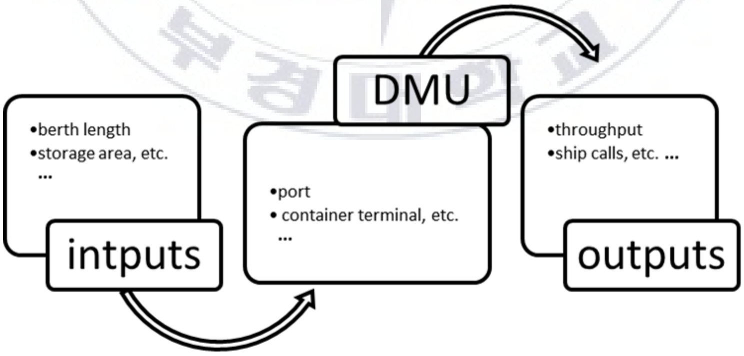
We can elaborate the energy consumers' inventory as following; the main energy consumers of electricity are ship-to-shore cranes, reefer containers, RMGs, terminal's lightning and buildings. While diesel consumers are equipment used in horizontal transport and stacking operations, e.g., reach stackers, yard tractors, forklifts, and RTGs.

Chapter V : DEA Methodology and Discussion of the Analysis Results

V.1. the Concept of Input Oriented Data Envelopment Analysis

DEA is a non-parametric analytic method that measures the relative efficiency of homogenous sets of organizations or Decision Making Units (DMUs), performing the same tasks to transform resources (Inputs) into final products or services (Outputs) <Figure V.1>, i.e., efficiency is the ratio of sum of weighted outputs to sum of weighted inputs Eq. (1).

Figure V.1: The Basic Concept of DEA



Source: Self Developed

$$Efficiency = \frac{\sum Weighted\ Output}{\sum Weighted\ Inputs} \quad (1)$$

Where the DMU is considered efficient when it achieves a score of 1 or mathematically as (Cooper, et al. 2006):

$$\theta = \frac{\sum_{p=1}^{P} u_p y_p, j}{\sum_{q=1}^{Q} v_q x_q, j} \quad (2)$$

Where ‘x’ and ‘y’ refer respectively to inputs and outputs, ‘v’ and ‘u’ are the respective weights of inputs and outputs, ‘q’ is the number of inputs (q = 1, 2,⋯, Q), ‘p’ represents the number of outputs (p =1, 2,⋯, P), and ‘j’ represent j^{th} DMU.

In our case the DMUs refer to Container Terminal Operators, the inputs are the electricity and diesel fuel consumed to perform the terminals’ Operations, and as outputs the total annual container throughput and the amount of equipment operated within each terminal have been considered.

In DEA there are two methods to improve the efficiency of an inefficient DMU, the first one is output oriented, it aims to increase the outputs level while holding the inputs level Constant, the second method is input oriented method were the outputs level is kept Constant while decreasing the level of inputs is needed, in our case we aim to decrease the consumption of energy for each inefficient DMU, therefore it is more appropriate to opt for an input oriented method.

DEA has two Basic Models, CCR Model developed by Charnes, Cooper and Rhodes (1978) on the assumption of Constant Return to Scale (CRS), and the BCC Model developed by Banker, Charnes and Cooper (1984) with Variable Return to Scale (VRS), thus the efficiency by DEA is defined according to three distinctive forms, Overall Technical Efficiency (TE) under CCR Model, that can be decomposed into Pure Technical Efficiency (PTE), and Scale Efficiency (SE) under BCC Model (Cooper et al., 2006), Eq. (3)

$$\mathrm{TE} = \mathrm{PTE} * \mathrm{SE} \tag{3}$$

This decomposition, which is unique, depicts the sources of the overall inefficiency, whether it is caused by inefficient operation (PTE) or by disadvantageous conditions displayed by the scale efficiency (SE) or by both.

V.1.1. Input-Oriented DEA Model with Constant Return to Scale

The Farrell (1957) input-oriented measure of technical efficiency of DMU_j is given by Eq. (4)

$$F(Y_j, X_j) = Min\,\{\lambda : \lambda X_j \in L(Y_j)\} \tag{4}$$

The Farrell measure projects observed production possibilities as far as possible, ensuring that the resulting projection is on Isoq L(Y). One of the maintained assumptions in traditional DEA models is that all observed production possibilities are feasible. Consequently, the approach does not allow for measurement errors or other statistical noises and requires proper selection of inputs and outputs.

$$Subject\ to\ \frac{\sum_{p=1}^{P} u_p\, y_{pj}}{\sum_{q=1}^{Q} v_q x_{qj}} \leq 1 \qquad (5)$$

$$u_p, v_q\ \geq 0\ for\ all\ p\ and\ q$$

This model can be algebraically rewritten as:

$$Minimize\ \theta_k = \sum_{p=1}^{P} u_p y_{pk}$$

$$Subject\ to\ \sum_{p=1}^{P} u_p y_{pj} \leq \sum_{q=1}^{Q} v_q x_{qj} \qquad (6)$$

With further manipulations the following linear programming formulation is obtained:

$$Minimize\ \theta_k = \sum_{p=1}^{P} u_p y_{pk}$$

Subject to:

$$\sum_{p=1}^{P} u_p y_{pj} - \sum_{q=1}^{Q} v_q x_{qj} \leq 0\ \ j = 1,2, \dots, J$$

$$\sum_{q=1}^{Q} v_q x_{qk} = 1 \tag{7}$$

$$u_p, v_q \geq 0$$

1. Weights Assessment

To observe the detailed information such as benchmarks and their weights "λ", as well as $\sum\lambda$ leading to returns to scale (RTS) assessments, we need to employ the dual linear program to model in Eq. (7). Charnes et al. (1978) developed the dual model <Figure V.2> as follows:

$$Minimize_{\theta_k,\lambda}\theta_k$$

Subject to:

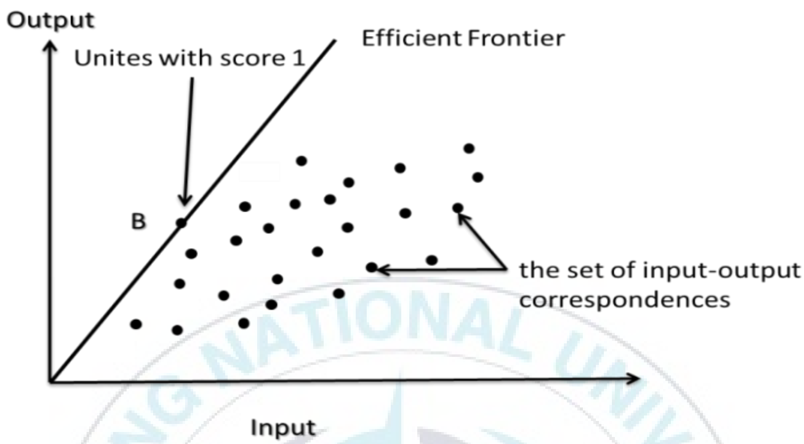
$$\sum_{j=1}^{J} \lambda_j y_{pj} \geq y_{pk}, (p = 1, 2, \ldots, P)$$

$$\sum_{j=1}^{J} \lambda_j x_{qj} \leq \theta\, x_{qk}, \ (q = 1, 2, \ldots, Q) \tag{8}$$

$$\lambda_j \geq 0, \ (j = 1, 2, \ldots, J)$$

Where λ_j is a vector of J elements representing the influence of each grower in determining the technical efficiency of the DMU_k under study and Θ is the technical efficiency.

Figure V.2: graphical Depiction of DEA-CCR Model



Source: Self Developed

In this dual formulation, Eq. (8), the linear program seeks efficiency by minimizing (dual) efficiency of a focal DMU "k" subject to two sets of inequality. The first inequality emphasizes that the weighted sum of inputs of the DMUs should be less than or equal to the inputs of focal DMU being evaluated. The second inequality similarly asserts that the weighted sum of the outputs of the non-focal DMUs should be greater than or equal to the focal DMU. The weights are the λ values. When a DMU is efficient, the λ values would be equal to 1. For those DMUs that are inefficient, the λ values will be expressed in their efficiency reference set.

2. Mathematical Details for Slacks

In DEA analysis the slacks can be obtained by solving a second stage linear programming model, after solving the dual linear programming model presented as Eq. (8).The second stage of the linear program is formulated for slack values as follows:

$$Maximize \sum_{q=1}^{Q} s_q^- + \sum_{p=1}^{P} s_p^+$$

$$\sum_{j=1}^{J} \lambda_j y_{pj} - s_p^+ = y_{pk}, (p \ = 1, 2, \dots, P)$$

$$\sum_{j=1}^{J} \lambda_j x_{qj} + s_q^- = \theta^* x_{qk}, \ \ (q = \ 1, 2, \dots, Q) \qquad (9)$$

$$\lambda_j \ \geq 0, \ \ (j \ = \ 1, 2, \dots, J)$$

Here, θ^* is the DEA efficiency score resulted from the initial run, Eq. (7), of the DEA model. Here, s_q^- and s_p^+ represent input and output slacks, respectively. It is to note that the superscripted minus sign on input slack indicates reduction, while the superscripted positive sign on output slacks require augmentation of outputs.

In fact, models in Eq. (7) and Eq. (9) can be combined and rewritten as:

Eq. (10), Input-Oriented CRS Model

$$Maximize\ \theta - \varepsilon \left(\sum_{q=1}^{Q} s_q^- + \sum_{p=1}^{P} s_p^+ \right)$$

$$\sum_{j=1}^{J}\lambda_j y_{pj} - s_p^{+} = y_{pk}, (p = 1, 2, \ldots, P)$$

$$\sum_{j=1}^{J}\lambda_j x_{qj} + s_q^{-} = \theta x_{qk},\ \ (q = 1, 2, \ldots, Q) \qquad (10)$$

$$\lambda_j \geq 0,\ \ (j = 1, 2, \ldots, J)$$

The ε in the objective function is called the non-Archimedean, which is defined as infinitely small, or less than any real positive number. The presence of ε allows a minimization over efficiency score θ to preempt the optimization of slacks, s_q^{-} and s_p^{+}. The model of Eq. (10) first obtains optimal efficiency scores θ^{*} from model of Eq. (7) and calculates them, and then obtains slack values and optimizes them to achieve the efficiency frontier.

3. Determination of Fully Efficient and Weakly efficient DMUs

According to the DEA literature, the performance of DMUs can be assessed either as fully efficient or weakly efficient (Ozcan, 2014). The following conditions on efficiency scores and slack values determine the full and weak efficiency status of DMU <Table V.1>

Table V.1: weakly and Fully Efficient DMUs

Condition	θ	θ^*	$all\ s_q^-$	$all\ s_p^+$
Fully Efficient	1.0	1.0	0	0
Weakly Efficient	1.0	1.0	at least one $s_q^- \neq 0$	at least one $s_p^+ \neq 0$

Source: Ozcan, Y. A., 2014

When model of Eq. (10), or those of Eq. (7) and Eq. (9) are sequentially run, weakly efficient DMUs cannot be in the efficient reference set of other inefficient DMUs. However, if only Eq. (7) is executed, then weakly efficient DMUs can appear in the efficient reference set of inefficient DMUs. The removal of weakly efficient DMUs from the analysis would not affect the frontier or the analytical results (Ozcan, 2014).

4. Calculation of Efficient Targets for Input-Oriented DEA-CCR Model

In input-oriented CRS models, the calculation of levels of efficient targets for inputs and outputs is as follows:

$$Outputs: \hat{y}_{pk} = y_{pk} + s_p^{+*} \quad p = 1, \dots, P$$

$$Inputs: \hat{x}_{qk} = \theta^* x_{qk} - s_q^{-*} \quad q = 1, \dots, Q \qquad (11)$$

V.1.2. Input-Oriented DEA Model with Variable Return to Scale

In 1984 Bankers et al. proposed the BCC Model based on variable return to scale (VRS), Adopted from the input-oriented model represented by Eq. (10). <Figure V.3>.

VRS input model formulation requires an additional set of constraints, in which summation of λ values are set equal to 1, Eq. (12).

$$Maximize\ \theta - \varepsilon\left(\sum_{q=1}^{Q} s_q^- + \sum_{p=1}^{P} s_p^+\right)$$

$$\sum_{j=1}^{J} \lambda_j y_{pj} - s_p^+ = y_{pk}, (p\ = 1, 2, \dots, P)$$

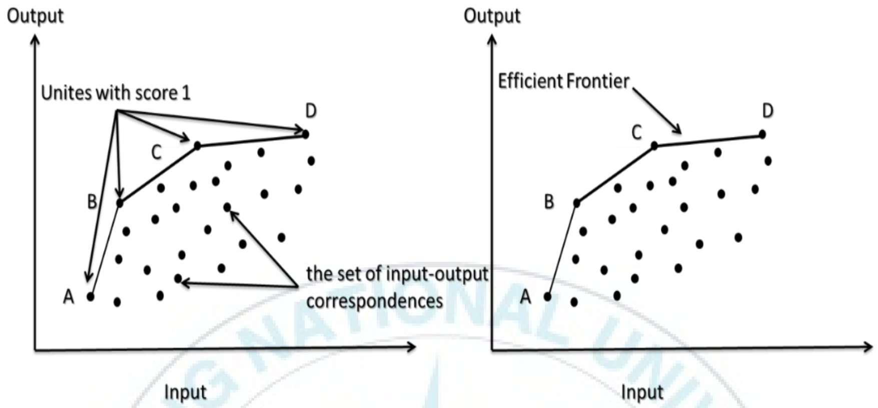
$$\sum_{j=1}^{J} \lambda_j x_{qj} + s_q^- = \theta x_{qk},\ \ (q\ =\ 1, 2, \dots, Q)$$

$$\sum_{j=1}^{J} \lambda_j = 1, \tag{12}$$

$$\lambda_j\ \geq 0, \qquad (j\ =\ 1, 2, \dots, J)$$

The equation $\sum_{j=1}^{J} \lambda_j = 1$ is the convexity constraint, which specifies the VRS framework. Without this convexity constraint, the BCC model will be a CCR model (Heidari et al., 2012).

Figure V.3: Graphical Depiction of DEA-BCC Model



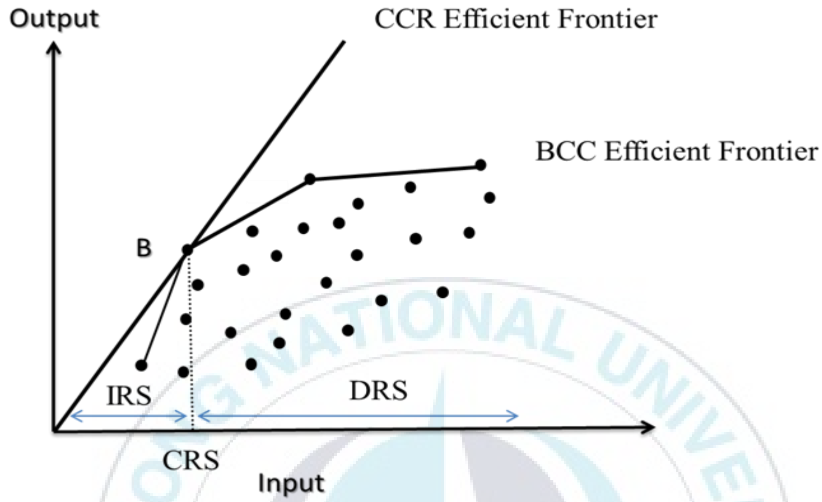
Source: Self Developed

V.1.3. DEA Scale Efficiency

Scale efficiency measures can be obtained for each Terminal by conducting both CCR and BCC DEA models, then decomposing the TE score obtained from CCR DEA into two components, scale efficiency and Pure Technical efficiency. If there is a difference in the CCR and BCC scores for a particular terminal, this indicates that the unit has scale inefficiency (Timothy J. Coelli et al. 2005), <Figure V.4>. Eq. (3) can be also defined by:

$$SE = \frac{TE_{CCR}}{PTE_{BCC}} \tag{13}$$

Figure V.4: Graphical Depiction of DEA Return to Scale



Source: Self Developed

V.1.4. DEA Super Efficiency

CCR and BCC models dichotomize DMUs into inefficient and efficient units. However, it is not possible to differentiate between the efficient units, since all of them receive the same efficiency score of "1", e.g., in our case we can differentiate between the most inefficient terminals and the least inefficient terminals according to their location from the efficient frontier, but we cannot differentiate between the most efficient terminals and the least efficient terminals, because all of them are located on the efficient frontier[1].

---

1 All efficient units have score equal to 1

To overcome this limitation Andersen and Petersen (1993) proposed the Super-Efficiency ranking method for only efficient DMUs. The Super-Efficiency measures how much can the inputs be increased (or the outputs decreased) while not become inefficient (So et al. 2007).

The super-efficiency model is identical to the DEA model previously described, but a DMU under evaluation (k) is excluded from the reference set. The formulation for the super-efficient model, follows Eq. (7), but is evaluated without unit k, (for $i=1,\ldots,n$, $i \neq k$). For an efficient unit, its exclusion from the reference set will alter the frontier and allow the unit to be located above the efficient frontier, and to be super-efficient.

V.2. Measuring Energy Efficiency of Container Terminals Using DEA

V.2.1. DEA Model Selection

1. The Sample's Size

There are two contrasting facts to consider when evaluating the size of the data set, the larger is the Number of DMUs included to the data set, the greater is the probability of capturing high performance units that would determine the efficient frontier, and improve discriminatory power. On the other hand, a larger data set includes more exogenous factors that may decrease the homogeneity of the sample.

Yet, academics fixed some rules of thumb on the minimum number of DMUs to include in the data set, by considering their relation to the number of selected inputs and outputs. For example; Bowlin (1998) stipulates that to get a good discriminatory power the model needs to have three times the number of DMUs as there are input and output variables. While Golany and Roll (1989) established a rule of thumb that limits the minimum number of units at twice the number of inputs and outputs considered. Boussofiane et al. (1991) mention the need to have the number of DMUs equal to the multiple of the number of inputs and the number of outputs. And Dyson et al. (2001) recommend that the total of DMUs should correspond to two times the product of the number of input and output variables.

2. Selection of Inputs and Outputs

The basic functions of a container terminal are the transfer and the storage of containers. Container handling productivity is directly related to the transfer function. The efficient use of energy relates to the way the equipment is operated and to the terminal's layout, e.g., improving the utilization of ground space typically reduces movement of the equipment and optimizes its energy consumption. As we saw in chapter IV the major energy sources for container terminals are electricity and diesel, thus these two elements are selected as energy inputs. However, to provide more robustness to our model there is a factor of heterogeneity to overcome, the energy consumption profile differs between automated terminals and traditional ones, i.e., regardless the efficiency use of energy automated terminals will relatively consume more electricity than traditional ones, on the other hand traditional terminals will consume more fossil fuel than automated ones, do not consider this major difference may affect the accuracy of the analysis. To overcome this issue instead of using the energy sources according to their respective units, each input will be converted into its equivalent in Joule[2] then their sum will be used as one single input.

Outputs include, ship to shore gantry cranes, yard vehicles and machinery, reefer plugs, and buildings and yard lighting. As representative to buildings and yard lighting the terminal's size is considered. To ensure that the low consumption of energy is due to efficiency and not to operational underperformance, container throughput is included as an additional output variable. <Table V.2> shows data summary statistics of the year 2012, for more details refer to <Appendix 1>.

Table V.2: Summary Statistics for Input and Outputs

Name	Minimum	Maximum	Mean	Standard Derivation
Total Energy "GJ"	19774.8	566736.102	186927.0542	132688.5878
Terminal's Area "m^2"	155000	1202000	561071.3333	319060.1128
Nº Equipment	404	6180	1440.0556	1268.4654
Throughput "TEU"	150000	5450000	1570775.6111	1291787.1895

2 1 kwh of electricity = 36 10^{-4} GJ, and 1 liter of diesel = 387 10^{-4} GJ

3. Correlation among Inputs and Outputs

The degree of correlation between inputs and outputs is an important issue that has a great impact on the robustness of the DEA model. Thus, a correlation analysis is crucial in order to select the appropriate inputs and outputs. If for example a very high correlation is found between an input variable and any other input variable, this input variable may be thought of as a proxy of the other variable. Therefore, this input could be excluded from the model. On the other hand, if the input variable has a very low or a negative correlation with all the output variables, it may indicate that this variable does not fit the model, i.e., an increase in any input should not result in a decrease in any output. Correlation analyses were done for each pair of variables, <Table V.3> shows the correlation matrix

Table V.3: Variables Correlation Coefficients

	Total Energy "GJ"	Terminal's Area "m^2"	Nº Equipment
Total Energy "GJ"	1		
Terminal's Area "m^2"	0.3481	1	
Nº Equipment	0.8238	0.0604	1
Throughput "TEU"	0.9301	0.2982	0.8785

No DMUs with inappropriate Data with respect to the sellected model have been detected, which is a validation for our DEA model.

V.2.2. DEA Input-Oriented Analysis

An online DEA software "DEAOS" has been run to analyze the respective energy efficiency scores of the units in our data set. To compute energy efficiency two input oriented models have been applied, DEA-CCR with constant return to scale, and DEA-BCC that assumes a variable return to scale, DEA is carried on eighteen container terminals from different regions in the world, among them six are automated, while the rest of them are traditional terminals, <Table V.4>.

Table V.4: List of Container Terminals in the Data Set

Country	Port	Container Terminal	Type
Algeria	Bejaia	BMT	Traditional
Brazil	Santos	Libra	Traditional
China	QingDao	Qianwan United	Traditional
India	L&T Kattupalli	Kattupalli International	Automated
Italy	Livorno	Darsena Toscana	Traditional
Korea	Busan New	BNCT	Automated

Korea	Busan North	DPCT	Traditional
Korea	Busan New	Hanjin Busan	Automated
Korea	Busan North	Hutchison	Traditional
Korea	Busan New	Hyundai	Automated
Korea	Busan North	KBCT	Traditional
Korea	Busan New	PNC	Automated
Korea	Busan New	PNIT	Automated
Korea	Busan North	SBCT	Traditional
Slovenia	Koper	Luka Koper	Traditional
Spain	Valencia	Noatum	Traditional
Sri Lanka	Colombo	Jaya	Traditional
Taiwan	Kaohsiung	Hanjin Pacific	Traditional

1. Interpretation of the Results for CCR Model

<Table V.5> depicts the abridged version of the efficiency report, where efficiency scores of all eighteen container terminals are reported. This one-input and three-output model shows that three of the eighteen terminals are efficient using these four dimensions. Among the efficient units, Jaya container terminal could be easily determined as efficient unit, because it is ranked in the fourth position in term of cargo volume handled, and in the thirteenth position for the amount of energy used. While, we observe that the efficiency of the two terminals BMT and Kattupalli International, that handled the smallest cargo volumes, respectively ranked in the seventeenth and eighteenth larger volumes, using also the seventeenth and eighteenth larger amounts of energy, respectively (Appendix I and Appendix II), Could not be determined in ratio based analysis. However, with DEA using multiple inputs and outputs at the same time, we are able to discover them.

Table V.5: Analysis results with Constant return to Scale

	Efficiency	Graph	
bmt	100 %	100%	✓
libra	41.9 %	42%	
qianwan united	61.3 %	61%	
kattupalli international	100 %	100%	✓
darsena toscana	70 %	70%	
bnct	73.7 %	74%	
dpct	59.5 %	59%	

hanjin busan	44.1 %	44%	
hutchison	69 %	69%	
hyundai	46.7 %	47%	
kbct	52.7 %	53%	
pnc	53.8 %	54%	
pnit	74.9 %	75%	
sbct	37.7 %	38%	
luka koper	34.5 %	34%	
noatum	50.2 %	50%	
jaya	100 %	100%	✓
hanjin pacific	31 %	31%	

✓ : Efficient

1) Efficiency and Inefficiency

Fifteen container terminals have scores of less than 1 but greater than 0, and thus they are identified as inefficient. These terminals can improve their efficiency, or reduce their inefficiencies proportionately, by reducing their inputs. For example, KBCT Container terminal can improve its efficiency by reducing inputs up to 47.3 % (1.0_0.527). However, PNIT container terminals is closer to an efficiency frontier and needs only a 25.1% reduction in resources. These input reductions are called total inefficiencies which comprise not only the amount of proportional reductions, but also an amount called “Slack” for those Terminals that cannot reach their efficiency targets (at frontier) despite the proportional reductions.

2) Slacks for Inputs and Outputs

<Table V.6> contains the “Slack” values of the DEA computation results. Mathematical derivation of these slacks is presented by Eq. (9). Here, we observe that none of the efficient terminals have any slacks. Slacks exist only for terminals identified as inefficient. However, slacks represent only the leftover portions of inefficiencies after proportional reductions in inputs, if a DMU cannot reach the efficiency frontier slacks are needed to help the DMU to reach the frontier. We can note that in our case there is no excess in inputs for the whole inefficient terminals after the proportional reduction. However there are outputs shortages for fourteen out of the fifteen inefficient units.

Table V.6: Inputs Slacks for CCR Model

	total energy "gj"	terminal's area "m^2"	n° equipment	throughput "teu"
bmt	0	0	0	0
libra	0	374248.225	0	0
qianwan united	0	1744629.363	0	0
kattupalli international	0	0	0	0
darsena toscana	0	0	21.985	0
bnct	0	0	248.578	67447.012
dpct	0	0	414.682	0
hanjin busan	0	0	354.479	0

hutchison	0	0	432.149	0
hyundai	0	0	1102.29	0
kbct	0	0	842.542	0
pnc	0	0	1177.783	0
pnit	0	0	0	0
sbct	0	0	67.718	0
luka koper	0	0	207.702	0
noatum	0	0	1519.886	0
jaya	0	0	0	0
hanjin pacific	0	0	248.209	0

For example we can notice that Darsena Toscana container terminal do not require additional reduction in its energy use. However, to achieve efficiency, Darsena Toscana container terminal should augment the number of its equipment by about 22 units, corresponding to about 3% of its original number of equipment. A similar situation in a different magnitude exists for ten out of the fifteen inefficient terminals[3]. On the other hand, Qianwan United terminal, cannot reduce any inputs, but to reach its efficient target this terminal must overcome shortage issues related to size[4]. A similar situation in a different magnitude exists for Libra terminal. Lastly, BNCT terminal should increase its equipment by about 21%, and the throughput by about 13.3%. It is to note that these

3 Any increase in the number of equipment is supposed to result in an increase in the throughput.

4 It is to notice that Qianwan United terminal has the largest number of equipment and throughput, and consumes the largest amount of energy in our data set, while it is ranked only sixteenth in term of size.

calculations are the results of Eq. (7) and Eq. (9) executed in succession or Eq. (10)[5].

3) Efficiency Targets

We can summarize the efficiency targets by examining <Table V.7>. Here, for each Terminal, target input and output levels are prescribed. These targets are the results of respective slack values added to proportional reduction amounts. To calculate the target values for inputs, the input value is multiplied with an optimal efficiency score, and then slack amounts are subtracted from this amount (Ozcan, 2014). For detailed formulations of these calculations, refer to Eq. (11).

Table V.7: Input and Outputs Efficiency Targets for CCR Model

	total energy "gj"	terminal's area "m²"	n° equipment	throughput "teu"
bmt	28951.077 to 28951.077	332000 to 332000	567 to 567	226856 to 226856
libra	159489.796 to 66809.957	155000 to 529248.225	1319 to 1319	648400 to 648400
qianwan united	566736.102 to 347204.106	244000 to 1988629.363	6180 to 6180	5450000 to 5450000
kattupalli international	19774.8 to 19774.8	172000 to 172000	404 to 404	150000 to 150000
darsena toscana	55981.876 to 39173.378	386000 to 386000	717 to 738.985	413800 to 413800

5 Refer to Chapter VI, VI.1, VI.1.1, Eq: (7), (9) & (10).

bnct	99351.446 to 73249.712	840000 to 840000	1186 to 1434.578	506526 to 573973.012
dpct	105875.479 to 62986.877	308000 to 308000	634 to 1048.682	1193690 to 1193690
hanjin busan	299287.436 to 132068.006	687590 to 687590	1863 to 2217.479	2432255 to 2432255
hutchison	128543.663 to 88662.045	624000 to 624000	1129 to 1561.149	1358431 to 1358431
hyundai	236951.884 to 110698.315	553068 to 553068	746 to 1848.29	2078010 to 2078010
kbct	274827.935 to 144801.332	1012159 to 1012159	1704 to 2546.542	2230306 to 2230306
pnc	368021.023 to 197854.603	1202000 to 1202000	2221 to 3398.783	3353330 to 3353330
pnit	134690.695 to 100840.891	840000 to 840000	1878 to 1878	1220000 to 1220000
sbct	167565.749 to 63217.536	446250 to 446250	1046 to 1113.718	966341 to 966341
luka koper	109952.96 to 37893.69	270000 to 270000	461 to 668.702	575000 to 575000
noatum	306702.485 to 153983.535	1152217 to 1152217	1222 to 2741.886	2243516 to 2243516
jaya	114878.637 to 114878.637	455000 to 455000	1865 to 1865	2357500 to 2357500
hanjin pacific	187103.933 to 58047.535	420000 to 420000	779 to 1027.209	870000 to 870000

As it can be observed from <Figure V.5>, the target values for efficient terminals are equivalent to their original input and output values. However, for the inefficient Units, the targets for input variables "$\hat{x}_{qk}$" in our DEA model will comprise proportional reduction in the input variables by the efficiency score of the DMU minus the slack value, if any, given by the formula:

$$\hat{x}_{qk} = \theta^* x_{qk} - s_q^{-*} \;\; q = 1, \dots, Q$$

For example, the input target calculation for the Energy Use (EU) of BNCT container terminal is calculated as the following:

$$\hat{x}_{EU.BNCT} = \theta^* x_{EU.BNCT} - s_{EU}^{-*}$$

$$\hat{x}_{EU.BNCT} = 0.418898004 * 159489.7956 - 0$$

$$\hat{x}_{EU.BNCT} = 73249.71213$$

Where 0.418898004 is the efficiency score <Table V.5>, 159489.7956350 is the amount of energy consumed in "GJ" < Appendix. II>, and 0 represents the slack value of the input <Table V.6>. The result can be confirm with <Table V.7>.

<Table V.7> shows the respective possible reduction in energy consumption for inefficient terminals

In an input-oriented model, efficient output targets are calculated as:

$$\hat{y}_{pk} = y_{pk} + s_p^{+*} \;\; p = 1, \dots, P$$

Using the same example of BNCT container terminal, Number of Equipment (NE), Terminal's Size (TS) and Throughput (TH) targets are:

$$\mathrm{NE}_{BNCT}\text{: } \hat{y}_{NE.BNCT} = y_{NE.BNCT} + s_{NE}^{+*}$$

$$\hat{y}_{NE.BNCT} = 1186 + 248.5783133$$

$$\hat{y}_{NE.BNCT} = 1434.578313 \approx 1435$$

$$\mathrm{TS}_{BNCT}\text{: } \hat{y}_{TS.BNCT} = y_{TS.BNCT} + s_{TS}^{+*}$$

$$\hat{y}_{TS.BNCT} = 840000 + 0$$

$$\hat{y}_{TS.BNCT} = 840000$$

$$TH_{BNCT}: \hat{y}_{TH.BNCT} = y_{TH.BNCT} + s_{TH}^{+*}$$

$$\hat{y}_{TH.BNCT} = 506526 + 67447.012$$

$$\hat{y}_{TH.BNCT} = 573973.012 \approx 573974$$

These results can be confirmed with <Table V.7> for BNCT container terminal. The other inefficient terminals' targets are calculated in the same manner.

4) Weights

Optimal input and output weights v_q and u_p, shown in Eq. (5), (6), and (7), are derived by solving the DEA based on relative evaluation of all DMUs in the data set.

These weights also provide information on how efficiency improvements can be achieved for the inefficient container terminals. For example, BNCT terminal has an efficiency ratio of 0.737. This means that this terminal must increase its rating by 2.63% (1 - 0.737 = 0.263) to become relatively efficient among the other terminals in the data set. Using the weights reported in <Table V.8>, this terminal can decrease its energy use by 26101.68 GJ ($0.263/1.0065*10^{-5} = 26101.68$), to an efficient target of 73249.71 GJ, as reported in <Table V.7>.

Table V.8: Optimal Input and Outputs Weights for CCR Model

	total energy "gj"	terminal's area "m²"	n° equipment	throughput "teu"
bmt	3.45E-05	3E-06	0	0
libra	6.3E-06	0	0.0002739	1E-07
qianwan united	1.8E-06	0	7.71E-05	0
kattupalli international	5.06E-05	7E-07	0.0021906	0
darsena toscana	1.79E-05	1.1E-06	0	7E-07
bnct	1.01E-05	9E-07	0	0
dpct	9.4E-06	6E-07	0	3E-07
hanjin busan	3.3E-06	2E-07	0	1E-07
hutchison	7.8E-06	5E-07	0	3E-07
hyundai	4.2E-06	3E-07	0	2E-07
kbct	3.6E-06	2E-07	0	1E-07
pnc	2.7E-06	2E-07	0	1E-07
pnit	7.4E-06	1E-07	0.0002861	1E-07
sbct	6E-06	4E-07	0	2E-07
luka koper	9.1E-06	6E-07	0	3E-07
noatum	3.3E-06	2E-07	0	1E-07
jaya	8.7E-06	0	0.0003803	1E-07
hanjin pacific	5.3E-06	3E-07	0	2E-07

5) Benchmarks

<Table V.9> provides benchmark results, "benchmarks" are created through the DEA computations. Here, terminal managers whose

container terminals are inefficient can observe the benchmark DMUs to improve their efficiency.

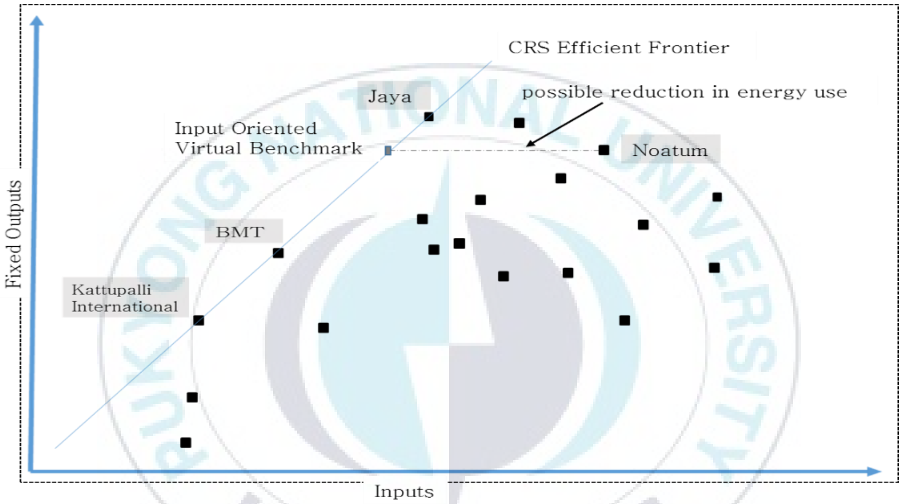
Table V.9: Benchmarks for CCR Model

	Peer Group	Frequencies	
bmt	bmt	14	✓
libra	kattupalli international,jaya	0	
qianwan united	kattupalli international,jaya	0	
kattupalli international	kattupalli international	4	✓
darsena toscana	bmt,jaya	0	
bnct	bmt	0	
dpct	bmt,jaya	0	
hanjin busan	bmt,jaya	0	
hutchison	bmt,jaya	0	
hyundai	bmt,jaya	0	
kbct	bmt,jaya	0	
pnc	bmt,jaya	0	
pnit	bmt,kattupalli international,jaya	0	
sbct	bmt,jaya	0	
luka koper	bmt,jaya	0	
noatum	bmt,jaya	0	
jaya	jaya	15	✓
hanjin pacific	bmt,jaya	0	

✓ : Referenced

Efficient units may consider themselves to be their own “benchmarks”; e.g., the benchmark for BMT terminal is BMT terminal. However, for inefficient Terminals, at least one of the efficient terminals is considered as a benchmarking peer; e.g., the benchmark for BNCT terminal is the efficient unit BMT terminal, and benchmarking peers for Noatum container terminal are two terminals, BMT and Jaya, i.e., to become efficient, Noatum terminal must use a virtual terminal that is the combination of BMT and Jaya to become efficient <Figure V.5>.

Figure V.5: Benchmarking Peers



The values of contribution of BMT terminal and Jaya terminal to form this virtual benchmark of efficiency achievement, are calculated and reported in <Table V.10> for each benchmarking peer terminal, i.e., λ (lambda) weights obtained from the dual version of the linear program that is solved to estimate these values[6].

6 Refer to Chapter VI, VI.1, VI.1.1, Eq. (7).

Table V.10: Lambda for CCR Model

	bmt	kattupalli international	jaya
bmt	1	0	0
libra	0	2.825	0.095
qianwan united	0	6.549	1.895
kattupalli international	0	1	0
darsena toscana	1.062	0	0.073
bnct	2.53	0	0
dpct	0.269	0	0.48
hanjin busan	0.757	0	0.959
hutchison	1.255	0	0.455
hyundai	0.527	0	0.831
kbct	2.018	0	0.752
pnc	1.925	0	1.237
pnit	1.564	1.075	0.299
sbct	0.901	0	0.323
luka koper	0.552	0	0.191
noatum	2.495	0	0.712
jaya	0	0	1
hanjin pacific	0.875	0	0.285

For example, Darsena Toscana terminal will attempt to become like BMT terminal more than Jaya terminal as observed from respective λ weights of these two terminals, becaue BMT terminal λ value

(λ_{BMT} =1.062174118) is larger than Jaya terminal λ value (λ_{Jaya}=0.07331471).

2. Interpretation of the Results for BCC Model

In BCC models more DMUs can find their way to the frontier. Additionally, BCC efficiency scores are generally higher than efficiency scores with constant return to scale. Thus, using this approach makes more terminals appear to be efficient using this approach.

1) Return to Scale

In order to calculate and assess the RTS (whether is increasing, constant, or decreasing) the summation of lambda "λ_j" weight values is needed. If the summation of lambda weights is $\sum \lambda < 1$, then for such DMU increasing return to scale prevail. On the other hand, if $\sum \lambda > 1$, then the DMU exhibits decreasing rates of return to scale. The efficient DMUs are considered as having constant returns to scale, and they will have $\sum \lambda = 1$.

<Table V.11> displays $\sum \lambda$ and RTS for the whole units in the data set. For terminals that have only one benchmark in their reference set, $\sum \lambda$ is equal to λ weight of that reference. On the other hand those with more than one terminal in their benchmarks set, $\sum \lambda$ is an addition of their respective λ weights; e.g., $\sum \lambda$ value of KBCT terminal, is calculated by adding λ weight of BNCT terminal and λ weight of PNC terminal, and PNIT terminal (0.006+ 0.476+ 0.518=1).

Table V.11: Return to Scale for BCC Model

	bmt	qianwan united	kattupalli international	bnct	pnc	pnit	noatum	jaya	$\sum \lambda$	RTS
bmt	1	0	0	0	0	0	0	0	1	Constant
libra	0.421	0	0	0	0	0	0	0.579	1	Constant
qianwan united	0	1	0	0	0	0	0	0	1	Constant
kattupalli internatio nal	0	0	1	0	0	0	0	0	1	Constant
darsena toscana	0.836	0	0	0.088	0	0	0	0.076	1	Constant
bnct	0	0	0	1	0	0	0	0	1	Constant
dpct	0.015	0	0.513	0	0	0	0	0.472	1	Constant
hanjin busan	0	0	0	0	0.238	0.143	0	0.62	1.001	Decreasing
hutchison	0.069	0	0	0.461	0	0	0	0.471	1.001	Decreasing
hyundai	0	0	0	0	0.003	0.249	0	0.748	1	Constant

kbct	0	0	0	0.006	0.476	0.518	0	0	1	Constant
pnc	0	0	0	0	1	0	0	0	1	Constant
pnit	0	0	0	0	0	1	0	0	1	Constant
sbct	0.527	0	0	0.145	0	0	0	0.328	1	Constant
luka koper	0.29	0	0.528	0	0	0	0	0.182	1	Constant
noatum	0	0	0	0	0	0	1	0	1	Constant
jaya	0	0	0	0	0	0	0	1	1	Constant
hanjin pacific	0.608	0	0	0.103	0	0	0	0.288	0.999	Increasing

2) Efficient Targets

<Table V.12> and <Table V.13> display together slacks and targets for the VRS model. The calculation of targets is the same as for the CRS model, refer to Eq. (11).

Table V.12: Input and output Slacks for BCC Model

	total energy "gj"	terminal's area "m^2"	n° equipment	throughput "teu"
bmt	0	0	0	0
libra	0	248260.401	0	812850.675
qianwan united	0	0	0	0
kattupalli international	0	0	0	0
darsena toscana	0	0	3.297	0
bnct	0	0	0	0
dpct	0	0	462.393	0
hanjin busan	0	0	88.544	0
hutchison	0	0	334.113	0
hyundai	0	0	1123.371	0
kbct	0	0	332.994	0
pnc	0	0	0	0
pnit	0	0	0	0
sbct	0	0	36.769	0
luka koper	0	0	256.778	0
noatum	0	0	0	0
jaya	0	0	0	0
hanjin pacific	0	0	226.207	0

Table V.13: Input and Output Targets for BCC

	total energy "gj"	terminal's area "m²"	n° equipment	throughput "teu"
bmt	28951.077 to 28951.077	332000 to 332000	567 to 567	226856 to 226856
libra	159489.796 to 78733.454	155000 to 403260.401	1319 to 1319	648400 to 1461250.675
qianwan united	566736.102 to 566736.102	244000 to 244000	6180 to 6180	5450000 to 5450000
kattupalli international	19774.8 to 19774.8	172000 to 172000	404 to 404	150000 to 150000
darsena toscana	55981.876 to 41684.046	386000 to 386000	717 to 720.297	413800 to 413800
bnct	99351.446 to 99351.446	840000 to 840000	1186 to 1186	506526 to 506526
dpct	105875.479 to 64825.129	308000 to 308000	634 to 1096.393	1193690 to 1193690
hanjin busan	299287.436 to 177924.502	687590 to 687590	1863 to 1951.544	2432255 to 2432255
hutchison	128543.663 to 101833.393	624000 to 624000	1129 to 1463.113	1358431 to 1358431
hyundai	236951.884 to 120612.732	553068 to 553068	746 to 1869.371	2078010 to 2078010
kbct	274827.935 to 245446.438	1012159 to 1012159	1704 to 2036.994	2230306 to 2230306
pnc	368021.023 to 368021.023	1202000 to 1202000	2221 to 2221	3353330 to 3353330
pnit	134690.695 to 134690.695	840000 to 840000	1878 to 1878	1220000 to 1220000
sbct	167565.749 to 67375.665	446250 to 446250	1046 to 1082.769	966341 to 966341

luka koper	109952.96 to 39784.538	270000 to 270000	461 to 717.778	575000 to 575000
noatum	306702.485 to 306702.485	1152217 to 1152217	1222 to 1222	2243516 to 2243516
jaya	114878.637 to 114878.637	455000 to 455000	1865 to 1865	2357500 to 2357500
hanjin pacific	187103.933 to 61003.534	420000 to 420000	779 to 1005.207	870000 to 870000

Now the number of inefficient terminals decreased to ten <Table V.14>, and they cannot reach the BCC frontier through input reduction only, outputs augmentations are needed. If we consider Hyundai terminal (HY) as example, using the values in <Appendix. II> and the target formulations from Eq. (11); for energy use (EU), we get:

$$\hat{x}_{qk} = \theta^{*} x_{qk} - s_q^{-*} \quad q = 1, \dots, Q$$

For Hyundai terminal it will be,

$$EU_{HY}: \hat{x}_{EU.Hy} = \theta^{*} x_{EU.Hy} - s_{EU}^{-*}$$

$$\hat{x}_{EU.Hy} = 0.509018 * 236951.88 - 0$$

$$\hat{x}_{EU.Hy} = 120612.73$$

Similarly for outputs, we get:

$$\hat{y}_{pk} = y_{pk} + s_p^{+*} \quad p = 1, \dots, P$$

For Hyundai terminal it will be,

$$NE_{HY}: \hat{y}_{NE.Hy} = y_{NE.Hy} + s_{NE}^{+*}$$

$$\hat{y}_{NE.Hy} = 746 + 1123.370612$$

$$\hat{y}_{NE.Hy} = 1869.370612 \approx \ 1870$$

$$TS_{HY}: \hat{y}_{TS.Hy} = y_{TS.Hy} + \ s_{TS}^{+*}$$

$$\hat{y}_{TS.Hy} = 553068 + 0$$

$$\hat{y}_{TS.Hy} = 553068$$

$$TH_{HY}: \hat{y}_{TH.Hy} = y_{TH.Hy} + \ s_{TH}^{+*}$$

$$\hat{y}_{TH.HY} = 2078010 + 0$$

$$\hat{y}_{TH.Hy} = 2078010$$

The results of these calculations can be verified by comparison with the target values of Hyundai terminal in <Table V.13>.

3) Benchmarking peers

Since the VRS model forms a different frontier, the benchmarks are certainly different than those of the CRS frontier. The λ weights corresponding to each reference terminal are shown in <Table V.11> and <Table V.14>.

Table V.14: Benchmarking Peers for BCC Model

	Peer Group	Frequencies	
bmt	bmt	8	✓
libra	bmt,jaya	0	
qianwan united	qianwan united	1	✓

kattupalli international	kattupalli international	3	✓
darsena toscana	bmt,bnct,jaya	0	
bnct	bnct	6	✓
dpct	bmt,kattupalli international,jaya	0	
hanjin busan	pnc,pnit,jaya	0	
hutchison	bmt,bnct,jaya	0	
hyundai	pnc,pnit,jaya	0	
kbct	bnct,pnc,pnit	0	
pnc	pnc	4	✓
pnit	pnit	4	✓
sbct	bmt,bnct,jaya	0	
luka koper	bmt,kattupalli international,jaya	0	
noatum	noatum	1	✓
jaya	jaya	10	✓
hanjin pacific	bmt,bnct,jaya	0	

✓ : Referenced

4) Comparing results of CCR, BCC Models, and Scale Efficiency

In this section we will provide a brief overview and compare efficiency results. <Table V.15> summarizes the results that were generated using input oriented CCR and BCC models.

Table V.15: Efficiency Score for CCR, Scale, and BCC Models

	CRS	VRS	SE
BMT	100 %	100 %	100 %
Libra	41.9 %	49.4 %	84.9 %
Qianwan United	61.3 %	100 %	61.3 %

Kattupalli International	100 %	100 %	100 %
Darsena Toscana	70 %	74.5 %	94 %
BNCT	73.7 %	100 %	73.7 %
DPCT	59.5 %	61.2 %	97.2 %
Hanjin Busan	44.1 %	59.4 %	74.2 %
Hutchison	69 %	79.2 %	87.1 %
Hyundai	46.7 %	50.9 %	91.8 %
KBCT	52.7 %	89.3 %	59 %
PNC	53.8 %	100 %	53.8 %
PNIT	74.9 %	100 %	74.9 %
SBCT	37.7 %	40.2 %	93.8 %
Luka Koper	34.5 %	36.2 %	95.2 %
Noatum	50.2 %	100 %	50.2 %
Jaya	100 %	100 %	100 %
Hanjin Pacific	31 %	32.6 %	95.2 %

Average efficiency scores for input oriented with VRS models are generally greater than those for an input oriented with CRS models.

In comparing CCR and BCC models, another important aspect of efficiency that is scale efficiency, can be depicted (Ozcan, 2014). The scale efficiency (SE) can be calculated by dividing the optimal CRS efficiency score by the optimal VRS efficiency score, Eq. (13). Hence, it can be written as:

$$SE = \frac{\theta^*_{CCR}}{\theta^*_{BCC}}$$

Applying this formula to our results, allows to obtain the SE scores shown in <Table V.15>.

The BCC efficiency scores "$\boldsymbol{\theta^*_{BCC}}$" are considered pure technical efficient, while CCR efficiency scores "$\boldsymbol{\theta^*_{CCR}}$" are considered technical efficient. Thus, from the formula above the technical efficiency is the product of pure technical efficiency and scale efficiency, as in:

$$\theta^*_{CCR} = SE * \theta^*_{BCC}$$

The conceptual distances from CCR and BCC fronts to an inefficient terminal were shown in <Figure V.6>. Once the distances are calculated, CCR and BCC efficiency scores are obtained, and by substituting these values into the above ratio, scale efficiency can be obtained by its turn (Ozcan, 2014).

If we take Luka Koper "LK" container terminal as example:

LK input oriented efficiency with CRS:

$$\theta^*_{CCR.LK} = LK_C/LK$$

$$\theta^*_{CCR.LK} = 37893.69004/109952.9595 = 0.344635472$$

The result can be verified from <Table V.6> and <Table V.14>

LK input oriented efficiency with VRS:

$$\theta^*_{BCC.LK} = LK_V/LK$$

$$\theta^*{}_{BCC.LK} = 39784.53773/109952.9595 = 0.36183235$$

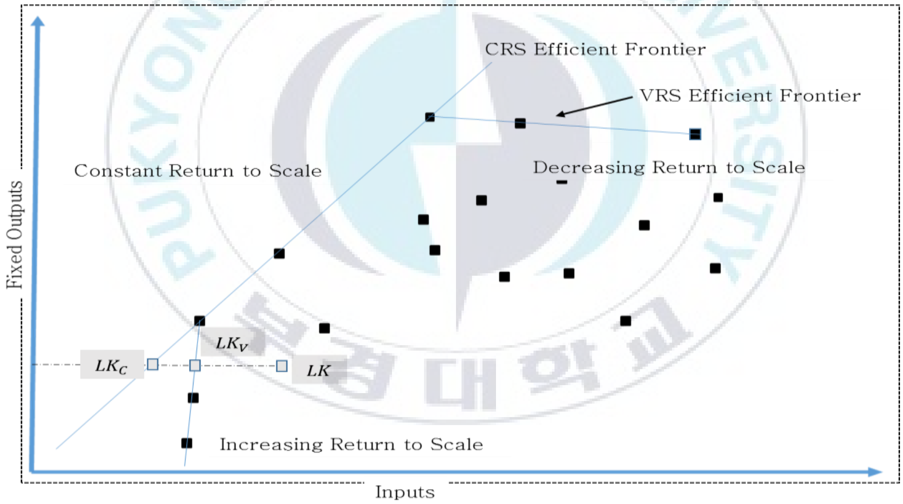
The result can be verified from <Table V.12> and <Table V.14>

LK input oriented SE:

$$SE_{LK} = \frac{\theta^*{}_{CCR.LK}}{\theta^*{}_{BCC.LK}} = \frac{0.344635472}{0.36183235} = 0.952472801$$

The result can be verified from <Table V.15>.

Figure V.6: Input Reductions and RTS



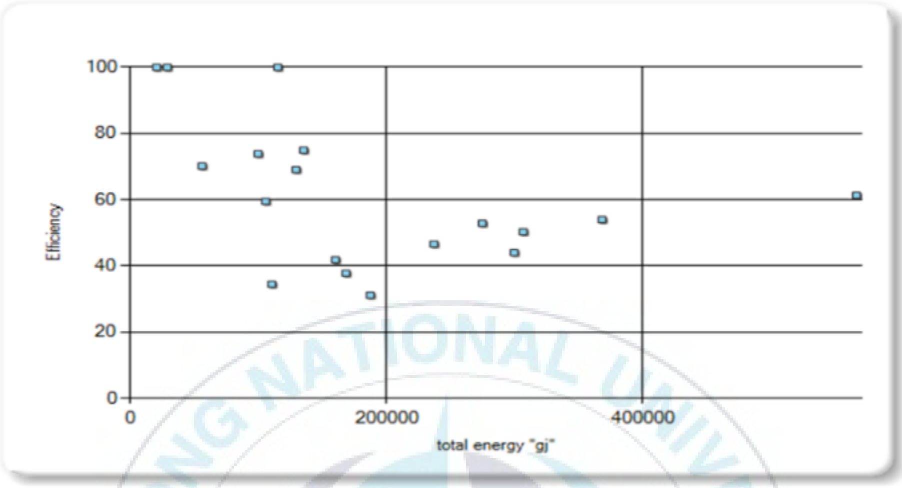
Chapter VI : Conclusion

VI.1. Research Finding

After running a DEA model with CRS, the results displayed in <Table V.5> show that energy technical efficiency scores for the eighteen container terminals, vary from 0.31 for the least inefficient to 1 for efficient units[7], with an average overall score of 0.61 indicating that on an average the terminals represent about 39% of inefficiency. Among the eighteen terminals only three are relatively efficient (BMT, Kattupalli International, and Jaya), they form the efficient frontier and represent the improvement benchmarks for the inefficient units, while the other fifteen terminals are inefficient with five terminals representing scores above the average and ten terminals have scores below the average <Figure VI.1>, as first ascertainment we can notice that in our data set 83% of terminals consume energy with an average of 39% of inefficiency.

[7] Score 1 means 100% efficient, and score 0.31 means efficient at 31% or a lack of 69% of efficiency.

Figure VI.1: Energy use Efficiency Plot for CCR Model



<Table V.7> shows the respective possible reduction in energy consumption for inefficient terminals. Each inefficient DMU has one or a set of efficient DMUs (Benchmarks)[8] with corresponding intensities (λ)[9] <Table V.11>, which can be identified as energy efficiency improvement references, <Table V.10> shows the frequency of each efficient terminal as efficiency improvement reference.

Inefficient terminals in the data set can reduce a total amount of 1523590.942 GJ from their total inputs while keeping the same level of outputs, which corresponds to about 47.59% from the sample's total energy use, and an individual average waste in energy equal to 46.6%.

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[8] Benchmarks are selected on the basis of their comparable variables to those of the inefficient DMUs.

[9] λ Is an optimal multiplier to identify the reference sets for each inefficient DMU.

After a DEA model with VRS has been applied, Technical efficiency scores are decomposed into pure technical and scale efficiencies. Which allows to find whether the overall inefficiency is due to pure technical inefficiency or scale inefficiency <Table V.15>.

The decomposition of the overall technical efficiency into its two components confirms that the overall inefficient terminals are also pure technical efficient, and have constant return to scales[10]. Among the terminals estimated inefficient under CCR model 5 terminals are pure technical efficient (Naotum, PNIT, PNC, BNCT, and Qianwan United), indicating that the origin of their energy waste is due to unfavorable return to scale conditions. While the remaining terminals represent both scale and pure technical inefficiencies. But 1 of them (KBCT) has its PTE score bigger than the SE score, which suggests that its overall inefficiency is mostly affected by operating at inappropriate return to scale, while the other 9 terminals (Libra, Darsena Toscana, DPCT, Hanjin Busan, Hutchison, Hyundai, KBCT, Luka Koper, Hanjin Pacific) have their SE score bigger than their PTE score, which indicates that the most dominant reason of their overall inefficiency is probably a managerial failure.

VI.2. Conclusion

According to the sample's analysis we conclude that, despite of the big similarities in types of equipment and machinery run by container

[10] Score 1 for both technical and pure technical efficiencies implies scale efficient.

terminals, the energy use can varies considerably from one container terminal to another.

Container terminals' size and automation do not have an apparent influence on their energy use efficiency, while the most dominant potential cause of inefficiency in our sample is likely to be more managerial, because among 15 inefficient terminals 9 have respectively their pure technical efficiency score smaller than their scale efficiency score, while 6 of them operate at unfavorable return to scale making technology related issues likely to be the dominant origin of their underperformance. We can conclude that there is no exclusive reason of inefficiency in term of energy use, and the cause can be either managerial or related to technology[11].

In their initiatives to improve energy efficiency, decision makers of inefficient units that the scale efficiency score is higher than the technical efficiency score, should concentrate their efforts on developing a better use of their inputs to reduce the energy consumption by adopting better practices developed by their respective benchmarks. On the other hand, those representing pure technical efficiency scores higher than scale efficiency scores, they should investigate technology related issues, and overcome them using as reference their respective benchmarks, to reach an optimal return to scale and reduce their energy consumption

[11] Even though we could notice that the managerial factor is more frequent, that stays limited to our sample.

VI.3. Study Limitation

Using DEA allowed to assess the relative energy efficiency of a sample of eighteen container terminals from different parts in the world, it helped us to identify efficient and inefficient terminals, and for each inefficient unit DEA calculated the potential amount of energy likely to be saved while keeping the same operational performance, attributed a benchmark peer or a set of benchmarks peers that can be used as reference, to establish best practices, and develop better policies to enhance their energy efficiency.

By considering a variable return to scale DEA allowed us to target the primary cause of energy inefficiency for each underperforming unit, whether it is due to technological issues leading to operate at an inappropriate return to scale, or due to managerial deficiency in the use of inputs that leads to an overuse of energy resources. However, DEA does not point exactly the actual causes of inefficiency, it is limited at indicating whether the problem is in technology, management or both, thus to get more precision in identifying the dominant reasons of inefficiency, we need to check further more by using an ordinary least square (OLS) analysis.

VI.4. Future Work

To bring more accuracy to the research, a multiple regression analysis can be used following the steps bellow;

First, increase the number of container terminals to reach at least an adequate sample's size for a regression analysis. Second, apply a DEA Super-Efficiency model that allows the efficient units under evaluation to be excluded from the reference set, and to get a score bigger than 1. This method makes possible the full ranking of the terminals from the relatively most efficient to the relatively most inefficient, allowing a full comparison of the terminals' respective performances. Third, establish assumptions that may explain the variation in energy efficiency scores. The following are some examples of assumptions to test, and the respective reasons to select them:

1) ISO 50001 certified container terminals are more energy efficient;

The company's certification can be a good indicator of the firm's general policy orientation, considering the terminal's "ISO 50001"[12] certification as a dummy variable, would allow to test whether the terminal's official policy orientation has an actual effect on its energy efficiency or not.

2) Container shipping lines terminals are more energy efficient than typical container terminals;

Container terminals can be divided into two main categories, typical container terminals, and container shipping lines terminals, while the first category's objective is simply to sell its services and technology; the second category aims to consolidate the control of the shipping line

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[12] ISO 50001 an energy management systems standards.

on the whole supply chain steps, by enhancing the efficiency, and reducing the costs, which may qualify them to be more energy efficient.

3) Container terminals located in exclusively container ports are more energy efficient than those located in general cargo ports;

During the collection of the data, I could notice that container terminals located in ports composed exclusively of container terminals systematically update their data of energy consumption, while single container terminals located in general cargo ports have more difficulty to provide their data, electricity in particular, in many cases the port authority was in charge of the electricity supply management, which make them prone to be less efficient in managing their energy consumption.

4) Automated container terminals are more energy efficient.

According to our study, the automation has no direct effect on the energy efficiency, however the sample's size is too small to allow a consistent inference to the whole international population, thus a more accurate study with a larger sample is recommended.

5) Container terminals using hybrid equipment and machinery are more energy efficient.

Some container terminals tend to use come hybrid cargo handling machinery that is supposed to combine productivity and energy saving.

The final step is to determine explanatory variables, considering one dependent variable that is the energy efficiency score obtained using DEA super efficiency. <Table VI.1> contains some examples of explanatory variables that can be used according to assumptions given above as example[13].

Table VI.1: Variables for Ordinary Least Square Analysis

Dependent Variable	Independent Variables	
DEA Super-Efficiency Score	Management Related Variables	Technology Related Variables
	1) ISO 50001 certified	4) Automation
	2) Shipping liner	5) Uses Hybrid Technologies
	3) Container Port or Single Container Terminal	

[13] The number of the variable indicates the corresponding assumption to be supported or not.

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Appendix I: Terminals' Initial Data

Location			Inputs		Outputs						Data Source
Country	Port	Container Terminal	Electricity "kwh"	Diesel "Liter"	Throughput "TEU"	№ Q/C	№ T/C	№ Yard Vehicles	№ Reefer Plugs	Terminal's Area "m²"	
Algeria	Bejaia	BMT	5187400	265541	226856	2	8	57	500	332000	Terminal Operator
Brazil	Santos	Libra	13098610	2902708	648400	10	16	93	1200	155000	Terminal Operator
China	QingDao	Qianwan United	59601695	9100000	5450000	28	60	116	5976	244000	Terminal Operator
India	L&T Kattupalli	Kattupalli International	3300000	204000	150000	6	15	23	360	172000	the Harbor Master Office

Italy	Livorno	Darsena Toscana	6238237	866259	413800	9	14	58	636	386000	Green Cranes Report 2013
Korea	Busan New	BNCT	16911124	994093	506526	8	38	36	1104	840000	Terminal Operator
Korea	Busan North	DPCT	13095408	1517623	1193690	7	19	42	566	308000	Terminal Operator
Korea	Busan New	Hanjin Busan	50003899	3082000	2432255	12	42	109	1700	687590	Terminal Operator
Korea	Busan North	Hutchison	16240000	1810844	1358431	14	33	92	990	624000	Terminal Operator
Korea	Busan New	Hyundai	40882580	2319757	2078010	11	38	97	600	553068	Terminal Operator

Korea	Busan North	KBCT	28932862	4410068	2230306	15	42	107	1540	1012159	Terminal Operator
Korea	Busan New	PNC	56433062	4260000	3353330	17	58	146	2000	1202000	Terminal Operator
Korea	Busan New	PNIT	22987582	1342000	1220000	9	28	57	1784	840000	Terminal Operator
Korea	Busan North	SBCT	11295910	3279082	966341	7	21	40	978	446250	Terminal Operator
Slovenia	Koper	Luka Koper	4853289	2389693	575000	8	18	91	344	270000	Green Cranes Report 2013
Spain	Valencia	Noatum	19401856	6120305	2243516	19	56	127	1020	1152217	Green Cranes Report 2013

Sri Lanka	Colombo	Jaya	22800000	847510	2357500	20	63	234	1548	455000	Internet Site
Taiwan	Kaohsiung	Hanjin Pacific	11566419	3758781	870000	10	0	47	722	420000	Terminal Operator

Appendix II: Terminals' Converted Data

Container Terminal	Total Energy "GJ"	Terminal's Area "m²"	Nº Equipment	Throughput "TEU"
BMT	28951.0767	332000	567	226856
Libra	159489.7956	155000	1319	648400
Qianwan United	566736.102	244000	6180	5450000
Kattupalli International	19774.8	172000	404	150000
Darsena Toscana	55981.8765	386000	717	413800
BNCT	99351.4455	840000	1186	506526
DPCT	105875.4789	308000	634	1193690
Hanjin Busan	299287.4364	687590	1863	2432255
Hutchison	128543.6628	624000	1129	1358431
Hyundai	236951.8839	553068	746	2078010
KBCT	274827.9348	1012159	1704	2230306
PNC	368021.0232	1202000	2221	3353330
PNIT	134690.6952	840000	1878	1220000
SBCT	167565.7494	446250	1046	966341
Luka Koper	109952.9595	270000	461	575000
Naotum	306702.4851	1152217	1222	2243516
Jaya	114878.637	455000	1865	2357500
Hanjin Pacific	187103.9331	420000	779	870000

Appendix III: Data Collection Questionnaire

Dear Madam/Sir;

My name is "Hermouche Toufik Sabri" from department of international commerce and logistics, Pukyong National University, Busan, South Korea.

We are making a study concerning Energy Use Efficiency in container terminals, the study is expected to be a contribution to enhance energy efficiency in the port industry, and promoting sustainability, using a comparative Analysis method among several container terminals all over the world.

We believe, that you are aware that such contribution is supposed to give a better image about port industry, and its participation to improve environment preservation and sustainability, toward a more responsible use of natural resources.

The questions are quite easy to answer (please refer to the sample bellow), for any additional explanation please do not hesitate to email me, I will be pleased to answer you back.

Email: hermouche_toufik@yahoo.fr

Sample:

Terminal Operator's name: Dongbu Pusan Container Terminal (DPCT)

Port, City, Country of location: Busan port, Busan, South Korea

Information for the year 2013

(If not available, data from the year 2012 are ok)

- Type of terminal (please check below):

  ☒ Traditional.

  ☐ Semi-automated.

  ☐ Full automated.

- Terminal's area size: 308000 m²
- Total annual Use of diesel for the terminal's operations (liter): 1517623 liters
- Total annual Use of Electricity for the terminal's operations (kWh): 13095408 kWh
- Is the terminal certified ISO 50001? : YES ☐ NO ☒
- Annual containers Throughput (TEU): 1193690 TEU
- Total Number of ship to shore cranes/portainers (Unites): 9
- Yard equipment (Unites):
- Yard transfer cranes: 19
- Straddle carriers: 0
- Yard tractors: 39
- Reach stackers: 3
- Forklifts: 0
- Empty container handlers: 2
- Automated guided vehicles (AGV): 0

- Reefer plugs: 566
- Other: none

Terminal's name:

Port, City, Country of location:

Information for the year 2013

(If not available, data from the year 2012 are ok)

- Type of terminal (please check below):

  ☐ Traditional

  ☐ Semi-automated

  ☐ Full automated.

- Terminal's total area size (m^2):
- Total annual Use of diesel for the terminal's operations (liter):
- Total annual Use of Electricity for the terminal's operations (kWh):
- Is the terminal certified ISO 50001? : YES ☐ NO ☐
- Annual containers Throughput (TEU):
- Total Number of ship to shore cranes -Portainers- (Unites): 20
- Yard equipment (Unites):
- Yard transfer cranes:
- Straddle carriers:
- Yard tractors:
- Reach stackers:
- Forklifts:
- Empty container handlers:
- Automated guided vehicles (AGV):
- Reefers Plugs:
- Other:

After completion please send the file to this e-mail:

hermouche_toufik@yahoo.fr

Thank you for your precious contribution ☺