Citation: Spengler, T.; Tovar, B. Wilmsmeier (2022): Are output disaggregation and energy variables, key when measuring container terminal efficiency? Maritime Policy & Management https://doi.org/10.1080/03088839.2022.2047812

ARE OUTPUT DISAGGREGATION AND ENERGY VARIABLES, KEY WHEN MEASURING CONTAINER TERMINAL EFFICIENCY?

Thomas Spengler
University of Las Palmas de Gran Canaria. Campus Universitario de Tafira, Módulo D, Las Palmas de Gran Canaria, Spain,
thomas.spengler101@alu.ulpgc.es

Beatriz Tovar (corresponding autor)
University Institute for Tourism and Sustainable Economic Development (TIDES), Universidad de Las Palmas de Gran Canaria. Campus Universitario de Tafira, Módulo D, 35017, Spain Tel: (0034) 928 45 17 94
ORCID ID: 0000-0002-3444-7842
beatriz.tovar@.ulpgc.es

Gordon Wilmsmeier,
Kühne Professorial Chair in Logistics, Facultad de Administración, Universidad de los Andes, Bogotá, Colombia
ORCID ID: 0000-0001-8848-9004
g.wilmsmeier@uniandes.edu.co

ABSTRACT

This paper addresses the question whether energy consumption variables and the disaggregation of output matter in the context of efficiency analysis of container terminals. While it is obvious that the energy consumption of refrigerated cargo is higher than the energy consumption of non-refrigerated cargo, this work investigates whether those differences show in an overall efficiency analysis of terminals. This would point to a potentially important input for efficiency measures, to be considered in future productivity and efficiency analysis of terminals. Starting with a discussion on theoretical concepts and variable selection for measuring the energy dimension of terminal efficiency, the is the first paper that applies Data envelopment analysis (DEA) comparing results with and without energy consumption, as well as differentiating productive outputs (dry and reefer container handling). The results reveal how the output disaggregation leads to substantially different efficiency scores and are a first step to show the relevance of output disaggregation and the inclusion of the energy variables as inputs in container terminal efficiency studies.

Keywords: Terminal efficiency; Output disaggregation; Energy consumption; Data envelopment analysis; dry container; reefer container.

1. INTRODUCTION

Two aspects have been widely ignored in container terminal efficiency research so far: the disaggregation of production outputs of container terminals and energy consumption variables. The former relates to the fact that terminal throughput whether measured in TEU or number of containers is an aggregated measure for handling a variety of goods with different characteristics and requirements inside a “standard size” box. Despite being of standard sizes, standard containers and refrigerated containers vary significantly in their handling requirements. By way of example, whenever perishable commodities are transported, cooling is of essence to ensure their safe arrival at the destination. Reefer containers fulfil this role maintaining a pre-set temperature within the container. Therefore, the input requirements throughout the handling in the terminal are different. Consequently, dry container and reefer container should be considered as different outputs when it comes to measure the terminal efficiency instead to be aggregated in a single measure (total number of container).

The relevance of reefer trades varies across different routes and therefore the proportion of dry/reefer managed for terminals as well. Some of the highest shares of reefer containers can be observed on trade routes from Brazil to Europe and Asia, where these, depending on the season, can reach up to 35% and 30% respectively. In trades between the United States and Northern Europe to Asia, the share of reefer containers ranges between 5% and 10%. On routes going to the Middle East from either the Mediterranean region or North Europe, the share is between 10% and 15% (Drewry Shipping Consultant Limited, 2018).

Energy consumption and consequently emissions in container terminals have started to receive more attention in recent years (He et al. 2017; Martinez-Moya et al. 2019; Spengler and Wilmsmeier, 2019). The increasing interest in this topic is closely linked to the prominence of the sustainable development discussion and increasing energy costs. Ports and container terminals are for once faced with the initial managerial decision whether to purchase diesel or electrically powered equipment. Investment in cold ironing infrastructure and its use will have a further effect on energy consumption pattern in terminals.

Given these considerations this paper applies Data envelopment analysis (DEA) to investigate, if energy consumption variables and the disaggregation of output matter in the context measuring efficiency in container terminals. To address this research question, this work is structured as follows. Section 2 reviews relevant research on container terminal energy consumption and provides a critical review on container terminal productivity and efficiency studies applying DEA. The DEA methodology, variables selected and models are described in section 3. Section 4 discusses the results of the DEA. Section 5 concludes.

2. LITERATURE REVIEW

The body of literature on efficiency and productivity in the port sector in general and specifically in the container terminal sector has grown to a considerable size during the past decades. This literature review does not pretend to give an exhaustive insight into all different approaches in productivity and efficiency studies in the port sector but focuses on a selection of articles on container terminal efficiency that are deemed to be useful to address the aforementioned research question (Table 1).

Two main methodological complementary approaches can be found in the literature: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). DEA is a deterministic method based on linear programming (Charnes et al.,1978) and Cullinane et al. (2006) identified high correlations between the results from DEA and SFA on port efficiencies. One advantage of applying DEA is that the functional form for the frontier does not have to be specified and thus results can be obtained with relatively small data sets (Tovar and Wall, 2015). DEA has been the predominant methodology in this research area (Woo et al, 2011). Given existing data limitations and in order to show the relevance of previously no considered variables, this paper also applies DEA. Consequently, the following literature review will focus on the application of DEA at container terminal level (Table 1).

Two key challenges when applying DEA or practically any quantitative methodology, are the selection of variables as well as the structure of the sample. It is generally agreed that the efficient allocation of land, labour and equipment (see for example Dowd and Leschine, 1990; Cullinane et al., 2005; Guerrero and Rivera, 2009) is at the very core of container terminal productivity and efficiency. This, in turn, leads to the question how land, labour and equipment are represented in the previously conducted studies (see Section 3).

The literature review is divided in two parts. The first reviews the literature on the emerging relevance of energy efficiency and energy consumption in container terminals, even if not necessarily conducted in the context of efficiency or productivity analysis. The second critically reviews previous efficiency studies at container terminal level applying DEA.

2.1. Energy Consumptions and Energy Efficiency Studies in Terminals and Ports

Energy consumption and energy efficiency in the context of container terminals have so far been addressed on either operational level, on terminal level or on policy level. To the best of the knowledge of the authors, no approach has been shown where energy variables were considered an input in a DEA or SFA model, the only exception being Guimaraes et al., (2014), who measure environmental efficiency.

The research covering the operational level, stretches from individual equipment, routing problems to new approaches to reduce energy consumption or even produce energy in a terminal. By way of example, Yang et. al. (2013) analysed the monetary as well as CO_2 saving potential of electric rubber-tired gantry cranes (RTGs). These authors mention a potential reduction in energy consumption of up to 60% through technological change. In the light of the apparent difficulties of identifying the actual consumption of equipment, Hangga and Shinoda (2015) proposed a methodology for obtaining energy consumption of straddle carriers. He et. al. (2015) discussed in their paper a novel approach to the yard crane scheduling problem where timesaving was not considered the ultimate goal but rather a trade-off with energy-saving. Budiyanto et. al. (2018) analysed the effect roof shades of refrigerated containers have on energy consumption pattern and estimated the savings to be about 17%. Van Duin et al. (2018) approached the question of how energy peaks of reefer racks can be reduced and found substantial opportunities for reducing energy consumption by applying peak shading.

While those findings and approaches underline the importance of research in the field of energy consumption and efficiency in the terminal sector, they provide very limited insights as to how an approach could look like that covers an entire terminal, let alone multiple terminals. It shows however, that energy consumption in terminals is difficult to be modelled accurately as many different external as well as internal factors play an important role.

Multiple approaches to coordinated collection and analysis of energy consumption data can be observed. Wilmsmeier et. al. (2014) collected data from 13 terminals in Argentina, Chile, Paraguay and Uruguay. This was done against the background of substantial traffic of refrigerated containers that are being moved through the terminals of those countries. Following an activity-based approach, they reported on energy consumption patterns in terminals in those countries. However, the findings were presented on a rather descriptive level without offering insights into the potential ramifications on productivity or efficiency. Also, the kind of comparison of diesel and electricity consumption that was carried out made it necessary to convert those energy sources to the same unit. It was not accounted for energy conversion efficiency. In contrast, DEA allows to have the inputs electricity consumption as well as diesel consumption in their native unit of measurement.

Wilmsmeier et. al. (2014) found that the energy consumption patterns differ vastly between terminals when a differentiation of dry and reefer TEU is carried out. Also, on equipment level, it was found that energy consumption can hardly be seen as mere function of the operating hours of the equipment which contradicted some modelling approaches like the one of Geerlings and van Duin (2011). Wilmsmeier and Spengler (2016) continued to build upon Wilmsmeier et. al. (2014) and reported among other things on the differences in consumption patterns of small, medium and large terminals. They also observed great differences in consumption patterns across terminals from different countries. This, in turn, raises the question if energy in and by itself should be considered an input in the analysis of terminal productivity and efficiency.

Azarkamand et al. (2020) introduced an online tool, similar to the one developed by Wilmsmeier and Spengler (2016), for calculating carbon footprints in ports.

Martínez-Moya et. al. (2019) followed a similar, activity-based, approach for the NCTV terminal of the port of Valencia. They report that roughly 50% of the electricity consumption in the terminal can be allocated to refrigerated containers. This figure as well as the other findings are aligned with the findings presented by Wilmsmeier et. al. (2014) and Wilmsmeier and Spengler (2016).

Apart from the more practical approaches, certain publications address mostly the matter of policy implications. Acciaro et. al. (2014) describe the role port authorities could have for energy management based on a case study for the port of Hamburg and the port of Genoa. They found that at least in Hamburg the city seems to be more of the driving force towards more energy efficiency while in Genoa the port authority is taking this role. Wilmsmeier (2020) does similarly report that the Colombian government has adopted the methodology described by Wilmsmeier et. al. (2014) and Wilmsmeier and Spengler (2016).

Iris and Lam (2019) carried out a review of the currently present operational strategies, technologies as well as energy management systems. In terms of operational strategies, they described two relevant options: (1) optimization of operations such as quay crane assignment and reduction of port stay time and (2) peak shaving as for example also described by van Duin et al. (2018). With respect to technologies, following aspects are mentioned: (1) cold-ironing, referring to supplying electricity to vessels from the shore side (2) improvements in the equipment as well as alternative fuels for equipment (3) more energy efficient handling of reefer containers, in particular shading as also mentioned by Budiyanto et. al. (2018) and (4) improvements in lighting through, by way of example, LED lamps. In terms of energy management, Iris and Lam (2019) mention (1) measuring as well as estimating of energy consumption which can be seen as a foundation for improvements and (2) the energy supply which could preferably be renewable or cleaner than conventional energy sources. Also mention is made of (3) smart grids as well as (4) policy frameworks for energy management.

Consequently, the further understanding of energy consumption patterns as part of productivity and efficiency analysis are of increasing relevance in the port industry.

2.2. Productivity and Efficiency Studies in Container Terminals: a critical view

It is paramount to point out that in numerous existing studies on port and terminal efficiency not all authors clearly define the unit of analysis. Frequently, the terminology "container port" is used as synonymous for "container terminal", despite the fact that each corresponds to different realities[1]. Additionally, it can be observed that the unit of analysis is referred to as "container port", but the sample includes ports that have significant movement of other cargo types (e.g. general cargo or even bulk cargo) (e.g. Gonzalez and Trujillo, 2009). Either of the two mentioned inaccuracies allows for questioning the actual comparability and validity of these studies. The research in this paper is specifically interested in analysing container terminals as they are one specific decision-making unit (DMU) (Yip et al., 2011). Thus, only those papers which verifiably define the unit of analysis as container terminal are included in the literature review. Throughout the text, the term terminal[2] always refers to container terminal, unless stated otherwise.

Obtaining reliable and sufficient data has been (Neufville and Tsunokawa, 1981) and continues to be a common challenge in the study of productivity and efficiency in terminals. Pjevčević et. al. (2011) as well as Yip et al. (2011) argue for the importance of a clear DMU definition, when setting up their simulation exercise. Most of the here reviewed papers struggled with data availability as well (e.g. Yang and Yip, 2019). Bichou (2011) reported that he had to reduce the original sample size from 50 to 10 because of data availability issues. Lu and Wang (2012) used data from 31 terminals but were limited in the selection of input variables.

The authors identified three works that analyse productivity (Wilmsmeier et al., 2013, Yang and Yip, 2019 and Chandrasekhar and Nihar, 2021), the majority of of studies apply DEA-CCR and DEA-BCC (Table 1), Munin (2020) being an exception applying also FDH. By way of example Lu and Wang (2012) analysed the operating efficiency of 31 major container terminals in east-Asia, namely China and Korea. Their study was strongly following Cullinane et al. (2005) and the resulting findings were likewise aligned with those of Cullinane et al. (2005). By way of example, they found that terminals with a throughput of more than 0.5 million TEU show constant returns to scale, while terminals with a throughput of less than 0.5 million TEU show increasing returns to scale. Also, it should be noted that the variable selection of Lu and Wang (2012) was also influenced by Cullinane et al. (2005) in the sense that they did not consider labour as an input which stands in contrast to the findings of Itoh (2002).

Rios and Maçada (2006) analysed the efficiency of container terminals of the Mercosur trade bloc. With respect to the input variables, it should be noted that an arbitrary aggregate is used for the number of yard equipment. This has to be seen critical, as yard equipment can range from a simple forklift to elaborated equipment such as Rail-Mounted Gantry Cranes (RMGs). Considering such an aggregate as input would mean that, ceteris paribus, a terminal with nine RMGs and one forklift is as efficient as a terminal with one RMG and nine forklifts.

Despite the fact that Yang and Yip (2019) find that container efficiency changes have not been studied sufficiently in Asia, most recent studies focus on that region, Middle East or India,

---

[1] As Cullinane and Wang (2004) recognized: "*This study initially intended to investigate individual container terminals. However, data sources often reported the required data at the aggregate level of the whole port, ... In these cases, the input and output of a port are defined as the aggregation of the input and output of individual terminals within the port.* ***It is important to recognise, however, that such aggregation may prove problematic in reflecting the true production efficiency of the individual terminals within the same port***"

[2] The efficiency of terminals with multipurpose facilities (those handling also non-container cargoes) is out of the scope of the present paper but the interested reader could be found some example in Chang and Tovar (2014ab and 2017ab).

Wiegmans and Witte (2017) and the two studies from Bichou (2011, 2013) being exceptions. In several cases an application of almost similar input and output variables can be observed.

Mokhtar (2013) applied DEA to six major container terminals in Malaysia. This work excludes labour, without given any arguments for the decision. A remarkable feature in his input selection is the one of Quay Crane Index, which was defined as the product of the number of quay cranes and their average lifting capacity. Given common weight restrictions for standard ISO containers, considering lifting capacity of cranes a relevant input for terminal efficiency or productivity is hard to justify. Still, accounting for different types of cranes such as mobile cranes can be a challenge. In this document the approach of Wilmsmeier et al. (2013) is followed as described in subsection 3.2.3.

Sharma and Yu (2010) proposed a decision tree based DEA and illustrated its application to the container port industry. The authors argue that the labour was not included due to the unavailability of data and because they think it is undesirable to follow the suggestion of Tongzon (2001) to make some proxy estimation, as this may give biased results. What the author seems to forget is that their decision to ignore labour as an input also produces biased results.

Few papers address productivity and efficiency in terminals in other regions. Dias et al (2012) assess the efficiency of 10 Iberian container terminals in 2007 applying a recursive DEA model. Almawsheki and Shah (2015) analysed 19 container terminals in the middle eastern region, aggregating yard equipment similar to Rios and Maçada (2006).

Lim et al (2011) proposed a method based on the idea of the context-dependent DEA. To illustrate the proposed methodology, they evaluate the relative efficiency of 26 Asian container terminals in the year of 2004. In the empirical application they included a brief summary of input and output used for some previous DEA studies, they do not explain what the reasons behind their election of input and output are. It should be noted that they do not considered labour as an input.

The inclusion or omission of labour variables has stimulated controversial discussions. Itoh (2002), was able to obtain rich data for eight terminals. In a similar approach to the research conducted in this research, regarding the relevance and representation of labour, Itoh (2002) analysed container port efficiency in Japan and the effect labour as an input variable on the obtained scores. Applying DEA, he was able to show how labour as an input changes the obtained efficiency scores substantially and argued that labour "is a key input in the port production and cannot be totally neglected.". Notwithstanding these results and to the best of the authors´ knowledge, only four later works (Rios and Maçada, 2006; Wilmsmeier et al., 2013, Wiegmans and Witte, 2017; Park, et al., 2020) include labour variables in the analysis of container terminals applying DEA.

The arguments for omitting labour variables vary. Almawsheki and Shah (2015) justified their decision to omit labour by referencing ten other studies that also did not use labour. An approach that actually does not justify their decision. Yang and Yip (2019) present three questionable argument for the omission. They argue for a "fairly close" relationship between the number of workers and the number of gantry cranes, which makes a separate inclusion of this input unnecessary, however they ignore that container terminals are much more than ship-to-shore operations. Further, they mention low reliability of port statistics, due to outsourcing, without providing evidence. Finally, they argue, citing Notteboom et al. (2000), that infrastructure and machineries inputs reflect a more accurate configuration of the ports than labour.

Bichou (2011) studied container terminal efficiency applying a two-stage supply chain DEA model. He criticized existing publications for inconsistent findings as well as trade-offs that are made in the variable selection. To approach those perceived shortcomings, Bichou (2011) and Park et al. (2020) split container operations in three sub-processes: the quay, the berth and the gate with their respective inputs and outputs. This high level of disaggregation requires naturally a high number of detailed data on the terminals under study. While these authors were able to obtain some of them, only Park et al. (2002) include labour as an input. While Bichou (2011) argued that not including labour was due that each configuration of generic operating typologies (for both quay and yard operating sites) in the different sub-processes would require "a corresponding set of capital and labour mix, and thus no cost or labour data is required [in this study]". However, Park et al. (2020) are able to contest this issue.

Kuo et al (2020), while considering the commonly used input variables, is the only work that uses the number of vessel calls as an output variable. Measuring container terminal output in this way might be questionable as the number of vessels which call or arrive at a particular port at any given time is a heterogenous measures as it does not take differences in vessel size into account. Li et al (2021), also using the commonly applied variables, applies a super-efficiency data envelopment analysis (SEDEA) approach. This approach allows for categorizing and ranking the efficiency of container terminals more comprehensively.

To sum up, the literature review reveals that no previous efficiency study applying DEA, has included energy variables or disaggregation of output at terminal level.

Second, a detrimental development can be observed in the case of labour as an input variable over time. Only four works include labour variables in their models. Wiegmans and Witte (2017) provide the most detailed approach to this issue using weekly worked hours as an input variable. The broad omission, of labour variables in the majority of the works ignores significant inputs in container terminal operations.

Third, with the only exception of Park et al (2020), who disaggregate the output in transhipment, inbound and outbound container, none of the existing studies addresses disaggregation of output by container type (dry and reefer), an approach that allows to analyse possible different input needs and productivity depending on the mix of containerised cargoes in a terminal.

Consequently, this work addresses the three identified gaps in literature, aiming to show the relevance of energy variables and disaggregation of outputs, based on a data set that also includes the relevant dimension of labour as an input.

Table 1 – Summary papers on container terminals applying DEA and use of variables

Paper	Region	Number of Terminals	DEA Model	Output	Input	Labour	Energy	Output disaggregation (dry/reefer)
Itoh (2002)	Japan 10-year period (1990-1999)	8	Window DEA-CCR Window DEA-BCC	• Throughput (TEU)	• Container terminal area (m^2) • Container berths (number) • Gantry cranes (number) • Workers (number)	YES	NO	NO
Rios and Maçada (2006)	Latin America 3-year period (2002-2004)	23	DEA-BCC	• Throughput (TEU) • Avg. number of containers moved per hour per ship	• Cranes (number) • Berths (number) • Terminal Area (m^2) • Employees (number) • Yard Equipment (number)	YES	NO	NO
Sharma and Yu (2010)	World Wide (not available)	70	Decision tree-based DEA	• Throughput (TEU)	• Quay cranes (number) • Transfer cranes (number) • Straddle carriers (number) • Reach stackers (number) • Quay length (m) • Terminal area (m^2)	NO	NO	NO
Bichou (2011)	World Wide 7-year period (2002-2008)	10	Supply Chain DEA-BCC	• Export TEUs • Yard dwell time • STS crane move/hour	• Gate lanes (n.a.) • Cut-off time (n.a.) • Yard stacking index (n.a.) • Free yard storage (n.a.) • STS crane index (n.a.) • LOA/max draft (n.a.)	NO	NO	NO
Dias et al (2012)	Iberian Peninsula (2009)	10	Recursive DEA	• Throughput (TEU)	• Total yard equipment (number) • Quay length (m) • Terminal area (m^2) • Container cranes (number)	NO	NO	NO
Lin et al (2011)	Asia (2004)	26	Context-dependent DEA	• Throughput per berth (TEU)	• Berth (number) • Quay length (m) • Total area (m^2) • Gantry cranes (number)	NO	NO	NO
Lu and Wang (2012)	China and Korea (2008)	31	DEA-CCR DEA-BCC DEA-Super Efficiency	• Throughput (TEU)	• Yard area per berth (n.a.) • Quay crane per berth (n.a.) • Terminal crane per berth (n.a.) • Yard tractor per berth (n.a.) • Berth length (n.a.) • Water depth (n.a.)	NO	NO	NO

Bichou (2013)	World Wide 7-year period (2004-2010)	60	DEA-CCR DEA-BCC	• Throughput (TEU)	• Terminal (m^2) • Maximum draft (m) • Total quay length (m) • Quay crane index (TEU) • Yard-stacking index (TEU/1000 m2) • Trucks & vehicles (number) • Gates (number)	NO	NO	NO
Mokhtar (2013)	Peninsular Malaysia 8-year period (2003-2010)	6	DEA-CCR DEA-BCC	• Throughput (TEU)	• Total terminal area (m^2) • Maximum draft (m) • Berth length (m) • Quay crane index (n.a.) • Yard-stacking index (n.a.) • Vehicles (n.a.) • Gate lanes (number)	NO	NO	NO
Wilmsmeier et al (2013)	Latin America and the Caribbean and Spain (2005-2011)	20	DEA-CCR DEA-BCC Malmquist	• Throughput (TEU)	• Labour (number of employees) • Terminal area (m^2) • STS equivalent (number)	YES	NO	NO
Almawsheki and Shah (2015)	Middle East (2012)	19	DEA-CCR DEA-BCC	• Throughput (TEU)	• Terminal area (Ha) • Quay length (m) • Quay cranes (number) • Yard equipment (number) • Maximum draft (m)	NO	NO	NO
Wiegmans, and Witte (2017)	Mostly Germany, Belgium and Netherlands	44	DEA-CCR DEA-BCC	• Handling capacity (TEU) • Throughput (TEU)	• Working hours (week) • Terminal area (m^2) • Stacking Yard (TEU) • Quay Length (m) • Draught (m) • Cranes (number) • Reach stackers (number)	YES	NO	NO
Yang and Yip (2019)	Asia (2000-2007)	23	Malmquist	• Throughput (TEU)	• Berth length (m) • Terminal Area (m^2) • Crane Capacity (Ton)	NO	NO	NO
Munin (2020)	(Asia)	38	DEA-CCR DEA-BCC FDH	• Throughput (TEU)	• Berth (number) • Berth length (m) • Depth (m) • Terminal area • Yard gantry cranes (number) • Ship-shore and quay gantries (number).	NO	NO	NO

Kuo, Lu, and Le (2020).	Vietnam (2017)	53	DEA-CCR DEA-BCC	• Tons • Ship (calls)	• Total terminal area (m^2) • Terminal length (m) • Equipment (number)	NO	NO	NO
Park, Lee, and Low (2020).	South Korea (2014-2018)	9	Two-stage parallel network DEA DEA-CCR	• Outbound (TEU) • Inbound (TEU) • Transhipment (TEU)	• Wharf length (m) • Employees (number) • Yard area (m^2) • Quay cranes (number) • Yard cranes (number) • Supporting machines (number) • Vehicles (number) • Level of service (n.a.) • Market exposure (number of operating years) • Planned throughput Capacity (n.a.)	YES	NO	NO
Chandrasekhar & Nihar (2021)	India (2015-2018)	26	Malmquist	• Throughput (TEU)	• Draft (m) • Quay Length (m) • Quay Cranes (number) • Yard equipment (number) • Yard Area (Ha)	NO	NO	NO
Li, Seo, and Ha (2021).	China 2018	20	Super-efficiency DEA	• Throughput (TEU)	• Berth length (m) • Yard area (m^2) • Bridge Crane and RTG (number) • Dock front water depth (m)	NO	NO	NO
Present paper	Worldwide (2013)	26	DEA-CCR DEA-BCC	• Throughput container (number of boxes) • Throughput dry container (number of boxes) • Throughput reefer container (number of boxes)	• Labour (number of employees) • Berth length (m) • STS equivalent (number) • Electricity (kWh) • Diesel (litres)	YES	YES	YES

Note: DEA = Data Envelopment Analysis; FDH = Free Disposal Hull; TEU= Twenty feet Equivalent Unit; LOA = Length overall; Not available (n.a.)

Source: Authors

3. METHODOLOGY

3.1. Data Envelopment Analysis (DEA)

Efficiency and productivity are often used interchangeably (Wang and Cullinane, 2015), however they are two different but related concepts. Productivity is defined as the comparison between outputs over inputs, thus it can be asserted that the higher the rate between outputs and inputs the higher the productivity level. Besides, technical efficiency is defined as the maximum output that can be obtained from a given amount of input or the minimum input to achieve a given amount of output, depending on the output/input orientation of the model.

Therefore, both concepts are defined in terms of a comparison of two components (inputs and outputs) and are equivalent if one component (inputs or outputs) does not change. However, when both change, what is the usual situation in the real world, there are important differences between both that could produce situations where not always an improvement in efficiency comes with an improvement in productivity.

Moreover, to estimate technical efficiency it is necessary to estimate the best practice frontier whereas productivity could be calculated without it. If the frontier is estimated, it is possible not only to identify productivity changes but also it is also possible to decompose the productivity change to identify whether this originates from efficiency change and/or technological change.

Given the previous definitions, measuring the efficiency or productivity of firms could be considered to be a trivial mathematical task. However, the production frontier of an industry is virtually never known, but using a variety of parametric and non-parametric approaches an efficient (best practice) frontier can be estimated.

Container terminals in the context of DEA are referred to as one decision making unit (DMU). This implies that they are individual firms striving to achieve an objective. While the authors recognize that other possibilities exist, the authors assume that the objective can either be to maximize throughput (output) from a certain level of input or to achieve a certain level of output with as little input as possible. The following equation shows an input-oriented CRS DEA model:

$\min \theta$ (1) s.t.:

$-y_i + Y\lambda \geq 0;$

$\theta x_i - X\lambda \geq 0;$

$\lambda \geq 0.$

This equation is the most commonly solved envelopment form of the problem. The scalar θ is representing the efficiency of the container terminal and λ is a column vector "*that describes the percentage of other companies, and is used for constructing the efficient company. X and Y are the companies' input and output vectors, and [x_i] and [y_i] are the inputs and outputs of the company that is being evaluated*" (Pérez-Reyes and Tovar, 2009). The calculations were carried out in Python with the help of numpy.

3.2. Data Source and Variable Selection

Reliable and sufficiently detailed data has been identified as a key challenge in the reviewed literature on terminal efficiency/productivity. Data used in this work, originate from a concerted effort that was led by the United Nations Economic Commission for Latin America and the Caribbean (UNECLAC) in collaboration with Hochschule Bremen and stakeholders from the industry as well as governmental entities across Latin America (Wilmsmeier and Spengler, 2016; Spengler and Wilmsmeier, 2019) and was collected through UNECLAC/HS Bremen port productivity and efficiency surveys. One challenge of the collected data, is the level of fragmentation. While data was collected from more than 100 terminals, it was not possible to fill in missing values in all dimensions in order to create sufficiently large panel data, which would be required to make sound statements from a time series perspective while maintaining the high number of variables.

The data set for this research comprise 26 terminals for the year 2013. Given the nature of the research question, it is key to work with data that comply with the expected level of detail for all selected input and output variables as the research is focusing on a structural discussion of data requirements in terminal efficiency studies. While more recent data in general is available for some variables, particularly detailed data on energy consumption, which includes the composition of energy source is difficult to obtain. However, more recent data cannot be thought to increase the validity of this research. All terminals under study are specialized in container handling, but with varying functions within the container terminal system. Their functions vary between import/export, hybrid and transhipment terminals. The data set covers a wide array of terminals, reaching from rather small terminals in developing countries to large terminals in developed countries. Table 2.1 and Table 2.2 depict the maximum, minimum, standard deviation, average and median of the selected variables. The distributions of some of the variables are somewhat skewed considering a comparison of the median and the average. It is worth pointing out that the relation of dry to reefer containers tends to differ significantly between terminals. The terminals situated in Latin America have a generally higher share of reefer containers, which was to be expected given the different characteristics of trade routes.

Table 2.1: Descriptive Statistics of output variables

	Throughput (number of boxes)		
	Total Container	Dry Container	Reefer Container
Minimum	75989	50877	913
Maximum	2206438	1967770	238668
Standard Deviation	428393.98	381242.16	48520.12
Median	425003	412986	15064
Average	496831.96	460293.15	36538.81

Source: Authors

Note: Total container represents the aggregated output variable, Dry and Reefer container represent the disaggregated output variables.

Table 2.1 depicts the descriptive statistics of the chosen output variables. A longer discussion as to why those variables were chosen, is provided in the following subsection. Total container throughput is equal to the sum of dry containers and reefer containers at individual terminal level. Within the sample the share of reefer containers in relationship to dry container handling varies. Some terminals handle close to no reefer containers while others handle a very substantial amount of reefer containers.

Table 2.2: Descriptive Statistics of input variables

	Diesel (Litres)	Electricity (kWh)	Labour (number)	Total Berth Length (m)	Ship-to-Shore Crane Equivalent (number)

Minimum	570000	1724029	216	320	3
Maximum	8284658	46761686	4878	2884	25
Standard Deviation	1796396.36	8999166.98	878.65	624.58	4.26
Median	2718971	13509486.5	573	948.5	6.5
Average	2767282.35	14103842.15	778.23	1081.88	7.19

Source: Authors

Table 2.2 depicts the descriptive statistics of the chosen input variables. Given the diverse sample, it is not surprising that the input variables show a relatively large standard deviation as well as a large spread between the maximum and minimum.

As mentioned above, a common and almost generally accepted argument in the field of productivity and efficiency analysis in ports and terminals is the one of land, labour and equipment being the key deciding factors (Dowd and Leschine, 1990; Roll and Hayuth, 1993). The chosen input variables represent the physical characteristics, technology, and the type of operation in the terminals. Different to existing studies the authors include the energy consumption as an input variable. The following subsections (1) provide the rational of the selected variables, and (2) specify insights on required or unacceptable trade-offs when choosing these.

3.2.1. Labour

As exemplified in the literature review, only few works include direct labour variables. However, all of them recognize this lack as an important limitation of both the investigation and conclusions. Indeed, it is well-known that excluding labour input from the model may lead to a biased estimate of terminal efficiency if labour and capital are not perfectly complementary (Chang and Tovar, 2021). The latter assumption (perfect complementarity) means that all container terminals follow a Leontief technology that implies the factors of production will be used in fixed (technologically predetermined) proportions, as there is no substitutability between factors, which is implicit when labour is excluded from the analysis. To the best knowledge of the authors this relationship (perfect complementary between labour and capital in this industry) has neither been demonstrated in previous port studies nor can it easily be deduced, considering that the relationship between capital and labour can be affected by various factors, including the technological one. Therefore, we conclude that the inclusion of labour is of utmost relevance to avoid biased results.

In those studies, where labour variables are included, the total number of employees is the most common variable. Only very rarely, the hours worked (Wiegmans and Witte, 2017) or labour cost can be found as input variables. It certainly can be argued that labour cost would be the most favourable input variable, since it would capture the rather fine differences between different equipment configurations, automatization, and labour conditions, as well as the more apparent differences between blue-collar and white-collar workers. At the same time, introducing a monetary variable also comes with caveats: if data from various periods is to be used, it must be deflated and, if data from a variety of countries is used, it must be expressed in a common currency. Following Wilmsmeier et al. (2013), the authors include the total number of employees of the container terminals as an input as no sufficient salary data is available to the authors.

3.2.2. Land

The factor of land is usually represented by variables such as berth length, terminal size, or terminal storage area. Each of them having specific advantages and disadvantages.

Total berth length is often calculated as the sum of the lengths of a variety of berths (e.g. Yang and Yip, 2019), which can give a somewhat skewed representation of the actual input. By way of example, one terminal could potentially have one berth of approximately 200 metres while another terminal could have 2 berths with a length of 100 metres per berth. The former would be able to accommodate significantly larger vessels while the latter could not. An advantage of using total berth length is that a very general understanding of this input exists. While total berth length indisputably is a measure for the available space in a container terminal to which ships can be moored, the actual berth capacity will depend on the distribution of this length in relation to the number of berths in the terminal.

Terminal storage area and terminal size cannot be considered as intuitive input factors. Terminal size might yield different interpretations, depending on what might be considered as the terminal area. By way of example, parking areas for employees might be part of the terminal or not, so could the area where terminal buildings are placed. These challenges could be overcome, e.g. if the exact size from a potential concession contract would be available. Though, this exact information is not available in the dataset of this research.

Terminal storage area also might not accurately capture land as an input. Measuring storage area in a two-dimensional way omits the fact that operations in a container terminal are rather three than two dimensional, meaning that the efficient use of the surface area at hand also depends on the stacking height of containers. Further, stacking height might differ in different areas of the terminal.

One might argue that these issues are possible to overcome if primary data are collected and a very clear definition of variables is provided. Still, it is believed that the person who will provide the data has very little incentive to review the size of the terminal or storage area according to the variable definition and will rather provide the values that are readily available.

Given the described restrictions of land input variables in combination with actual data availability, the authors decided to include total berth length in metres as a proxy input variable to the model, even though certain points can be made in favour of including a measure of area rather than length.

3.2.3. Equipment

It can be argued that this input factor is the most challenging to accurately represent in the model (Spengler and Wilmsmeier, 2019), given the variety of different possibilities to equip any given terminal. By way of example, the inclusion of only one particular kind or group of equipment, such as straddle carrier (SC) or rail mounted gantry crane (RMG), might lead to a restricted reference set. An aggregation of a variety of different equipment would also be difficult to justify as one would be required to argue that the overall aggregated number of equipment is in some way, shape or form related to the objective of a given terminal. An introduction of monetary variables for equipment and its operation, could be a future option, but would have the similar caveats as mentioned in the case of labour.

While it would be desirable to account for different types of equipment as well or potentially even cluster the terminals by operational layout, this is not feasible with the available data and the limited sample size. Hence, the decision is made to restrict the equipment variable to berth side operating equipment, represented by the number of quay cranes equivalent. This variable is derived as a weighted aggregation (summation) of mobile and ship-to-shore cranes following the approach of Wilmsmeier et al. (2013).

3.2.4. Energy

A unique feature of this research is the inclusion of energy consumption variables, namely diesel and electricity, as an input. Energy can be referred to in different ways. The most intuitive way is to treat the various energy sources in their own unit of measurement since a conversion of electricity (kWh) and diesel (litres) to a common energy related unit such as Joule or Watt is all but trivial.

Other potential measures could be energy expenses. While energy expenses can be thought to be rather a desirable measure for the energy input, it has to be acknowledged that such data are difficult to obtain and bear similar challenges in measurement and comparability as other monetary measures.

Based on the described challenges the authors include two variables for representing energy consumption: diesel (litres) and electricity (kWh). It should also be noted that an initial data review checked for other potential energy sources such as petrol, liquefied natural gas (LNG), liquefied petroleum gas (LPG) and compressed natural gas. These energy sources are either not used in the terminals or used in negligible quantities and thus were excluded from the model.

3.2.5. Outputs

Roll and Hayuth (1993) argue that terminals provide a significant variety of outputs. Including, not only "the quantities and the variety of cargoes handled", but also "the types of ships serviced, the interchange with land transport modes, the additional services rendered (e.g. interim warehousing) ...". In the majority of studies on container terminals this output is reduced to the measure of TEU or at best number of containers handled.

The outputs of a container terminal would actually best be represented by a rather high level of disaggregation, since the activities related to handling a container in a terminal will vary according to the combination of the type of trade (e.g. import, export, or transhipment), the specific container types, (e.g. refrigerated, open top, dry), the size (e.g. 20 or 40 foot) and the condition (e.g. full or empty). For a discussion on the differences of energy consumption between dry and reefer containers see Wilmsmeier and Spengler (2016).

Such level of disaggregation would be ideal; however, it would require an overwhelmingly large number of DMUs which is not available in this case. Since total energy consumption is considered as an input and based on the difference of the energy consumed by full refrigerated containers in comparison to other container types, the decision is made to disaggregate the output only by the refrigerated or dry property of a container. In some models an aggregate of container throughput will be used for the sake of comparison. In this respect, reefer containers as well as dry containers are measured in the unit of *box* rather than TEU.

3.3. The Models

To address the set-out research question a sequence of four models is built. The variables included, in order to investigate the impact of container terminal output disaggregation and the inclusion of energy consumption variables as an additional proxy to the traditional input factor proxies are: total berth length, ship-to-shore crane equivalent and labour.

Table 3 summarises the estimated models, indicating the respective input and output variables. By way of example, in model 1, labour, berth length and STS crane equivalent are considered as input variables. As output variable, only total container movements is considered.

Table 3: Models with their respective inputs and outputs

	Output disaggregation	Inputs					Outputs		
		Labour	Berth Length	STS Crane Equivalent	Electricity	Diesel	Dry	Reefer	Total
Model 1		√	√	√					√
Model 2		√	√	√	√	√			√
Model 3	Yes	√	√	√			√	√	
Model 4	Yes	√	√	√	√	√	√	√	

Source: Authors

For each model, the variable return to scale (VRS) as well as constant return to scale (CRS) are estimated. The matter of orientation is not straightforward. As shown in the literature review, terminals are said to follow two approaches. Either terminals seek to maximize output, given a certain level of input, or terminals seek to minimize inputs, given a certain level of output that they might be able to anticipate. Experience shows that terminal operators generally try to increase market share, particularly in emerging markets, rather than maintaining a given share with as little input as possible. Therefore, the authors argue that the terminal operators included in this research rather seek to maximize output.

Due to data confidentiality agreements with the terminals, the specific names of the terminals and their operators are not disclosed. The names are replaced by the ISO 3166-1 alpha-3 code of the country where the terminal is located, followed by a single number to differentiate various terminals within the same country.

The data set comprises container terminals from different countries that to the authors' belief are comparable as they belong to the same population. However, given that the sample includes import/export, hybrid and transhipment terminals the authors applied the non-parametric Mann–Whitney U (MW) to test the null hypothesis that the samples come from the same population (Table 4)[3].

Table 4: Non-parametric Mann–Whitney U test

	Z	P(1)	P(2)	Statistic U
Model 1	-1.53	0.063	0.126	28.5
Model 2	-1.01	0.1562	0.3125	36.5
Model 3	-0.88	0.1894	0.3789	38.5
Model 4	-0.65	0.2578	0.5157	42

Note: with na=21, nb=5, (1) one-tailed probabilities, (2) two-tailed probabilities, U tabulated (α = 0.05) = 22

Source: Authors

[3] All calculated p values are greater than 0.05, meaning that the null hypothesis cannot be rejected on those bases. Given that the approximation of U by the normal distribution is best when both populations are equal or greater than 10, it is recommended to work with the tabulated value for respective sample sizes. In this respect, the statistic U is never below the tabulated value, indicating against this background the null hypothesis cannot be rejected, either. This indicates that there is no difference in the computed efficiency scores whether a terminal is a transshipment/hybrid terminal or an import/export terminal.

4. ANALYSIS AND DISCUSSION

This section discusses the results of the DEA model estimation. Table 5 depicts the efficiency scores for CRS and VRS models, with and without aggregation of outputs (models 1 to 4).

An initial finding, due to the nature of DEA, is that both CRS and VRS models yield higher efficiency scores if they include a greater number of dimensions; read model 4 with output disaggregation and including energy variables (Table 5). Likewise, the generally higher efficiency scores of VRS in comparison to CRS models are owed to the applied methodology.

Even though, there are certain variations that are inherently related to the addition or omission of variables, other relevant results can be discussed. One of these cases are the scores for BRA_01, which turns out to be efficient when the analysis is done with energy as input and output disaggregation into dry and reefer container (Model 4) but is far from efficient when output is aggregated and energy is omitted (Model 1, see Table 5). It is worth noting in this context, that BRA_01 has not been moved into a multidimensional space where it can only be a peer to itself but is still forming part of the frontier for ARG_01 and GEO_01 (see Appendix Tables 8 and 9). The fact that BRA_01 is efficient in Model 4 (Table 5) is arguably related to the fact that BRA_01 has a significantly higher share of reefer containers (28%) compared to the average terminal in the data set (8%).

Another terminal with a high share of reefer containers is COL_02, which also happens to be the terminal with the smallest overall container throughput. Moreover, while it had a different peer in the model with output disaggregation and energy input (Model 4), the efficiency score is still considerably low, whether under the assumption of variable return to scale as well as under the assumption of constant return to scale.

A further interesting case are Chilean (CHL) terminals, which partly are far from efficient in Model 1, but turn out to get an efficiency score of one in Model 4 (Table 5). As in the case of BRA_01, it can be noted that the Chilean terminals have not been moved into an area where they are only a peer to themselves but form part of the frontier for other terminals (see Appendix Tables 8 and 9). This is in particular interesting as the Chilean terminals move much higher shares of reefer containers, between 14% to 30% in comparison to the average terminal in the sample.

Table 5: DEA scores for model 1 to 4

Terminals	Model 1: no output disaggregation no energy consumption as input		Model 2: no output disaggregation, energy consumption as input		Model 3: output disaggregation, no energy consumption as input		Model 4: output disaggregation, energy consumption as input	
	CRS	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**
ARG_01	0.363	0.471	0.425	0.557	0.41	0.556	0.455	0.671
ARG_02	0.276	0.294	0.289	0.327	0.297	0.308	0.316	0.338
BRA_01	0.492	0.555	0.594	0.663	1	1	1	1
BRA_02	0.318	0.362	0.426	0.463	0.321	0.372	0.426	0.474
BRA_03	0.241	0.311	0.328	0.376	0.254	0.322	0.341	0.383
BRH_01	0.438	0.484	0.492	0.501	0.46	0.485	0.503	0.505
BHS_01	0.956	1	1	1	1	1	1	1
CHL_01	0.71	0.822	0.714	0.829	1	1	1	1
CHL_02	0.446	0.446	1	1	1	1	1	1
CHL_03	0.87	0.888	0.87	0.888	1	1	1	1
COL_01	0.498	0.565	0.501	0.565	0.505	0.584	0.508	0.584
COL_02	0.158	0.158	0.174	0.228	0.383	0.383	0.383	0.383
COL_03	0.562	0.773	0.562	0.773	0.57	0.809	0.57	0.809
GEO_01	0.272	0.335	0.441	0.455	0.304	0.337	0.467	0.472
MEX_01	0.166	0.227	0.318	1	0.178	0.253	0.32	1
MEX_02	0.57	0.603	0.704	0.732	0.592	0.632	0.726	0.765
MEX_03	0.738	1	0.81	1	0.771	1	0.846	1
MOR_01	1	1	1	1	1	1	1	1
NIG_01	0.388	0.431	0.508	0.509	0.398	0.447	0.521	0.523
PAN_01	0.798	1	0.994	1	0.97	1	1	1
RUS_01	0.66	0.668	0.660	0.668	0.754	0.756	0.754	0.756
RUS_02	0.343	1	0.407	1	0.344	1	0.411	1
RUS_03	0.899	1	0.916	1	0.980	1	0.995	1
SWE_01	0.517	0.59	0.572	0.622	0.521	0.609	0.581	0.643
USA_01	1	1	1	1	1	1	1	1
VIE_01	0.908	1	1	1	0.915	1	1	1

Note: (ARG – Argentina, BHS - Bahamas, BRA – Brazil, BRH – Bahrain, CHL – Chile, COL – Colombia, GEO – Georgia, MEX – Mexico, MOR – Morocco, NIG – Nigeria, PAN – Panama, RUS – Russia, SWE – Sweden, VIE – Vietnam). Source: Authors

In fact, the terminal that only has itself as a peer and is not a peer to any other terminal in the model with energy and disaggregated output (model 4) is MEX_01 (Table 10). This, in turn, can be seen as an indication that output disaggregation and the inclusion of energy as an input leads to more advantageous comparisons, which reflects the differences in the multi-product nature of container terminals.

Peer-wise, when disaggregating output and considering energy as input (model 4), the container terminal from Latin America or the Caribbean are more often a peer to another terminal (see table 10). If this is compared to the reported peers in Table 7 (model 1), a clear difference can be noted. If said disaggregation is not done and energy is not considered as an input (model1), most DMUs are benchmarked against highly specialized transhipment terminals (e.g. MOR_01 and PAN_01) independent of their geographic location as can be clearly seen when comparing tables 7 and 10 (Appendix).

One limitation of the comparisons above is that they do not provide any insight as to why certain changes might or might not have occurred. To address this matter the models 2 and 3 are compared with model 1 and 4 respectively. In Model 2 the energy variables are added but the output is not disaggregated (Table 5). In Model 3 output is disaggregated but no energy variables are added (Table 5).

When comparing the results between model 3 and 4, an initial finding is that the obtained efficiency scores between do not differ significantly (Table 5). However, that by itself does not provide much insight with regard to the frontier that has been modelled. Similar efficiency scores, being scalars after all, might be similar for a number of reasons. A comparison of the peers reported in Table 8 and 9 (Appendix) does provide insights as to whether a terminal is inefficient in relation to the same terminals as in the other model or if it is in fact benchmarked against other terminals.

From that perspective, COL_02 is interesting as it is benchmarked against CHL_02 regardless of the fact whether energy is considered as an input or not. Similar are the cases of COL_01, COL_03 and RUS_01 that are all benchmarked against the same peers regardless of the energy variables. The terminal MEX_02 gained more peers with the energy variables and ARG_01 and ARG_02 also maintained a very similar set of peers (cf. Table 8 and Table 9). These findings indicate that the inclusion of energy variables contributes to additional insights (model 2), in comparison to using disaggregated output, but no energy variables (model 3).

The fact that the overall efficiency scores are similar in the different models and that the peers of the terminals did not change much can point towards one of two things: Either energy as an input does not add much to the model in general or the changes that are caused by adding energy as an input are similar to those caused by disaggregating output, meaning that energy consumption could also be accounted for by disaggregating output.

The obtained efficiency scores, again, appear to be rather similarly independent of whether energy is considered as an input or not. This must be understood against the background that, in this case, effects that energy might or might not have on the obtained efficiency score is not potentially captured by a disaggregated output as it could have been the case with the efficiency scores.

It is necessary to investigate, if the peers have changed to derive better insight regarding the question if energy matters in the context of efficiency analysis in container terminals. To do so, the reported peers in Table 7 are compared with those of Table 8.

The terminals CHL_03, COL_01, COL_03 and RUS_01 have the exact same peers regardless of whether energy is added as an input or not. The terminals ARG_01, ARG_02 and BRA_03 also still maintain almost the same peers when energy is added. Moreover, all of the following terminals BHS, CHL2, MEX3, MOR1, PAN1, RUS2, RUS3, USA1, VIE1 are potential peers in both models. It is not surprising both models have similar sets of peers. Most likely this does not mean more than these terminals are efficient regardless of whether the output is disaggregated or the model includes energy variables. This reinforces the idea that these variables are highly correlated and contain similar information, but at the same underlines the relevance of energy consumption and the output disaggregation when measuring efficiency.

Table 6 demonstrates the changes in inputs and outputs which might be necessary to make inefficient terminals full-efficient according to the VRS results of model 4. The results reveal significant inefficiencies in container terminal production. The sample terminals exhibit a mix of decreasing, increasing and constant returns to scale. Only one terminal exhibits constant returns to scale. The majority of terminals are operating at decreasing returns to scale, revealing that their size is too large regarding the activities performed. These terminals should reduce their operational scale to improve their level of efficiency. However, eight terminals show increasing returns to scale and given their small size of production need to enhance their efficiency by selecting a scaling up strategy.

In general several terminals could improve their efficiency by increasing its outputs or reduce its inputs (Table 6). For example, Given its current size, BRA_02 to be fully efficient could increase its dry and reefer output by 111% and 222% respectively. As for the inputs BRA_02 could decrease its crane capacity by 2%, labour by 18% and berth length by 23% respectively.

Table 6. Changes in outputs and inputs which are necessary to make inefficient terminals full-efficient according to Model 4

	Model 4				Potential improvement (%)						
	CRS	VRS	ES	Returns	Dry (output)	Reefer (output)	Electr-icity	diesel	STS crane equiv.	Labour	Berth length
ARG_01	0.455	0.671	0,679	irs	49	49	0	0	0	-5	0
ARG_02	0.316	0.338	0,936	drs	196	196	0	0	-27	0	-23
BRA_02	0.426	0.474	0,899	drs	111	222	0	0	-2	-18	-8
BRA_03	0.341	0.383	0,889	irs	161	908	-2	0	-2	-22	0
BRH_01	0.503	0.505	0,996	irs	98	98	-18	0	0	-45	-64
COL_01	0.508	0.584	0,87	drs	71	698	-23	-9	-30	0	0
COL_02	0.383	0.383	1	-	191	161	-90	-14	0	-28	-16
COL_03	0.57	0.809	0,705	drs	24	643	-37	-33	0	0	-20
GEO_01	0.467	0.472	0,989	irs	112	112	-4	0	0	-60	-77
MEX_01	0.32	1	0,32	irs	0	0	0	0	0	0	0
MEX_02	0.726	0.765	0,948	drs	31	285	0	0	0	-20	-1
MEX_03	0.846	1	0,846	irs	0	0	0	0	0	0	0
NIG_01	0.521	0.523	0,996	drs	91	260	0	-54	0	-41	-4
RUS_01	0.754	0.756	0,996	irs	32	32	-7	-26	-22	-2	0
RUS_02	0.411	1	0,411	irs	0	0	0	0	0	0	0

RUS_03	0.995	1	0,995	drs	0	0	0	0	0	0	0
SWE_01	0.581	0.643	0,902	drs	55	400	0	-6	0	0	-28

Source: Authors

5. CONCLUSIONS

DEA as other methods based on the frontier approach, allow to contrast the efficiency of an individual DMU relative to a set of other DMU that are homogenous. Following the initial research question, the output disaggregation in terms of reefer and dry containers did lead to efficiency scores substantially different from the ones obtained from a model considering container throughput in a generic way without such disaggregation.

This confirms the assumption that the strategies of individual DMUs vary according to their containerized cargo mixes. The results reflect the different production processes, services and decision-making processes according to specific types of outputs.

Consequently, these findings are in particular relevant when analysing the efficiency of terminals with significant volumes of reefer traffic and comparing them to terminals with dry container only traffic. The relevance of reefer traffic varies across geographic regions. In this research, the differences are very apparent as the majority of the container terminals under study are located in the Latin American and Caribbean region, one of the main export regions of reefer cargo.

While theory suggests that a significant relationship exists between the volume of reefer container throughput and electricity consumption, said relationship could not be found in the obtained efficiency scores. This is not an argument against the relationship per se but rather an indication that other input variables that are highly linked to the volume of handled reefer containers contain similar information. Thus, a certain level of collinearity exists between the variables. One example for such relationship between inputs in the present research could be the one found between labour and energy consumption (i.e. electricity) inputs. Indeed, and in relation to the previous argument it might be that terminals with a greater share of reefer traffic require a greater number of workers, since reefer cargo requires a greater level of supervision than cargo in standard containers. This matter certainly deserves further research.

From a policy perspective the proposed output differentiation can be considered as highly relevant in scenarios where the environmental performance of terminals becomes a more relevant topic in the current efforts to lead ports and terminals towards sustainable performance. In general, full reefer containers have a higher carbon footprint than standard container due to their additional energy need for cooling of cargo, which is represented by a relative increase in electricity or diesel consumption in terminals with greater reefer cargo traffic. Thus, regulatory efforts regarding the performance and efficiency of terminals will benefit from a deeper understanding of a container terminal´s traffic mix. Since consumers are requiring more detailed information on the external effects caused by the supply chains of the products they purchase, a differentiation of energy consumption and thus emissions according to different cargo types will enable terminals to define and report their share in the overall supply chain external effects. In order to avoid a misleading comparisons between container terminals, the full variety of existing container terminal lay-outs, handling technologies and operating strategies should also be accounted for as detailed as possible.

Wang and Cullinane (2015) discuss the limitations of estimating efficiency limited to land, labour and equipment as key factors. They argue that numerous other factors can influence the way these factor endowments are interacting (e.g. operator model, level of vertical integration between shipping lines and terminal). Thus, this paper contributes to the consideration of a greater range of factors,and underscores the different needs and strategies in container terminals depending on the output formation.

Data availability still is a key challenge in port and container terminal analysis and this document is no exception to it. Firstly, it must be noted that certainly more recent data would have been desirable. Secondly, a more complex model and sounder statement could have been made if panel data were available.

In terms of variables, it would be desirable to construct future models with data that are more closely related to some of the economic objectives of a terminal. None of the variables used in this research are of monetary nature. In the case of output disaggregation, the difference in the price for handling one reefer container in comparison to a standard dry container might be of relevance. While the focus of this document was merely technical efficiency, the matter of economic efficiency is of significant interest for future investigation.

6. REFERENCES

Acciaro, M., Ghiara, H. and Cusano, M., (2014). Energy management in seaports: A new role for port authorities. *Energy Policy*, 71. 4-12.

Almawsheki, E. S., and Shah, M. Z. (2015). Technical efficiency analysis of container terminals in the middle eastern region. *The Asian Journal of Shipping and Logistics*, 31(4), 477-486.

Azarkamand, S., Ferré, G., and Darbra, R. M. (2020). Calculating the Carbon Footprint in ports by using a standardized tool. *Science of The Total Environment*, 139407.

Bichou, K. (2011). A two-stage supply chain DEA model for measuring container-terminal efficiency. *International Journal of Shipping and Transport Logistics*, 3(1), 6-26.

Bichou, K. (2013). An empirical study of the impacts of operating and market conditions on container-port efficiency and benchmarking. *Research in Transportation Economics*, 42, 28-37.

Budiyanto, M. A., Shinoda, T., Nugroho, F. A., and Wibowo, B. (2018). Estimated of energy saving from the application of roof shade on the refrigerated container storage yard. *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, 46(1), 114-121.

Chandrasekhar Iyer, K. & Nihar Nanyamb, V.P.S. (2021). Technical efficiency analysis of container terminals in India. *The Asian Journal of Shipping and Logistics,* 37, 61-72

Chang, V. and Tovar, B. (2014a). Efficiency and productivity changes for Peruvian and Chilean ports terminals: A parametric distance functions approach, *Transport Policy*, 31, 83-94.

Chang, V. and Tovar, B. (2014b). Drivers explaining the inefficiency of Peruvian and Chilean ports terminals, *Transportation Research Part E*, 67, 190-203.

Chang, V. and Tovar, B. (2017a). Heterogeneity unobserved and efficiency: A latent class model for west coast of south pacific port terminals, *Journal of Transport Economics and Policy*, 51(2), 139-156.

Chang, V. and Tovar, B. (2017b). Metafrontier analysis on efficiency and productivity for west coast of south pacific terminals, *Transportation Research Part A: Policy and Practice*, 103, 118-134.

Chang, V. and Tovar, B. (2021). Efficiency drivers for the south pacific west coast port terminals: a two-stage non-convex metafrontier DEA approach. *Operational Research*, DOI: 10.1007/s12351-021-00626-5.

Charnes, A., Cooper, W.W., Rhodes, E., (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research,* 2 (6), 429–444.

Cullinane, K., Song, D. W. and, Wang, T. (2005). The application of mathematical programming approaches to estimating container port production efficiency. *Journal of Productivity Analysis*, 24(1), 73-92.

Cullinane, K., Song, D. W., Ji, P. and, Wang, T. F. (2004). An application of DEA windows analysis to container port production efficiency. *Review of Network Economics*, 3(2), 1-23.

Cullinane, K., Wang, T.F., Song, D.W., Ji, P., (2006). The technical efficiency of container ports: comparing data envelopment analysis and stochastic frontier analysis. *Transportation Research Part A,* 40 (4), 354–374.

Dias, J.C.Q., Azevedo, S.G., Ferreira, J. and Palma, S.F. (2012. Seaport performance comparison using data envelopment analysis: the case of Iberian container terminals. *International Journal of Business Performance Management*, 13 (3/4), 426-449.

Dowd, T. J. and Leschine, T. M. (1990). Container terminal productivity: a perspective. *Maritime Policy & Management*, 17(2), 107-112.

Drewry Shipping Consultant Limited (2018) Perishable reefer trade growth to remain strong [online] https://www.drewry.co.uk/news/news/perishable-reefer-trade-growth-to-remainstrong.

Geerlings, H. and Van Duin, J.H.R. (2011). A new method for assessing CO2-emissions from container terminals: A promising approach applied in Rotterdam. *Journal of Cleaner Production*, 19, 657-666.

Gonzalez, M.M., Trujillo, L., (2009). Efficiency measurement in the port industry: a survey of the empirical evidence. *Journal of Transport Economics and Policy* 43 (2), 157–192.

Guerrero, C. and Rivera, T. (2009). Mexico: total productivity changes at the principal container ports. ECLAC, Review.

Guimaraes, V.A., Junior, I.C.L. and Garcia, P.A.A. (2014) Environmental performance of Brazilian container terminals: a data envelopment analysis approach. *Social and Behavioral Sciences*, 160, 178-187.

Hangga, P. and Shinoda, T. (2015). Motion-Based Energy Analysis Methodology for Hybrid Straddle Carrier Towards Eco-Friendly Container Handling System. *Journal of the Eastern Asia Society for Transportation Studies,* 11, 2412-2431.

He, J., Huang, Y., and Yan, W. (2015). Yard crane scheduling in a container terminal for the trade-off between efficiency and energy consumption. *Advanced Engineering Informatics*, 29(1), 59-75.

He, J., Huang, Y., Yan, W. and Wang, S. (2017). Integrated internal truck, yard crane and quay crane scheduling in a container terminal considering energy consumption, Expert Systems with Applications, 42 (5), 2464-2487, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2014.11.016.

Iris, C. and Lam, J.S.L. (2019). A review of energy efficiency in ports: Operational strategies, technologies and energy management systems. *Renewable and Sustainable Energy Reviews*, 112(C), 170-182.

Itoh, H. (2002). Efficiency changes at major container ports in Japan: A window application of data envelopment analysis. *Review of urban & regional development studies*, 14(2), 133-152.

Kuo, K.C., Lu, W.M., and Le, M.H. (2020). Exploring the performance and competitiveness of Vietnam port industry using DEA. *The Asian Journal of Shipping and Logistics*, 36(3) 136-144.

Li, L.-L., Seo, Y.-J. and Ha, M.-H. (2021). The efficiency of major container terminals in China: super-efficiency data envelopment analysis approach. *Maritime Business Review*. DOI 10.1108/MABR-08-2020-0051

Lim, S., Bae, H. and Lee, L.H. (2011). A study on the selection of benchmarking paths in DEA. *Expert Systems with Applications*, 38, 7665-7673

Lu, B. and Wang, X. (2012). Application of DEA on the measurement of operating efficiencies for east-Asia major container terminals. *Journal of Systems and Management Sciences*, 2(1), 1-18.

Martínez-Moya, J., Vazquez-Paja, B. and Gimenez Maldonado, J.A. (2019). Energy efficiency and CO2 emissions of port container terminal equipment: Evidence from the Port of Valencia, *Energy Policy*, 131, 312-319, ISSN 0301-4215, https://doi.org/10.1016/j.enpol.2019.04.044.

Mokhtar, K. (2013). Technical efficiency of container terminal operations: A DEA approach. *Journal of Operations and Supply Chain Management*, 6(2), 1-19.

Munin, H.Z. (2020). Does higher technical efficiency induce a higher service level? A paradox association in the context of port operations. *The Asian Journal of Shipping and Logistics,* 36, 157-168

Neufville, R. D. and Tsunokawa, K. (1981). Productivity and returns to scale of container ports. *Maritime Policy and Management*, 8(2), 121-129.

Notteboom, T., Coeck, C. and van den Broeck, J. (2000), Measuring and explaining the relative efficiency of container terminals by means of Bayesian stochastic frontier models, *International Journal of Maritime Economics*, Vol. 2 No. 2, pp. 83-106.

Park, J., Lee, B.K. and Low, J.M.W. (2020). A two-stage parallel network DEA model for analysing the operational capability of container terminals. *Maritime Policy & Management.* DOI: 10.1080/03088839.2020.1859148

Pérez-Reyes, R. and, Tovar, B. (2009). Measuring efficiency and productivity change (PTF) in the Peruvian electricity distribution companies after reforms. *Energy Policy*, 37(6), 2249-2261.

Pjevčević, D., Vladisavljević, I., Vukadinović, K., and Teodorović, D. (2011). Application of DEA to the analysis of AGV fleet operations in a port container terminal. *Procedia-Social and Behavioral Sciences*, 20, 816-825.

Rios, L. R., and Maçada, A. C. G. (2006). Analysing the relative efficiency of container terminals of Mercosur using DEA. *Maritime Economics & Logistics*, 8(4), 331-346.

Roll, Y. and Hayuth, Y. (1993). Port performance comparison applying data envelopment analysis (DEA). *Maritime policy and Management*, 20(2), 153-161.

Sharma, M. and Yu, S. (2010). Benchmark optimization and attribute identification for improvement of container terminals. *European Journal of Operational Research,* 201, 568-580.

Spengler, T. and Wilmsmeier, G. (2019). Sustainable Performance and Benchmarking in Container Terminals—The Energy Dimension. In: Monios, J. and Bergqvist, R. (eds) Green Ports: Inland and Seaside Sustainable Transportation Strategies. 125-154. Elsevier.

Tongzon, J., (2001). Efficiency measurement of selected Australian and other international ports using data envelopment analysis. *Transportation Research Part A*, 35, 113-128

Tovar, B., Wall, A., (2015). Can ports increase traffic while reducing inputs? Technical efficiency of Spanish port authorities using a directional distance function approach. *Transportation. Research Part A,* 71, 128–144.

Van Duin, J.h.R., Geerlings, H., Verbraeck, A., Nafde T. (2018). Cooling down: A simulation approach to reduce energy peaks of reefers at terminals, *Journal of Cleaner Production*, 192, 72-86.

Wang T. and Cullinane K. (2015). The Efficiency of European Container Terminals and Implications for Supply Chain Management. In: Haralambides H.E. (eds) Port Management. Palgrave Readers in Economics. Palgrave Macmillan, London.

Wiegmans, B., and Witte, P. (2017). Efficiency of inland waterway container terminals: Stochastic frontier and data envelopment analysis to analyse the capacity design- and throughput efficiency. *Transportation Research Part A: Policy and Practice,* 106, 12-21.

Wilmsmeier, G., Froese, J., Zotz, A., and Meyer, A. (2014): Energy Consumption and Efficiency: Emerging Challenges from Reefer Trade in South American Container Terminals. FAL Bulletin 329. ECLAC.

Wilmsmeier, G. (2020). Climate change adaptation and mitigation in ports. *Maritime Transport and Regional Sustainability*, 133–150. doi:10.1016/b978-0-12-819134-7.00008-3

Wilmsmeier, G., and Spengler, T. (2016). Energy consumption and container terminal efficiency. FAL Bulletin 350, ECLAC

Wilmsmeier, G., Tovar, B., and Sanchez, R. J. (2013). The evolution of container terminal productivity and efficiency under changing economic environments. *Research in Transportation Business & Management*, 8, 50-66.

Woo S-H., Pettit, S.J., Kwak, D-W. and Beresford, A.K.C. (2011). Seaport research: A structured literature review on methodological issues since the 1980s. *Transportation Research Part A*, 45, 667-685.

Yang, X., and Yip, T.L. (2019). Sources of efficiency changes at Asian container ports. *Maritime Business Review*, 4(1), 71-93.

Yang, Y-C. and Chang W-M (2013). Impacts of electric rubber-tired gantries on green port performance. *Research in Transportation Business & Management*, 8, 67-76.

Appendix

Table 7: DMUs with their peers under VRS assumption - Model 1

DMU	**Peers**			
ARG_01	USA_01	MOR_01	MEX_03	RUS_02
ARG_02	BHS_01	MOR_01		
BRA_01	MOR_01	USA_01	RUS_02	
BRA_02	PAN_01	MOR_01		
BRA_03	USA_01	MOR_01	MEX_03	RUS_02
BRH_01	MOR_01	USA_01		
BHS_01	BHS_01			
CHL_01	RUS_03	BHS_01	USA_01	
CHL_02	USA_01			
CHL_03	MOR_01	USA_01		
COL_01	BHS_01	RUS_03	USA_01	
COL_02	USA_01			
COL_03	MOR_01	RUS_03	USA_01	
GEO_01	USA_01	MOR_01		
MEX_01	USA_01	MOR_01	MEX_03	RUS_02
MEX_02	MOR_01	PAN_01		
MEX_03	MEX_03			
MOR_01	MOR_01			
NIG_01	PAN_01	MOR_01		
PAN_01	PAN_01			
RUS_01	MOR_01	MEX_03		
RUS_02	RUS_02			
RUS_03	RUS_03			
SWE_01	MOR_01	RUS_03	USA_01	
USA_01	USA_01			
VIE_01	VIE_01			

Note: (ARG – Argentina, BHS - Bahamas, BRA – Brazil, BRH – Bahrain, CHL – Chile, COL – Colombia, GEO - Georgia, MEX – Mexico, MOR – Morocco, NIG – Nigeria, PAN – Panama, RUS – Russia, SWE – Sweden, VIE – Vietnam).

Source: Authors

Table 8: DMUs with their peers under VRS assumption - Model 2

DMU	Peers			
ARG_01	VIE_01	USA_01	RUS_02	CHL_02
ARG_02	VIE_01	RUS_03	BHS_01	MOR_01
BRA_01	MOR_01	VIE_01	RUS_02	
BRA_02	VIE_01	BHS_01	PAN_01	
BRA_03	VIE_01	RUS_02	MOR_01	MEX_03
BRH_01	VIE_01	USA_01	MOR_01	
BHS_01	BHS_01			
CHL_01	VIE_01	BHS_01	RUS_03	USA_01
CHL_02	CHL_02			
CHL_03	USA_01	MOR_01		
COL_01	RUS_03	BHS_01	USA_01	
COL_02	USA_01	CHL_02		
COL_03	MOR_01	RUS_03	USA_01	
GEO_01	PAN_01	MOR_01	VIE_01	
MEX_01	MEX_01			
MEX_02	PAN_01	BHS_01	MOR_01	VIE_01
MEX_03	MEX_03			
MOR_01	MOR_01			
NIG_01	BHS_01	USA_01	MOR_01	
PAN_01	PAN_01			
RUS_01	MOR_01	MEX_03		
RUS_02	RUS_02			
RUS_03	RUS_03			
SWE_01	BHS_01	USA_01	RUS_03	VIE_01
USA_01	USA_01			
VIE_01	VIE_01			

Note: (ARG – Argentina, BHS - Bahamas, BRA – Brazil, BRH – Bahrain, CHL – Chile, COL – Colombia, GEO - Georgia, MEX – Mexico, MOR – Morocco, NIG – Nigeria, PAN – Panama, RUS – Russia, SWE – Sweden, VIE – Vietnam

Source: Authors

Table 9: DMUs with their peers under VRS assumption – Model 3.

DMU	Peers				
ARG_01	USA_01	CHL_03	BRA_01	MOR_01	RUS_02
ARG_02	CHL_01	BHS_01	PAN_01	MOR_01	
BRA_01	BRA_01				
BRA_02	PAN_01	MOR_01			
BRA_03	USA_01	MOR_01	MEX_03	RUS_02	
BRH_01	MOR_01	CHL_03	USA_01		
BHS_01	BHS_01				
CHL_01	CHL_01				
CHL_02	CHL_02				
CHL_03	CHL_03				
COL_01	BHS_01	RUS_03	USA_01		
COL_02	CHL_02				
COL_03	MOR_01	RUS_03	USA_01		
GEO_01	USA_01	MOR_01	CHL_03		
MEX_01	USA_01	CHL_03	BRA_01	MOR_01	RUS_02
MEX_02	MOR_01	PAN_01			
MEX_03	MEX_03				
MOR_01	MOR_01				
NIG_01	PAN_01	MOR_01			
PAN_01	PAN_01				
RUS_01	RUS_02	CHL_03	MOR_01		
RUS_02	RUS_02				
RUS_03	RUS_03				
SWE_01	MOR_01	RUS_03	USA_01		
USA_01	USA_01				
VIE_01	VIE_01				

Note: (ARG – Argentina, BHS - Bahamas, BRA – Brazil, BRH – Bahrain, CHL – Chile, COL – Colombia, GEO - Georgia, MEX – Mexico, MOR – Morocco, NIG – Nigeria, PAN – Panama, RUS – Russia, SWE – Sweden, VIE – Vietnam).

Source: Authors

Table 10 (antes 8/7): DMUs with their peers under VRS assumption – Model 4

DMU	Peers					
ARG_01	USA_01	MOR_01	RUS_02	CHL_02	VIE_01	BRA_01
ARG_02	BHS_01	CHL_02	MOR_01	VIE_01	CHL_01	
BRA_01	BRA_01					
BRA_02	VIE_01	BHS_01	PAN_01			
BRA_03	VIE_01	RUS_02	MEX_03			
BRH_01	USA_01	VIE_01	MOR_01	CHL_02		
BHS_01	BHS_01					
CHL_01	CHL_01					
CHL_02	CHL_02					
CHL_03	CHL_03					
COL_01	BHS_01	RUS_03	USA_01			
COL_02	CHL_02					
COL_03	MOR_01	RUS_03	USA_01			
GEO_01	PAN_01	MOR_01	BRA_01	VIE_01		
MEX_01	MEX_01					
MEX_02	MOR_01	BHS_01	PAN_01	VIE_01		
MEX_03	MEX_03					
MOR_01	MOR_01					
NIG_01	BHS_01	MOR_01	USA_01			
PAN_01	PAN_01					
RUS_01	MOR_01	CHL_03	RUS_02			
RUS_02	RUS_02					
RUS_03	RUS_03					
SWE_01	USA_01	RUS_03	BHS_01	VIE_01		
USA_01	USA_01					
VIE_01	VIE_01					

Notes: (ARG – Argentina, BHS - Bahamas, BRA – Brazil, BRH – Bahrain, CHL – Chile, COL – Colombia, GEO – Georgia, MEX – Mexico, MOR – Morocco, NIG – Nigeria, PAN – Panama, RUS – Russia, SWE – Sweden, VIE – Vietnam).

Source: Authors