Improving Ship Fleet Performance Using a Non-Parametric Model

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The world merchant fleet has increased in the last decade producing an increase of fuel consumption and greenhouse gas emissions (GHGs). Thus, the concerns of ship-owners to implement alternatives to improve the fleet efficiency are growing. However, shipowners are facing barriers to implement energy efficiency technologies mainly due to reliability, financial and economic constraints as well as complexity of change. Actually several shipowners are using onboard data measurements systems that collect navigation and propulsion information of their ships. Therefore, after being sent via satellite and stored in data warehouse, these data are being made available to assess the performance of their fleets. This paper describes the use of these data to generate models in order to answer to the following questions: What is the ship with least efficiency in my fleet? What is the best strategy to improve the overall efficiency of my fleet? What is the ship that I should sell in priority? What is the influence of this maintenance policy on the performance of my fleet? The application case of this paper is based on one fleet of 13 ships containing 223 trips that gather approximately 6,844 traveling days. After the definition of the key performance indicators (KPIs), a data envelopment analysis (DEA) models is discussed. Then, a multicriterion decision analysis (MCDA) model is compared to the DEA outputs. The results suggest that this new methodology can efficiently provide a multicriteria decision framework to shipowners avoiding engineers' subjectivity. These findings offer a new way to address efficiency and performance in ship management.

KEY WORDS: Greenhouse gas emissions; DEA; MCDA; ship performance.

INTRODUCTION

There are around 70,000 ships dedicated to international trade; this industry is responsible for 90% of world trade (ICS, 2009). This world merchant fleet increased in the last decade having a total of 26,186 ships in 2005 around the world with a total international cargo demand of 5,979 millions of tons with a rise of 24% in 2012 and 46% to 2020 (RTI, 2008).

This increase of the world ship fleet produced a growth of fuel consumption and consequently GHG emissions. In an effort to reduce the pollution, each responsible entity is taking actions to fight this problem (Ballou, 2013).

International Maritime Organization (IMO)

In May 2005, IMO implemented the MARPOL Annex VI regulation to control the utilization of international marine bunker fuels (RTI, 2008). Moreover, in July 2011, this regulation was amended to implement the Ship Energy Efficiency Management Plan (SEEMP) to all ships over 400 gross tons (GT) (Ballou, 2013) with the aim to reduce the GHG emissions.

MARPOL Annex VI regulations include limits on sulfur content of fuel oil as a measure to control SO_X emissions and, indirectly, particulate matter (PM) emissions. Different environmental control areas (ECAs) have been established along coastlines of the United States (US) and Europe. In those areas a special fuel quality requirement exists for SO_X (SO_X ECA also called SECA). That limits or actually forces the shipowners to switch to cleaner yet more costly fuel, e.g. marine diesel oil (MDO) instead of intermediate fuel oil (IFO), as well as to reduce the speed of their ships, (Ballou, 2013). Also, due to increasing pollution of harbor cities, the SECAs have agreed to limit the SO_X content to 0.1% in marine fuels for harbor surrounding region. Sulphur limits and implementation dates are illustrated in Figure 1, (Pedersen, 2011) and (EMSA, 2012).

NO_X emission limits are set for diesel engines depending on the engine maximum operating speed (rpm), as shown in Figure 2. Tier I and Tier II limits are global, while Tier III standards apply only in NO_X Emission Control Areas (Pedersen, 2011).

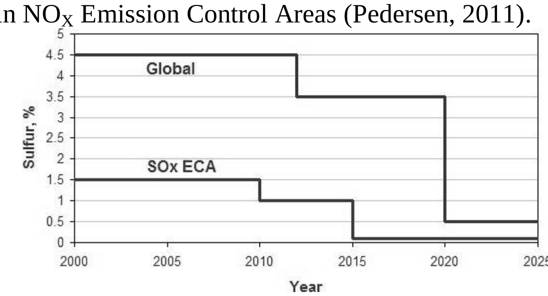

Figure 1. MARPOL Annex VI - Fuel Sulfur Limits

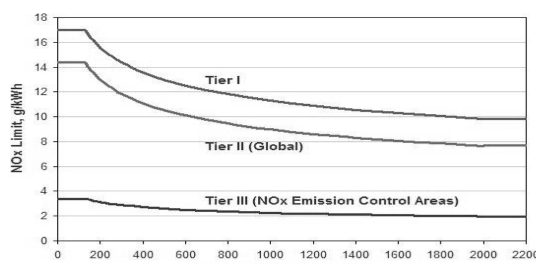

Figure 2. MARPOL Annex VI – NO_X Limits

Governments

Governments are implementing in their regulation actions to control the emissions inside the ECAs. The use of devices for real-time control of fuel quality, engine speed and other parameters is one of the methods to monitor the vessels in these countries. The US Environmental Protection Agency (EPA) has also adopted ship emissions standards for NO_X, CO_2 and PM for all US ships with engines manufactured after 1st January 2004 (EPA, 2002), and new standards for diesel engines onboard large ocean vessels (Eyring, et al, 2010).

Shipowners

Shipowners are searching for alternatives to reduce the fuel consumption. Examples include implementing slow steaming strategies (speed reduction), improving their vessels with the use of new maintenance policies, using retrofitting or progressively renewing their fleets. Others alternatives to improve the propulsion efficiency are to redesign propellers, use antifouling methods, use better engines and slow steaming strategy (Corbett, Wang and Winebrake 2009).

Although there is a need to improve the efficiency of ships, the shipowners have different reasons such as barriers to energy efficiency in which they refuse to implement the options to increase the efficiency mainly due to: reliability, financial and economic constraints, and complexity of change. To understand the perspective of shipowners, a research of 2013 shows that many barriers are related to the information available (Acciaro, Hoffmann and Eide, 2013).

For shipowners, ship performance is the cost for a traveled distance divided by the amount of cargo which is transported at a certain speed. Operational cost is direct proportional to fuel consumption and energy output of the engine, when maintenance, consumables, crew and fixed cost are not included (Pundt, 2011).

From the viewpoint of naval engineering, ship performance is described by the correlation between ship speed, delivered power to the propeller, and resistance force opposite to the direction of movement.

However, this speed power curve is determined during model tests for calm weather conditions in an ideal condition (best conditions concerning weather, ship and engine). Yet, it is found that the ship always needs more fuel or power than estimated by model tests. So, in order to calculate ship performance, all aspects of resistance, propulsion, and speed should be considered (Pundt, 2011). The parameters that affect ship performance refer to the influence of resistance, propulsion, and speed (Figure 3). As defined by the International Standardization Organization (ISO, 2002).

Ship resistance is composed of three parts: frictional, wave, and residual resistance without external influences. For a defined ship speed, waves and residual resistance are considered constant, Frictional resistance is variable depending on kinematic viscosity, salinity and water temperature. Other factors influence the resistance such as the ship conditions (trim and draft of the ship, and fouling) and weather conditions (wind, waves, currents).

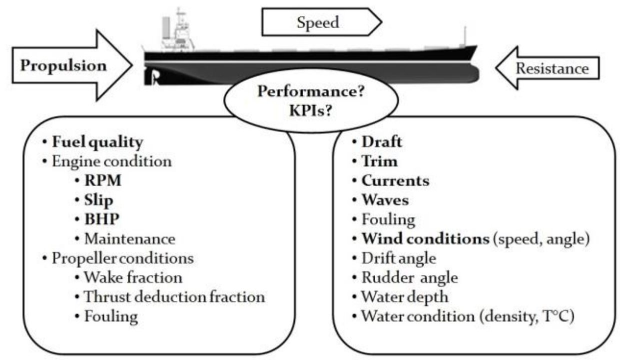

Figure 3. Factors affecting Ship Performance

Propulsion on ships is also influenced by environment. Propulsion power is produced by the stored fuel on board, transformed into rotational mechanical power in the engine, transmitted by shaft line to propeller which turns it into thrust. All conversions go with power losses which are expressed as efficiency coefficients. All these parameters are not perfectly constant, therefore they must be taken into account. Several factors influence the propulsion such as the fuel quality, the engine efficiency and the propeller conditions (fouling).

Considering that propulsion, speed, and resistance drivers are constantly in evolution, ship performance is always changing. Therefore, there is a need to assess the system efficiency to further optimize it. Good efficiency provides lower costs, minimal fuel consumption, better performance, minimum amount of emissions, and economical advantages.

Reducing emissions of CO_2, NO_X and SO_X is a great challenge that today's society is facing, and operational efficiency is reflected in these reductions. The effect of fuel composition (quality), the use of the main engines operated in nonideal loads, and logistics are important factors on the ship's efficiency.

Control entities strictly require compliance with national and international standards of safety and environment. The main concern of shipowners is to reduce operating costs and maximize revenues. Developing global indicators will provide a tool to fulfill both shipowner operational requirements and required regulations.

The aim of this paper is to develop a fleet efficiency model using an operational database in order to improve the quality of decision-making in the management of a ship fleet. This paper focus the implementation of a non-parametric method, i.e. data envelopment analysis (DEA) then compare the results with a multicriteria decision analysis (MCDA) method developed in a previous study (Caprace and Coronel,2013).

State of the Art

In many marine engineering applications like fishery, container ships or supply vessels, when efficiency is analyzed, technical efficiency (TE), and key performance indicators (KPIs) are also mentioned. This section compiles the latest research regarding TE and KPIs.

Recently measurements of fishery fleet efficiency through evaluation of TE were presented by (Jamnia, Mazloumzadeh and Keikha, 2015). They highlighted the importance of the amount of input data to have reliable results. Important contributions were provided by TE measurements. However, various new frontier estimation techniques were recently developed to improve this methodology in the transportation sector. (Brons, et al, 2005) depicted for instance an efficiency analysis of urban public transport.

Another study leaded by (Ballou, 2013) developed an efficiency management strategy through a comprehensive plan that includes the following elements: a selection of KPI to measure the efficiency of a ship fleet, a methods to obtain input data, as well as the implementation of a analytical tool to process data to generate the results.

Efficiency of containership and a cruise ship in the Caribbean has been analyzed by (Salonen, Heikkinen and Ilus, 2012). Energy efficiency operational indicator (EEOI) as a KPI based in specific fuel consumption (SFC), and emission factors were used to simulate and assess the efficiency of various routes scenarios depending on level of emissions, fuel consumption and calculation of optimal load distribution.

The efficiency of a fleet of supply vessels has been recently assessed by (Aas, Halskau and Wallace, 2009) considering ship size, ship quantity, speed, capacity and types of vessels.

A recent report showed that decreasing unproductive waiting time in port not only helps fleet efficiency but also helps to decrease the GHG emissions indicated in SEEMP (Johnson and Styhre, 2015).

The previous aforementioned studies shown the importance of using mathematical tools to analyze the ship performance and efficiency. This implementation allows us to understand the behavior of vessels in a fleet and make better decisions about it.

In the next section the concepts of data envelopment analysis (DEA) methodology and multicriteria decision analysis (MCDA) are introduced. This is followed by a description of the database used to assess the ships efficiency. Results are then presented, followed by a summary of major points and conclusions.

METHODOLOGY

This paper present the development of a methodology based on DEA to measure the performance of various decision-making units (DMU) represented by ships. Thereafter, the results are compared with the outcome of a multicriterion decision analysis (MCDA) of ship fleet efficiency published by (Caprace and Coronel 2013) whereas MCDA refers to analyzing and making decisions in the presence of multiple and usually conflicting criteria.

The next sections are briefly describing the two methodologies.

Data Envelopment Analysis (DEA) Techniques

Efficiency frontiers in engineering can be determined based on empirical knowledge of manufacturing operations (parametric specification). This can be done using a deterministic or stochastic approach. Moreover, efficiency frontiers can also be estimated by observing manufacturing operations (non-parametric specification).

The stochastic parametric frontiers method and the deterministic method are similar, but measurement error in the frontier is allowed. Therefore, the error term consists of two elements (Brons, et al, 2005): a technical inefficiency component (deviation from the frontier) and a random error term with zero means (measurement error of the frontier). A categorization of frontier methodologies is shown in Table 1.

Table 1. Categorization of frontier methodologies.

	Deterministic specification	Stochastic specification
Parametric technology	Frontiers based on corrected ordinary least squares (OLS) or maximum likelihood estimation (ML) models.	Frontiers with explicit distributional assumptions for TE values
Non-parametric technology	Frontiers based on free disposal hull (FDH) and data envelopment analysis (DEA) techniques.	Resampling, chance constrained programming.

Deterministic non-parametric methods do not assume a particular production function (Brons, et al, 2005). Mathematical programming techniques are used to construct a linear frontier from the observations. The main methodologies are the DEA method and the free disposal hull (FDH) method (Kerstens, 1996).

The first to propose the DEA methodology as an evaluation tool for decision making unit (DMU) were Charnes, Cooper and Rhodes, 1978). DEA has been applied successfully as a performance evaluation tool in many fields including manufacturing, academic institutions, banks, pharmaceutical firms, small business development centers, and nursing home chains.

The efficiency measures are distances to an empirical production frontier, and the values are calculated on the basis of standard Pareto efficiency. The frontier is constructed based on the assumption that any linear combination of observation units is feasible, and the assumption of strong input and output disposability is vital (Brons, et al, 2005).

Strong input disposability means that a feasible output level remains feasible after increasing any input levels; strong output disposability means that it is always possible to reduce the output level without changing input levels (Brons, et al, 2005). The variable returns to scale DEA model are illustrated for output maximization in Figure 4. Points A–E are observational units. The model assumes that an observed output vector can be smaller than the linear combination of observations D and E.

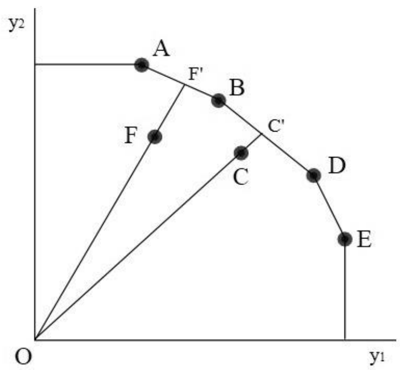

Figure 4. Frontier of DEA Technology

All observations to the southwest of the line segment D – E are feasible. This explains the line originating in observation E and extending parallel to the horizontal axis. Using a similar reasoning for all line segments and allowing for all linear combinations yields the set of possible output combinations bounded by the production frontier that consists of the line segments A – B – D – E. However, point C and F are not efficient according to DEA assumptions because they are not on the frontier. The degree of technical inefficiency for points C and F is measured by the fraction (OC)/(OC') and (OF)/(OF'), respectively (Brons, et al, 2005).

DEA evaluated the relative efficiency of DMUs using multiple inputs to produce multiple outputs. The basic idea of DEA is to identify the most efficient DMU among all DMUs. DEA determines for each DMU a measure of efficiency obtained as a ratio of weighted outputs to weighted inputs (Wanke, 2012).

The most efficient DMU is called a Pareto-optimal unit and is considered the reference for all other DMUs. An efficient bond can have higher rating scores of unity, while an inefficient bond would receive DEA scores of less than unity. This method is applied to shipping industry bond ratings (Liang, Liu and Lin, 2006).

From the early 1980s, various frontier estimation techniques have been developed to determine best practice behavior in an industry (i.e. know if economic targets were reached such as cost minimization or output maximization). Frontier methodologies allow for distinguishing between efficient and inefficient production and the estimation of the degree of (in) efficiency. In the transportation literature, frontier methods have been used in efficiency studies on almost all transport modes (Kerstens, 1996), (Lan and Lin 2003).

Reports were made on the use of different approaches of DEA and free disposal hull (FDH) models for measuring efficiency in 65 major Brazilian airports showing the efficiency rankings calculated (Wanke, 2012). The findings corroborate evidences regarding a capacity shortfall within Brazilian airports, where the short-term potential for passenger/cargo consolidation per landing/takeoff is virtually nonexistent.

During the early 1990s economic recession caused changes in the automotive industry worldwide.) This case was discussed with the use of DEA to identify the empirical efficiency frontier (Chen, 2011). In this work productivity standards and management strategies were identified for companies individually.

(Oliveira, Camanho and Gaspar 2010) analyzed an artisanal bivalve dredge fleet using the data collected employing DEA models, identifying characteristics and practices of the best ships to determine the efficiency of vessels improving fishing results.

To investigate the technical tfficiency (TE) and service effectiveness (SE) for some selected 76 railways (DMU) in the world during the period 1999-2001 (LAN and LIN, 2003) adopts various DEA approaches. Using TE by input-oriented DEA models and SE by output-oriented DEA models. The results shows that railways efficiency and effectiveness vary between the regions, but the boundaries are static during the study period. Outliers were detected and a sensitivity analysis was performed for the efficient DMU.

DEA and FDH models were also used by (Kerstens, 1996) to study the performance of a sample of French urban transit companies. The results confirm findings reported elsewhere: the relevance of the property, the use of incentives to share the risks in hiring, the harmful impact of subsidies, etc. In addition, the network structure causes differences in performance.

Multicriteria Decision Analysis (MCDA)

Multicriteria decision analysis (MCDA) is a methodology for supporting decision making that has been used to support complex decision problems. The MCDA models in real world should be structured as follow: articulated, defined and measured by attributes. Providing an accurate MCDA model can often bring difficulties, (Franco and Montibeller 2009).

Inadequate definition of a problem will cause poorly structured decisions. In the opposite case decisions will have a higher level of understanding and provide a wealth of new information about the problem (Mabin and Beattie 2006).

The outcome of any decision-making model depends on the information available, and the type of decision criterion may vary according to the kind of ship operation. Therefore, models of decision-making should consider all available information as a whole. In multiple criteria decision making (MCDM), to make decisions, different elements to be examined and evaluated should be chosen using a set of criteria. These elements are called alternatives (Caprace and Coronel 2013).

The selection of alternatives submitted to a multicriteria evaluation represents a complex problem. Usually there is no optimal solution; no alternative is the best one on each criterion. A better quality implies a higher price. Sometimes, the criteria are conflicting and compromise solutions should be considered (Brans and Mareschal, 1994).

Over time it many mathematical methods have been proposed to simplify the decision-making process, where one of the most used is presented by (Brans and Mareschal, 1994) called Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE).

This method is based on a mutual comparison of each alternative pair with respect to each of the selected criteria. In order to rank the alternative, it is necessary to define preference function *P (a,b)* for alternatives *a* and *b* after defining the criteria. Alternatives *a* and *b* are evaluated according to the criteria functions. It is considered that alternative *a* is better than alternative *b* according to criterion f, if $f(a) > f(b)$. The decision maker has the possibility to assign the preference to one of the alternatives on the basis of such comparison (Tomic, Marinkovic and Janosevic, 2011).

DATA DESCRIPTION

This paper focused the study on a ship fleet of 13 vessels as described in Table 2. These ships completed a total of 223 voyages (individual travels) as described in Table 3. Each voyage is composed of daily records (mean value of the day, i.e. the noon report) of the navigational data. In this paper these items have been called route points and represent a total of 6,844 records.

Table 2. Ship Fleet Description (13 vessels)

Description	Mean	Standard Deviation
Total Length (m)	289.48	16.68
Design speed (Knots)	14.22	0.77
DWT (Tons)	179 437.62	33 350.56
Breadth (m)	46.69	3.64
Depth (m)	24.46	0.88
Draught (m)	17.98	0.71
Max. displacement (Tons)	202 052.08	36 273.87

Table 3. Voyage Description (223 elements)

Description	Mean	Standard Deviation
Number of routes	16.86	11.38
Average daily performance speed (Knots)	12.70	1.40
Total IFO consumption	810.80	547.18
Total covered distance (Nautical Miles)	4886.58	3199.98
Total Cargo (Tons)	140592.91	59615.69

Both laden and ballast condition have been considered separately for the next part of the study.

MODEL

The model developed is using DEA at the route point level, for both ballast and laden conditions. The estimates presented here are based on output-orientated DEA-CCR (Charnes, Cooper and Rhodes 1978) and DEA-BCC (Banker, Charnes and Cooper 1984) models, which means that outputs are maximized while inputs are kept constant. Afterwards the results are gathered by voyage and finally by ship. The outranking of the ships efficiency is then calculated. Finally the DEA model is compared with a MCDA model calculated by (Caprace and Coronel 2013).

Definition of KPIs

In this paper, ship efficiency is obtained through the assessment of various key performance indicators (KPIs) that are measuring the relative performance of each studied criterion. The number of KPIs is heavily dependent on the availability of both quantitative and qualitative data (Caprace and Coronel 2013). The definition of these criteria, based on knowledge and expertise is presented below:

- The average daily performance speed (S)
- The ship delivery year (DY)
- The gross tonnage (GT)
- The specific fuel oil consumption (SC)
- The admiralty coefficient (A_C) that refers to propulsion efficiency (PE_A)
- The CO_2 emission (ECO_2)
- The NO_X emission (ENO_X)
- The SO_X emission (ESO_X)
- The ship work per deadweight (SW)
- The payload/cargo (C)

Average Daily Performance Speed Route (*S*)

S is the real average daily speed of the ship in knots. This KPI is measuring how far a ship is operating on its design speed.

Delivered year (*DY*)
DY is defined as the delivery year of the ship. This KPI is measuring how old is a ship in the fleet. An older ship will normally be assumed to perform worse than a newer ship.

The Gross Tonnage (*GT*)
GT denotes the gross registered tonnage for each vessel. This KPI is measuring the relative size of the ships of the fleet. A bigger ship will normally be assumed to be more efficient than a smaller one (effect of scale).

Specific consumption (*SC*)
SC, defined in Equation 1, represents the specific fuel oil consumption for both Intermediate Fuel Oil (IFO) and Marine Diesel Oil (MDO) per knot, per nautical mile, per hour and per ton of payload/cargo. To obtain the two fuel oil consumptions, an equivalent cost factor f has been considered. A higher specific consumption denotes a lower efficiency.

$$SC = \frac{IFO + \left(f \cdot MDO\right)}{V \cdot D \cdot t \cdot M} \qquad \textbf{(1)}$$

Where V [knots] speed,
D [nautical mile] distance of travel,
t [t] hour,
M [tons] payload/cargo carried,
f [constant] cost factor equal to 1.46.

Admiralty Coefficient (A_C) - propulsion efficiency
If two ships are similar in type, displacement, power and speed, then their Admiralty Coefficient (A_C), defined by the Equation 2, will be similar in values, (Barrass, 2004). Their A_C varies between 300-600 with the higher values representing the more efficient vessels.

$$A_C = \frac{W^{2/3} \cdot V^3}{P} \qquad \textbf{(2)}$$

Where W [tons] ship displacement,
V [knots] speed, with $V \leq 20$ knots,
P [kW] power measured at the thrust block.

CO_2 emission (*ECO_2*)
(IMO, 2009) defined an expression of emission efficiency expressed in the form of CO_2 emitted per unit of transport work. This coefficient is called the energy efficiency operational indicator (EEOI). The ECO_2 is measured in tons CO_2/(tons * Nautical miles) and given in Equation 3. When considering the overall form of the ECO_2, it is clear that in order to reduce the CO_2 for a given ship at a given speed, a decrease in propulsive power must be achieved and/or improvements made in engine efficiency with a reduction in C_F (Acomi and Acomi, 2014). A higher value of this indicator denotes a lower efficiency.

$$ECO_2 = \frac{\sum_j FC_j \cdot CF_j}{M \cdot D} \qquad \textbf{(3)}$$

Where j the fuel type
FC [kg] the mass of consumed fuel
CF [t- CO_2/t-fuel] the fuel mass to CO_2 mass conversion factor, see Table 4.
D [nautical mile] distance of travel
M [tons] cargo carried.

Table 4. Fuel mass to CO_2 mass conversion factors C_F

Type of fuel	Carbon content	C_F
Diesel/Gas Oil	0.875	3.20600
LFO – Light Fuel Oil	0.860	3.15104
HFO – Heavy Fuel Oil	0.850	3.11440
LPG – Liquefied Petroleum Gas – Propane	0.819	3.00000
LPG – Liquefied Petroleum Gas – Butane	0.827	3.03000
LNG – Liquefied Natural Gas	0.750	2.75000

NO_X emission (*ENO_X*)
The NO_X emissions are empirical (European Environment Agency, 2009) and are defined by Table 5 depending on engine and fuel type.

Table 5. NO_X emission factor given in [kg/tons fuel]

	RPM	BFO	MDO or MGO
Slow speed engine	≤ 300	89.7	88.6
Medium speed engine	>300 and ≤900	63.4	63.1
High speed engine	>900	57.7	57.1

Equation 4 gives the expression to assess ENO_X in kg-NO_X/t-fuel depending of Table 5. A higher value of this indicator denotes a lower efficiency.

$$ENO_x = \frac{\sum_j FC_j \cdot CN_j}{M \cdot D} \qquad \textbf{(4)}$$

Where j the fuel type,
FC [kg] the mass of consumed fuel,
CN [kg- NO_X/t-fuel] the fuel mass to NO_X mass conversion factor,
D [nautical mile] distance of travel,
M [tons] cargo carried,

SO_X emission (*ESO_X*)
The equation 5 gives the expression to assess ESO_X emissions in kg-SO_X/t-fuel depending on the type and sulfur content of the fuel (Cooper 2002). One has to multiply total bunker consumption by the percentage of sulfur present in the fuel and subsequently by a factor of 20 to compute SO_2 emissions. The 20 SO_X factor is exact and comes from the chemical reaction of sulfur and oxygen to produce SO_2. We made the hypothesis that the average sulfur content is respectively for IFO and MDO,

2.5% and 0.2%. A higher value of this indicator denotes a lower efficiency.

$$ESO_x = \frac{\sum_j FC_j \cdot CS_j}{M \cdot D} \qquad \textbf{(5)}$$

Where
- j — the fuel type,
- FC — [kg] the mass of consumed fuel,
- CS — [kg- SO_X/t-fuel] the fuel mass to SO_X mass conversion factor,
- D — [nautical mile] distance of travel,
- M — [tons] cargo carried,

Ship work per deadweight (*SW*)
This KPI is defined as the ship work divided by the deadweight in tons. Ship work as explained above is the cargo/payload carried in tons multiplied by the distance traveled in nautical miles defined in the Equation 6. The higher this indicator is, the better the efficiency.

$$SW = \frac{M \cdot D}{DWT} \qquad \textbf{(6)}$$

Where
- D — [nautical mile] distance of travel,
- M — [tons] cargo carried,
- DWT — [tons] deadweight,

Cargo (*C*)
C represents the total cargo/payload quantity carried in tons. In the case of ballast condition, the *C* value corresponds to the average quantity of ballast water carried onboard.

Data preparation

All inputs and outputs parameters were normalized using Equation 7:

$$X_{i,0\ to\ 1} = \frac{X_i - X_{Min}}{X_{Max} - X_{Min}} \qquad \textbf{(7)}$$

Where
- X_i — each data point *i*,
- X_{Min} — the minimal among all the data points,
- X_{Max} — the maximal among all the data points,
- $X_{i,0\ to\ 1}$ — the data point *i* normalized between 0 and 1.

After data treatment, extreme outliers were excluded using Equations 8 and 9. The outliers represents 3,102 records of 6,844 which means 45%. See Figure 5 for DEA inputs and Figure 6 for DEA outputs.

$$p < Q_1 - (3 \cdot IQR) \qquad \textbf{(8)}$$

$$p < Q_3 - (3 \cdot IQR) \qquad \textbf{(9)}$$

Where
- p — data points,
- Q_1 — the lower quartile,
- Q_3 — the upper quartile,
- IQR — the distance between Q_1 and Q_3.

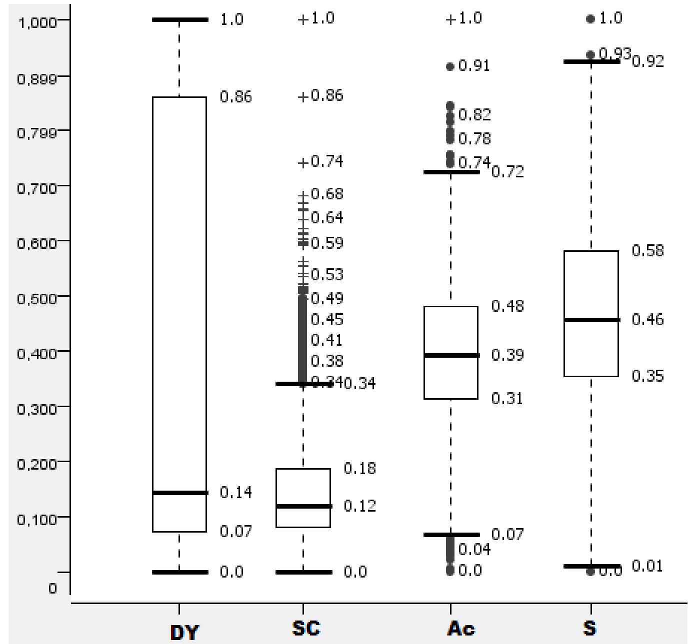

Figure 5. Inputs boxplot including outliers' values

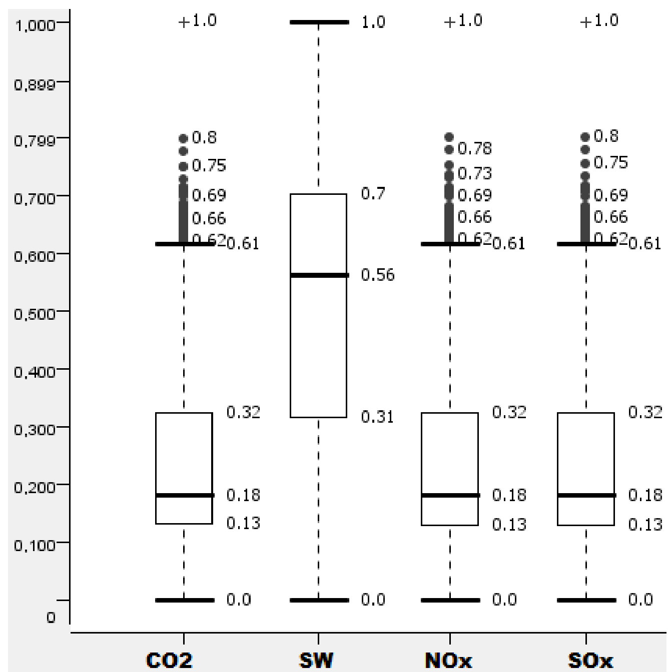

Figure 6. Outputs boxplot including outliers' values

Models definition

Model 1 – Data Envelopment Analysis (DEA)
DEA has been applied separately on ballast and laden conditions at route point level. For each submodel, inputs and outputs are detailed in the Table 6 and Table 7 respectively. The difference states in the ship work and cargo quantity KPIs that we are trying to minimize for ballast conditions and maximize for laden condition. Therefore, the DEA results were gathered (ballast and laden condition together) at voyage level and then at ship level.

Table 6. Input and output values for ballast condition

Inputs	Outputs
S: Average daily performance speed route.	1-ECO$_2$: CO_2 emission
DY: Ship delivered year.	1-ENO$_X$: NO_X emission
GT: Gross tonnage.	1-ESO$_X$: SO_X emission
SC: Specific Consumption (IFO and MDO) per ton of cargo.	1-SW: Ship work per deadweight
A_c: Admiralty coefficient.	1-C: Cargo quantity carried.

Table 7. Input and output values for laden condition

Inputs	Outputs
S: Average daily performance speed route.	1-CO$_2$: CO_2 emission
DY: Ship delivered year.	1-NO$_X$: NO_X emission
GT: Gross tonnage.	1-SO$_X$: SO_X emission
SC: Specific Consumption (IFO and MDO) per ton of cargo.	SW: Ship work per deadweight
A_c: Admiralty coefficient.	C: Cargo quantity carried.

Table 6 shows the output values, the emissions output values are one minus the value that corresponds to minimize the emission factor or output orientation in the model. The ship work per deadweight and cargo quantity carried have the same characteristics as emissions.

Model 2 – Multicriterion Decision Analysis (MCDA)
The second model considers the ship level. This is based on a MCDA methodology called PROMETHEE previously published by (Caprace and Coronel, 2013).

This model indicates that the results of multicriteria analysis hinge on the weighting allocated and the thresholds set. The importance of each criterion depends on the weights and can influence the final outcome of the entire calculation procedure. Three scenarios with three different weight vectors were formulated to highlight the influence of the weight of the emissions on the decision corresponding to Table 8.

Table 8. Definition of weights per criteria in different scenarios

Group	Criteria	W1 [%]	W2 [%]	W3 [%]
Propulsion efficiency [PE]	Admiralty coefficient (A_C)	7	6	8
	Heickel coefficient (H_C)	7	6	8
Emissions [EM]	CO_2 emission (ECO_2)	4.66	9.66	1.67
	NO_X emission (ENO_X)	4.66	9.66	1.67
	SO_X emission (ESO_X)	4.66	9.66	1.67
	Specific fuel oil consumption (*SC*)	14	12	16
	Deadweight (*DW*)	14	12	16
	Average daily performance speed (*S*)	14	12	16
	Ship delivery year (*DY*)	14	12	16
	Ship work per deadweight (*SW*)	14	12	16

To compare the results of DEA with MCDA, the results of Model 1 are gathered per voyage, and subsequently per ship.

RESULTS AND DISCUSSION

Results are presented in each level of information in the next sections.

Ship Level

Figure 7 presents the results of output-oriented DEA methodology corresponding to ballast and laden conditions. A higher outranking flow represents a better alternative. A third curve is plotted on the figure and represents the global model, i.e. the average between ballast and laden condition. The results show that the efficiency of ships is generally lower in ballast condition. In contrast to the other ships, SHIP2 has a better performance in ballast condition than in laden condition. It is explained by the fact that this ship requires less ballast water than other ships to be operated in ballast condition.

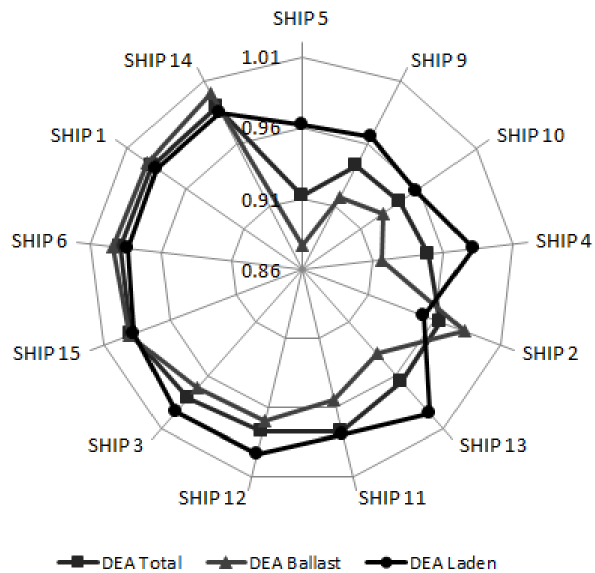

Figure 7. DEA classification of ship efficiency in ballast and laden conditions.

With the selected inputs and outputs, the values of SHIP5 show the weakest performance, while the highest outranking flow is given for SHIP14. SHIP5 is one of the newest ship, but present high emissions, high consumption of oil, high speed, while Admiralty coefficient is medium to low. In contrast, SHIP14 is the oldest ship, but present low emissions, low consumption of oil, low speed, while Admiralty coefficient is medium to low too.

Figure 8 shows the classification of the DEA model compared to the delivery year of the ship, where it can be seen that not necessarily the older ships have the worst efficiency or the newer ships the best efficiency. In this case, SHIP5 is one of the newest ships but has worst efficiency. It is explained by the high oil consumption (rank 4) and high emissions (rank 3). So, despite being among the newest is providing poor performance due to the characteristics of the indicators shown.

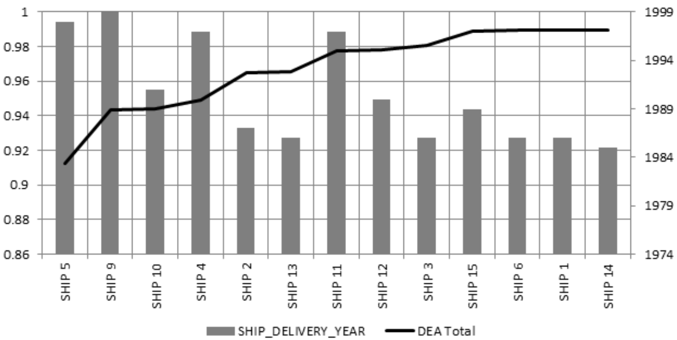

Figure 8. DEA classification of ship performance (black line) and delivery year (bars)

To fulfill the SEEMP, GHG emissions must be reduced. Figure 9 shows that SHIP 6, 14 and 15 are amongst the most efficient ships in laden conditions. Concurrently they are also the best for emissions. In opposite, SHIP1 presents high emissions whilst it is one the most efficient vessel (rank 2). It is explained by the fact that the SHIP1 route points (DMUs values) are in majority defining the DEA frontier (see Figure 10).

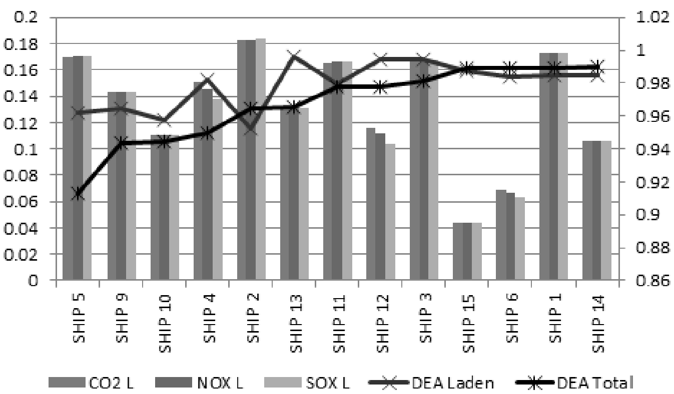

Figure 9. DEA classification of ship performance and emissions in laden conditions

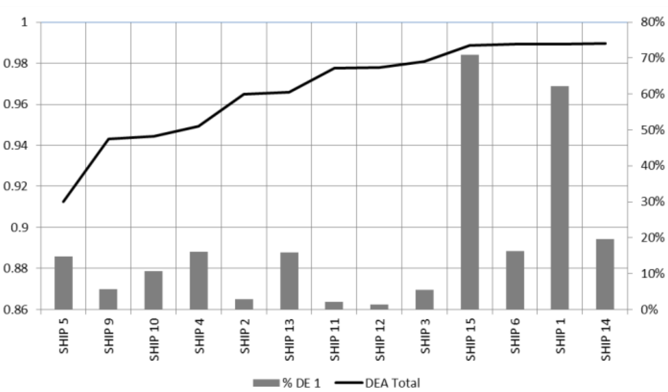

Figure 10. DEA classification of ship performance and percentage of DMUs (route points) on DEA frontier

Figure 11 presents the results of PROMETHEE methodology. Again a higher outranking flow is a better alternative. With the selected inputs, the rankings of SHIP1, SHIP2 and SHIP3 indicate weak performance of most criteria, whereas the ranking values of SHIP10 indicates strong criteria performance. However, it is notable that weights given to each criterion in MCDA methodology make the difference in making decisions knowing that the SHIP10 is the newest, and SHIP1, SHIP2 and SHIP3 are the oldest in the fleet.

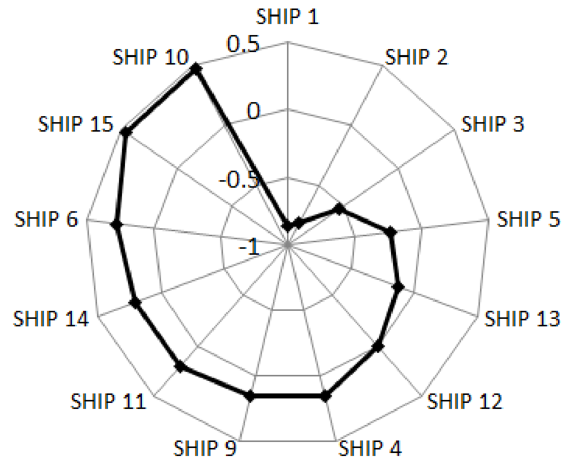

Figure 11. PROMETHEE classification of ship performance

Both models, the DEA and MCDA are bringing different information at different levels.

MCDA model is applied at the ship level. The outranking flow will depend on weights applied to each criterion. A ship will have the best rank if it maximizes each measured criterion. This explains why SHIP1, which is performing badly in almost all KPIs, is obtaining the worst position in the ranking, e.g. it is an old ship which has a poor propulsion efficiency, high consumption and high emissions.

In contrast, DEA gave an outranking of the fleet depending on how the ships are performing, i.e. how the ships are using the input to give a maximum of outputs. In that case SHIP1 is close to the DEA frontier which means that it is one of the best alternatives. Therefore, even if SHIP1 is an old ship, with poor efficiency, high consumption and high emission, it uses efficiently the given input to provide the outputs (DEA frontier).

Another interesting outcome of the study can be highlighted looking at SHIP5 that is one of the youngest ship in the fleet. However, it is ranked in last position in DEA model and amongst the worst in MCDA model. An analysis of MCDA model shows that SHIP5 has low propulsion efficiency, high consumption and high level of emissions. In addition, it can be concluded from the DEA model that SHIP5 does not efficiently use the input to maximize the creation of outputs. This means that both models indicate that this ship is has bad performances.

Hence, if the shipowner should sell one ship, the preference to sell will not go to the oldest ships (e.g. SHIP1, SHIP2 or SHIP3), but rather on one ship that is performing badly (e.g. SHIP 5).

From this analysis we conclude that both models are making sense and can help the decision making of shipowners and operators.

Voyage Level

Figure 12 represents the results of output-oriented DEA methodology for both ballast and laden conditions gathered by voyage. As an example, consecutive voyages of SHIP9 have been plotted. That represents a time frame of 2.5 years. Ship efficiency performance is clearly degraded after voyages and faster for ballast condition than for laden condition. In average, we observe a loss of 2% of efficiency in about 20 voyages.

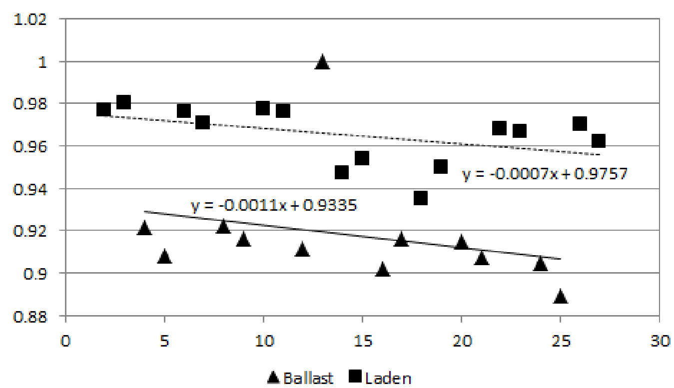

Figure 12. DEA classification of ship efficiency indicator for SHIP9 in ballast and laden conditions

One reason to explain this efficiency reduction is that hull surface condition due to fouling has a major influence on power demand and consequently in ship performance. That directly depends on ship age and date of the last hull maintenance. Therefore, various maintenance policies could be applied to try to recover a part of the lost efficiency. For instance, the shipowner can try to change the frequency of hull fairing or order an underwater propeller cleaning.

CONCLUSIONS AND FUTURE WORK

Shipowners and ship operators are constantly seeking to raise their profit margins and reduce their risks. Better use of the resources involved in the ship operation, i.e. maximizing outputs while keeping input constants, is therefore a solution that can be considered to solve this issue.

A methodology to outrank the efficiency of various ships in a fleet has been introduced in this paper using both DEA and MCDA. This provides a way to compare similar and dissimilar ship types and size during their operation. MCDA have been applied at the ship level while DEA has been applied at the route point level.

The results show that the two models are bringing different level of information. MCDA will give an outranking of the fleet where the best alternative is represented by the ship which is performing well in almost all KPIs. While DEA gives an outranking of the fleet depending on how the ships are performing, i.e. how the ships are using the input to give the outputs. We discussed that both models are making sense and can help the decision making of the shipowners and operators.

A future work that will focus the development of time depends on KPIs that will allow to follow the ship efficiency over time. This is important to take into account the various contingency methods used to try to recover a part of the fleet efficiency such as maintenance policies, dry docking frequency, etc. Robustness of the model will also be tested deeper with the use of bootstrapping methods.

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REFERENCES

Aas, Bjornar, Oyvind Halskau, and Stei Wallace. "The role of supply vessels in offshore logistics." *Maritime Economics and Logistics*, SEPTEMBER de 2009: 302-325.

Acciaro, Michele, Peter Nyegaard Hoffmann, and Magnus Strandmyr Eide. "The Energy Efficiency Gap in Maritime Transport." *Journal of Shipping and Ocean Engineering*, 2013: 1-10.

Acomi, Nicoleta , and Ovidiu Cristian Acomi. "Improving the Voyage Energy Efficiency by Using EEOI." *Procedia - Social and Behavioral Sciences* , JULY de 2014: 531 - 536.

Ballou, Philip J. "Ship Energy Efficiency Management Requires a Total Solution Approach." *Marine Technology Society Journal*, 2013: 83-95.

Banker, Rajiv D., A. Charnes, and W. W. Cooper. "Some models for the estimation of technical and scale inefficiencies in Data Envelopment Analysis." *Management Science* 30, nº 9 (September 1984): 1078–1092.

Barrass, Bryan . "Power coefficients on ships." Em *Ship Design and Performance for Masters and Mates*, 74-81. Oxford: BUTTERWORTH HEINEMANN, 2004.

Brans, Jean-Pierre, and Bertrand Mareschal. "How to Decide with PROMETHEE." *ULB and VUB Brussels Free Universities*, 1994.

Brons, Martijn , Peter Nijkamp, Eric Pels, and Piet Rietveld. "Efficiency of urban public transit: A meta analysis." *Transportation*, 2005: 1-21.

Caprace, J. -D., and J. R. C. Coronel. "Measuring the efficiency of a ship fleet." *Libro de Ponencias y Conferencias del XXIII Congreso Panamericano de Ingenieria Naval, Costa Afuera and Ingenieria Portuaria COPINAVAL 2013*. Margarita: IPEN, 2013. 665-679.

Charnes, A. , W.W. Cooper, and E. Rhodes. “Measuring the efficiency of decision making units .” *European Journal of Operational Research*, 1978: 429 - 444.

Chen, Yao . “Productivity of Automobile Industries using the Malmquist Index: Evidence from the Last Economic Recession.” *Journal of CENTRUM Cathedra: The Business and Economics Research Journal*, 2011: 165-181.

Cooper, David . *Quantification of emissions from ships associated with ship movements between ports in the European Community.* FINAL REPORT, Goteborg: IVL - Swedish Environmental Research Institute Ltd., 2002.

Corbett, James J., Haifeng Wang, and James J. Winebrake. “The effectiveness and costs of speed reductions on emissions from international shipping .” *Transportation Research Part D: Transport and Environment*, 2009: 593 - 598.

EMSA. *Air pollution - SOx and NOx.* 2012. http://www.emsa.europa.eu/main/air-pollution.html.

EPA, Environmental Protection Agency. *Control of Emissions from Compression-Ignition Marine Diesel Engines At or Above 30 Liters per Cylinder.* U.S. Environmental Protection Agency, 2002.

Etzkorn, Ben. “Data Normalization and Standardization.” *BEBLOG FINANCE THOUGHTS.* NOVEMBER de 2011. http://www.benetzkorn.com/2011/11/data-normalization-and-standardization/.

European Environment Agency. *EMEP/EEA air pollutant emission inventory guidebook.* Technical Report, European Environment Agency, 2009.

Eyring, Veronika, et al. “Transport impacts on atmosphere and climate: Shipping .” *Atmospheric Environment*, 2010: 4735 - 4771.

Franco, L. Alberto, and Gilberto Montibeller. *Problem structuring for multi-criteria decision analysis interventions.* Operational Research Group, Department of Management London School of Economics and Political Science, 2009.

ICS, BIMCO, Intercargo, INTERTANKO and OCIMF. *MANAGEMENT TOOL ON ENERGY EFFICIENCY FOR SHIPS - Guidance on the Development of a Ship Efficiency Management Plan.* Tech. Rep. 6, International Maritime Organization, 2009.

IMO. *Guidelines for Voluntary Use of the Ship Energy Efficiency Operational Indicator (EEOI).* Technical Report, IMO - International Maritime Organization, 2009.

ISO. “Ships and marine technology -- Guidelines for the assessment of speed and power performance by analysis of speed trial data.” Em *ISO 15016:2015*, por ISO. ISO, 2002.

Jamnia, A.R. , S.M. Mazloumzadeh, and A.A. Keikha. “Estimate the technical efficiency of fishing vessels operating in Chabahar region, Southern Iran .” *Journal of the Saudi Society of Agricultural Sciences*, 2015: 26 - 32.

Johnson, Hannes, and Linda Styhre. “Increased energy efficiency in short sea shipping through decreased time in port .” *Transportation Research Part A: Policy and Practice*, JANUARY de 2015: 167 - 178.

Kerstens, K. “Technical efficiency measurement and explanation of French urban transit companies.” *Transportation Research Part A: Policy and Practice*, NOVEMBER de 1996: 431 - 452.

Koelher, H. “NOx Emissions from Oceangoing Ships: Calculation and Evaluation.” *ICES03 -- Spring Technical Conference of the ASME Internal Combustion Engine Division.* Salzburg, Austria: ASME, 2003. 255-261.

Lan, Lawrence W., and Erwin T. J. Lin. “Technical efficiency and service effectiveness for railways industry: DEA approaches.” *Journal of the Eastern Asia Society for Transportation Studies*, OCTOBER de 2003: 2934-2947.

Liang, Gin-Shuh , Chin-Feng Liu, and Wen-Cheng Lin. “A Data Envelopment Analysis of Shipping Industry Bond Ratings.” *Tamkang Journal of Science and Engineering*, 2006: 403-408.

Mabin, Vicky , and Michael Beattie. *A Practical Guide to Multi-Criteria Decision Analysis.* Wellington, New Zeland: Victoria University of Wellington, 2006.

Oliveira, Manuela M., Ana S. Camanho, and Miguel B. Gaspar. “Technical and economic efficiency analysis of the Portuguese artisanal dredge fleet.” *ICES Journal of Marine Science*, 2010: 1811 - 1821.

Pedersen, Michael F. *International: IMO Marine Engine Regulations.* SEPTEMBER de 2011. https://www.dieselnet.com/standards/inter/imo.php.

Pundt, Lennart. “Development of an On-board Performance and Trial Trip Analysis Tool.” *10th International Conference on Computer and IT Applications in the Maritime Industries.* 2011.

RTI, International Research Triangle Park. *Global Trade and Fuels Assessment -- Future Trends and Effects of Requiring Clean Fuels in the Marine Sector.* MA-USA: United States Environments Protection Agency, 2008.

Salonen, Sami , Aatos Heikkinen, and Tero Ilus. “Estimating Vessel Emissions and Efficiency A Data Driven Approach.” *Proceedings of COMPIT12.* LIEGE, BELGIUM: COMPIT, 2012. 269-283.

Tomic , Vojislav , Zoran Marinkovic, and Dragoslav Janosevic. “PROMETHEE method implementation with Multi-criteria decisions.” *Mechanical Engineering*, 2011: 193-202.

Wanke, Peter F. . “Efficiency of Brazil's airports: Evidences from bootstrapped DEA and FDH estimates.” *Journal of Air Transport Management*, 2012: 47 - 53.