NETWORK DEA APPROACH TO ASSESSING THE EFFICIENCY OF SHIPS PROCESSING AT A CONTAINER TERMINAL

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ABSTRACT

The processing of ships at a container terminal is divided into two stages, namely Berthing and Loading/Unloading. Both stages use labor and time as inputs. The Loading/Unloading stage also uses other resources, such as Quay and Stacking Cranes and other material handling equipment. Each stage has its own outputs. Thus, the outputs of the Berthing stage are the ship characteristic data, such as the Tonnage, Length and Depth. The single output of the Loading/Unloading stage is the number of TEUs loaded and unloaded. An input-oriented, parallel-process network DEA model is proposed to compute the overall system technical efficiency together with labor and time targets. A cost minimization network DEA model is also proposed so that the cost efficiency of previous ships processing can be assessed and a minimum cost resource allocation can be computed for an arriving ship. The proposed approach is illustrated on a real-world dataset.

Keywords: ship calls, time in port, network DEA, cost efficiency

1. INTRODUCTION

Data Envelopment Analysis (DEA) is a non-parametric technique widely used to assess the relative efficiency of a set of comparable units referred as Decision Making Units (DMUs). DMUs use certain inputs to produce certain outputs. There are many studies that have used DEA to study the efficiency and productivity change of seaports and container terminals (e.g. Barros 2006; Wang and Cullinane 2006; Lin and Tseng 2007; Lozano 2009; Lozano et al. 2011; Barros et al. 2012, Bang et al. 2012; Chang 2013; etc). DEA has also been used to measure the efficiency and productivity change of shipping companies and container shipping lines (Managi 2007, Gutiérrez et al. 2014) as well as the performance of shipbuilding yards (Pires and Lamb 2008). There are not however, to the best of our knowledge, DEA studies of the efficiency with which individual ships are processed at container terminals.

In this paper a DEA approach is proposed to assess the efficiency of these port operations. Specifically, a network DEA approach is used. Contrary to conventional DEA, which considers a DMU as a single, aggregated process (like a black box), network DEA considers different stages or sub-processes within the DMU, each stage consuming its own inputs and producing its own outputs and, in some cases, with internal flows between the stages. The literature on the theory of network DEA has grown rapidly in the last few years (e.g. Kao 2009a, 2009b; Tone and Tsutsui 2009, 2014; Fukuyama and Weber 2010; Lozano, 2011; Lozano et al. 2013, etc). The applications of network DEA have also increased, including transportation, with the most relevant being the two-stage supply chain model for measuring container terminal efficiency of Bichou (2011) and the two-stage network DEA approach to container shipping lines of Lozano et al. (2012).

The structure of the paper is the following. In Section 2, the proposed parallel-processes network DEA approach is presented and the corresponding technical efficiency model formulated. In Section 3, a minimum cost network DEA model is also introduced with the aim of estimating the optimal resource allocation and time-in-port for an arriving ship. Section 4 presents the results of the application of the proposed approach to a real-world dataset. Finally, in Section 5, the main conclusions of the study are drawn and further research outlined.

2. PROPOSED PARALLEL-PROCESSES NETWORK DEA APPROACH

In this section, a parallel-processes network DEA approach to container ships processing is presented. It considers that the processing of a container ship consists of two stages: Berthing (B) and Loading/Unloading (L/U). Although these two stages occur sequentially within the temporal dimension the corresponding network approach is deemed a parallel-processes one in the sense that the two stages have common inputs but there are no intermediate products that are produced in one stage and consumed in another. Thus, as shown in Figure 1, both Stages B and L/U use LABOR and TIME inputs. In addition, Stage L/U uses Quay Cranes (QCRANES), Stacking Cranes (SCRANES) and Automated Guided Vehicles or similar Shuttle Vehicles (SHUTTLES). In addition, Stage L/U consumes storage space. This is included through a non-discretionary input that represents Storage Space Availability (AVAILSS). Other resources used in either stage may be included if the corresponding data are available although that is not necessary if the amount of the resource consumed by a ship is constant for all ships (e.g. if one tug is used by every ship). With respect to the outputs of each stage, those of Berthing are the main data about the characteristics of the ship such as Gross Register Tonnage (TONNAGE), LENGTH and DEPTH while the output of Loading/Unloading is the total number of TEUs loaded and unloaded. The outputs of both stages are non-discretionary and, together with the non-discretionary input AVAILSS, can be handled as proposed in Banker and Morey (1986).

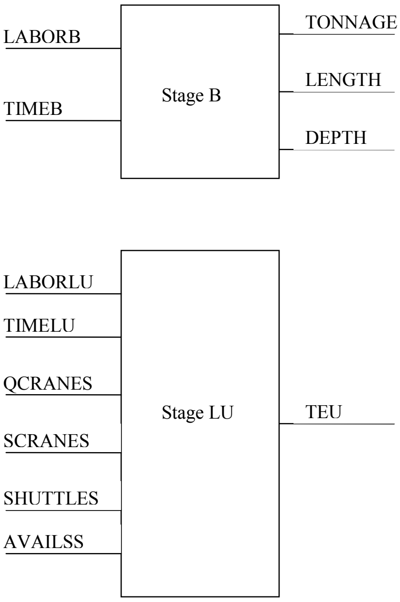

Figure 1. Inputs and outputs of Berthing and Loading/Unloading stages of a ship call

A conventional DEA approach would consider a single, aggregate process as shown in Figure 2 where LABOR and TIME correspond respectively to the total labor and time inputs of a ship, i.e. the sum of those of its two stages.

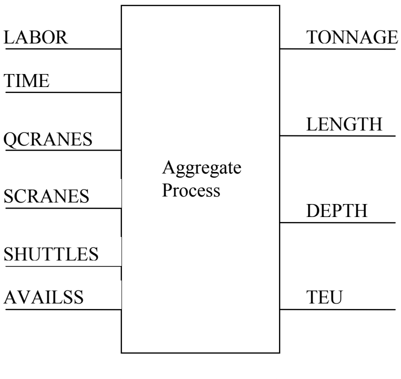

Figure 2: Inputs and outputs of a ship call considered as a single process

Before formulating the proposed input-oriented relational DEA model, let

n	number of DMUs
$j,J=1,2,\ldots,n$	indexes on the DMUs
$LABORB_j$	input LABOR of stage B of DMU j
$TIMEB_j$	input TIME of stage B of DMU j
$LABORLU_j$	input LABOR of stage LU of DMU j
$TIMELU_j$	input TIME of stage LU of DMU j
$QCRANES_j$	input QCRANES of stage LU of DMU j
$SCRANES_j$	input SCRANES of stage LU of DMU j
$SHUTTLES_j$	input SHUTTLES of stage LU DMU j
$AVAILSS_j$	non-discretionary input AVAILSS of stage LU of DMU j
$TONNAGE_j$	non-discretionary output TONNAGE of stage B of DMU j
$LENGTH_j$	value of the non-discretionary output LENGTH of stage B of DMU j
$DEPTH_j$	value of the non-discretionary output DEPTH of stage B of DMU j
TEU_j	value of the non-discretionary output TEU of stage LU of DMU j

The corresponding input-oriented Variable Returns to Scale (VRS) single-process (SP) DEA model for a certain DMU 0 is

SP DEA model

$$\text{Min} \quad \theta_0^{SP}$$

s.t.

$$\sum_{j=1}^{n} \eta_j \cdot LABOR_j \le \theta_0^{SP} \cdot LABOR_0$$

$$\sum_{j=1}^{n} \eta_j \cdot TIME_j \le \theta_0^{SP} \cdot TIME_0$$

$$\sum_{j=1}^{n} \eta_j \cdot QCRANES_j \le \theta_0^{SP} \cdot QCRANES_0 \qquad (1)$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{SCRANES}_j \leq \theta_0^{SP} \cdot \mathrm{SCRANES}_0$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{SHUTTLES}_j \leq \theta_0^{SP} \cdot \mathrm{SHUTTLES}_0$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{AVAILSS}_j \leq \mathrm{AVAILSS}_0$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{TONNAGE}_j \geq \mathrm{TONNAGE}_0$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{LENGTH}_j \geq \mathrm{LENGTH}_0$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{DEPTH}_j \geq \mathrm{DEPTH}_0$$

$$\sum_{j=1}^{n} \eta_j \cdot \mathrm{TEU}_j \geq \mathrm{TEU}_0$$

$$\sum_{j=1}^{n} \eta_j = 1$$

$$\eta_j \geq 0 \quad \forall j \qquad \theta_0^{SP} \text{ free}$$

An alternative DEA approach would be to consider the two stages B and LU separately and assess their efficiency as if they were independent processes. The corresponding input-oriented DEA models would be

Stage B DEA model

$$\text{Min} \quad \theta_0^{B}$$

s.t.

$$\sum_{j=1}^{n} \lambda_j \cdot \mathrm{LABORB}_j \leq \theta_0^{B} \cdot \mathrm{LABORB}_0$$

$$\sum_{j=1}^{n} \lambda_j \cdot \mathrm{TIMEB}_j \leq \theta_0^{B} \cdot \mathrm{TIMEB}_0$$

$$\sum_{j=1}^{n} \lambda_j \cdot \mathrm{TONNAGE}_j \geq \mathrm{TONNAGE}_0 \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j \cdot \mathrm{LENGTH}_j \geq \mathrm{LENGTH}_0$$

$$\sum_{j=1}^{n} \lambda_j \cdot \mathrm{DEPTH}_j \geq \mathrm{DEPTH}_0$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \quad \forall j \qquad \theta_0^{B} \text{ free}$$

Stage LU DEA model

$$\text{Min} \quad \theta_0^{LU}$$

s.t.

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{LABORLU}_j \leq \theta_0^{LU} \cdot \mathrm{LABORLU}_0$$

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{TIMELU}_j \leq \theta_0^{LU} \cdot \mathrm{TIMELU}_0$$

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{QCRANES}_j \leq \theta_0^{LU} \cdot \mathrm{QCRANES}_0$$

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{SCRANES}_j \leq \theta_0^{LU} \cdot \mathrm{SCRANES}_0 \tag{3}$$

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{SHUTTLES}_j \leq \theta_0^{LU} \cdot \mathrm{SHUTTLES}_0$$

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{AVAILSS}_j \leq \mathrm{AVAILSS}_0$$

$$\sum_{j=1}^{n} \mu_j \cdot \mathrm{TEU}_j \geq \mathrm{TEU}_0$$

$$\sum_{j=1}^{n} \mu_j = 1$$

$$\mu_j \geq 0 \quad \forall j \qquad \theta_0^{LU} \text{ free}$$

Finally, the proposed parallel-processes network DEA approach jointly considers the B and LU stages, aiming at reducing the total inputs consumed by both stages (see Kao 2009b). The corresponding input-oriented, VRS model is

Network DEA (NDEA) model

$$
\begin{aligned}
&\text{Min} \quad \theta_0^{NDEA} \\
&\text{s.t.} \\
&\sum_{j=1}^{n} \lambda_j \cdot TIMEB_j + \sum_{j=1}^{n} \mu_j \cdot TIMELU_j \\
&\qquad \le \theta_0^{NDEA} \cdot TIME_0 \\
&\sum_{j=1}^{n} \lambda_j \cdot LABORB_j + \sum_{j=1}^{n} \mu_j \cdot LABORLU_j \\
&\qquad \le \theta_0^{NDEA} \cdot LABOR_0 \\
&\sum_{j=1}^{n} \mu_j \cdot SCRANES_j \le \theta_0^{NDEA} \cdot SCRANES_0 \\
&\sum_{j=1}^{n} \mu_j \cdot SHUTTLES_j \le \theta_0^{NDEA} \cdot SHUTTLES_0 \\
&\sum_{j=1}^{n} \mu_j \cdot AVAILSS_j \le AVAILSS_0 \qquad (4) \\
&\sum_{j=1}^{n} \lambda_j \cdot TONNAGE_j \ge TONNAGE_0 \\
&\sum_{j=1}^{n} \lambda_j \cdot LENGTH_j \ge LENGTH_0 \\
&\sum_{j=1}^{n} \lambda_j \cdot DEPTH_j \ge DEPTH_0 \\
&\sum_{j=1}^{n} \mu_j \cdot QCRANES_j \le \theta_0^{NDEA} \cdot QCRANES_0 \\
&\sum_{j=1}^{n} \mu_j \cdot TEU_j \ge TEU_0 \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\sum_{j=1}^{n} \mu_j = 1 \\
&\lambda_j \ge 0 \quad \forall j \quad \mu_j \ge 0 \quad \forall j \qquad \theta_0^{NDEA} \text{ free}
\end{aligned}
$$

On the one hand, although this model decreases the total LABOR and TIME inputs of the two stages, as does the SP DEA model (1), it uses different intensity variables for each stage (λ_j,μ_j) instead of just one set of intensity variables (η_j) as in the SP DEA model. On the other hand, although the proposed NDEA model uses different intensity variables for each stage as do the separate models of each stage (2) and (3), it computes a single efficiency score for the whole system (as does also the SP DEA model) instead of two efficiency scores, one for each stage. Therefore, in some sense, the NDEA model is in between the other two approaches. Note also that all three models treat the non-discretionary input and outputs in the same manner.

3. MINIMUM COST NETWORK DEA MODEL

In this section the network DEA approach is extended so that a minimum cost model is formulated. It is assumed that the unit cost of each input of each stage is known so that the model computes the optimal resource level for each stage given the value of the outputs, i.e. given the ship characteristics and the number of TEUs to be loaded/unloaded. In particular, since the durations of the two stages are among the inputs that are computed, the model determines the optimal time-in-port value. The idea is to apply this model to plan in advance and optimally allocate the resources required for the processing of an arriving ship whose characteristics and cargo requirements are known.

Let

Data

LABORCOST	cost per unit of input LABOR (LABOR measured in man•hours)
TIMECOST	cost per unit of input TIME
QCRANESCOST	cost per unit of input QCRANES per unit of time
SCRANESCOST	cost per unit of input SCRANES per unit of time
SHUTTLESCOST	cost per unit of input SHUTTLES per unit of time
AVAILSS	value of the non-discretionary input AVAILSS of arriving ship
TONNAGE	value of the non-discretionary output TONNAGE of arriving ship
LENGTH	value of the non-discretionary output LENGTH of arriving ship
DEPTH	value of the non-discretionary output DEPTH of arriving ship
TEU	value of the non-discretionary output TEU of arriving ship

Variables

TLABORB	optimal value of input LABOR of stage B for arriving ship
TTIMEB	optimal value of input TIME of stage B for arriving ship
TLABORLU	optimal value of input LABOR of stage LU for arriving ship

TTIMELU	optimal value of input TIME of stage LU for arriving ship
TQCRANES	optimal value of input QCRANES for arriving ship
TSCRANES	optimal value of input SCRANES for arriving ship
TSHUTTLES	optimal value of input SHUTTLES for arriving ship

Note that in the case of the cranes and shuttle vehicles the above cost coefficients are per unit of time. This means that, if the corresponding input data represent the number of cranes and vehicles used, in order to compute the cost incurred due to these concepts it is necessary to multiply by the duration of the L/U stage, which would make the proposed model a quadratic, albeit easy-to-solve, optimization problem. On the contrary, if the corresponding input data already represent cumulative usage time of cranes and vehicles (i.e. cranes•hours and vehicles•hours) then the model is an ordinary Linear Programming optimization problem. Below the two alternative objective functions corresponding to both cases are formulated.

$$\begin{aligned} \text{Min} \\ & \text{LABORCOST}\cdot(\text{TLABORB}+\text{TLABORLU})+ \\ & +\text{TIMECOST}\cdot(\text{TTIMEB}+\text{TTIMELU})+ \\ & +\text{QCRANESCOST}\cdot\text{TTIMELU}\cdot\text{TQCRANES}+ \\ & +\text{SCRANESCOST}\cdot\text{TTIMELU}\cdot\text{TSCRANES}+ \\ & +\text{SHUTTLESCOST}\cdot\text{TTIMELU}\cdot\text{TSHUTTLES} \end{aligned}$$

or

$$\begin{aligned} \text{Min} \\ & \text{LABORCOST}\cdot(\text{TLABORB}+\text{TLABORLU})+ \\ & +\text{TIMECOST}\cdot(\text{TTIMEB}+\text{TTIMELU})+ \\ & +\text{QCRANESCOST}\cdot\text{TQCRANES}+ \\ & +\text{SCRANESCOST}\cdot\text{TSCRANES}+ \\ & +\text{SHUTTLESCOST}\cdot\text{TSHUTTLES} \end{aligned}$$

s.t.

$$\sum_{j=1}^{n}\lambda_j\cdot\text{LABORB}_j\le\text{TLABORB}$$

$$\sum_{j=1}^{n}\lambda_j\cdot\text{TIMEB}_j\le\text{TTIMEB}$$

$$\sum_{j=1}^{n}\lambda_j\cdot\text{TONNAGE}_j\ge\text{TONNAGE} \tag{5}$$

$$\sum_{j=1}^{n}\lambda_j\cdot\text{LENGTH}_j\ge\text{LENGTH}$$

$$\sum_{j=1}^{n}\lambda_j\cdot\text{DEPTH}_j\ge\text{DEPTH}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{TIMELU}_j\le\text{TTIMELU}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{LABORLU}_j\le\text{TLABORLU}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{QCRANES}_j\le\text{TQCRANES}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{SCRANES}_j\le\text{TSCRANES}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{SHUTTLES}_j\le\text{TSHUTTLES}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{AVAILSS}_j\le\text{AVAILSS}$$

$$\sum_{j=1}^{n}\mu_j\cdot\text{TEU}_j\ge\text{TEU}$$

$$\sum_{j=1}^{n}\lambda_j=1$$

$$\sum_{j=1}^{n}\mu_j=1$$

$$\lambda_j\ge 0\quad\forall j\quad\mu_j\ge 0\quad\forall j$$

Note that although in principle the solution to this minimum cost network DEA model gives the same solution that would be obtained solving a separate minimum cost DEA model for each stage, the network DEA approach is more general and allows for the inclusion of additional constraints involving the allocation of the shared resources. Thus, for example, maximum and/or minimum total LABOR and/or TIME constraints can be imposed, i.e.

$$\text{LABORLOWERBOUND}\le\text{TLABORB}+\text{TLABORLU}$$

$$\text{LABORUPPERBOUND}\ge\text{TLABORB}+\text{TLABORLU}$$

$$\text{TIMELOWERBOUND}\le\text{TTIMEB}+\text{TTIMELU}$$

$$\text{TIMEUPPERBOUND}\ge\text{TTIMEB}+\text{TTIMELU}$$

or constraints on the relative allocation of resources to the two stages can be imposed, i.e.

$$\text{RELLABORLOWERBOUND} \leq \frac{\text{TLABORB}}{\text{TLABORLU}}$$

$$\text{RELLABORUPPERBOUND} \geq \frac{\text{TLABORB}}{\text{TLABORLU}}$$

$$\text{RELTIMELOWERBOUND} \leq \frac{\text{TTIMEB}}{\text{TTIMELU}}$$

$$\text{RELTIMEUPPERBOUND} \geq \frac{\text{TTIMEB}}{\text{TTIMELU}} \leq$$

Take into account, however, that these or other possible joint constraints should only be used when there are enough reasons to impose them, since they generally reduce the feasibility region of the model and therefore increase the minimum cost of the optimal solution.

4. APPLICATION OF PROPOSED APPROACH TO CONTAINER TERMINAL OF BUENAVENTURA

In this section the results of the application of the proposed approach to a dataset comprising 46 ship calls that took place in a two-month period at the container terminal of Buenaventura, Colombia, are presented. The inputs and outputs considered are the ones mentioned in the previous section except that:

- the number of SHUTTLES used was not available and
- since in all cases in the sample two QCRANES were used and since VRS is assumed it was decided to exclude that constant input from the analysis

Therefore, stage B used two inputs and produced three non-discretionary outputs and stage L/U used four inputs (one of them non-discretionary) and produced one non-discretionary output. Tables 1 and show the input-oriented, VRS technical efficiency scores computed using the models of Section 2. Note that the results of the different models are rather consistent, with the SP approach having the least discriminant power of the three DEA approaches. Thus, SP has the highest average efficiency score and labels as many as 29 DMUs as technically efficient. The separate assessment of the efficiency of the two stages identifies 17 cases of stage B efficiency and 15 cases of stage L/U efficiency. Finally, the RN DEA approach identifies just 12 DMUs as technical efficient. Except in the cases of DMUs 25 and 39, min (θ_0^{B} , θ_0^{LU}) ≤ θ_0^{NDEA} ≤ max (θ_0^{B} , θ_0^{LU}) with θ_0^{RN} generally closer to θ_0^{LU} than to θ_0^{B}.

Table 1: Results of Stage B and Stage LU DEA Models

DMU	θ_0^{B} (%)	θ_0^{LU} (%)
1	**100.0**	72.4
2	95.4	83.3
3	**100.0**	84.6
4	**100.0**	**100.0**
5	69.6	86.5
6	81.6	**100.0**
7	74.4	81.6
8	72.4	83.9
9	75.1	**100.0**
10	89.0	81.3
11	**100.0**	**100.0**
12	92.2	77.7
13	97.5	68.1
14	77.7	84.7
15	76.3	99.0
16	**100.0**	80.9
17	89.9	84.4
18	90.1	**100.0**
19	95.1	63.3
20	78.6	**100.0**
21	100.0	80.6
22	93.2	80.1
23	77.9	84.7
24	**100.0**	62.9
25	88.8	90.6
26	**100.0**	72.6
27	90.9	82.8
28	**100.0**	**100.0**
29	77.7	**100.0**
30	87.9	**100.0**
31	62.4	**100.0**
32	56.3	89.3
33	99.8	77.8
34	**100.0**	**100.0**
35	**100.0**	75.7
36	89.8	99.7
37	**100.0**	81.3
38	**100.0**	**100.0**
39	89.9	82.8
40	**100.0**	**100.0**
41	**100.0**	94.4
42	**100.0**	**100.0**
43	**100.0**	83.9
44	85.9	96.6
45	66.6	84.7
46	71.9	**100.0**
Average	*89.0*	*88.1*

The correlation coefficient between θ_0^{RN} and θ_0^{LU} is 0.974 while that between θ_0^{RN} and θ_0^{B} is -0.106. The correlation coefficient between θ_0^{NDEA} and θ_0^{SP} is intermediate, 0.589, positive but not too high. Note that $\theta_0^{NDEA}=1$ whenever the two stages are assessed as efficient, i.e. $\theta_0^{B}=\theta_0^{LU}=1$, something which occurs to DMUS 4, 11, 28, 34, 38, 40 and 42.

Table 2: Results of SP and Network DEA Models

DMU	θ_0^{SP} (%)	θ_0^{NDEA} (%)
1	96.5	76.1
2	**100.0**	84.3
3	**100.0**	86.2
4	**100.0**	**100.0**
5	90.0	82.6
6	**100.0**	96.4
7	82.4	80.3
8	93.5	81.2
9	**100.0**	**100.0**
10	88.1	82.7
11	**100.0**	**100.0**
12	85.9	79.4
13	90.8	71.7
14	**100.0**	84.7
15	**100.0**	91.4
16	**100.0**	82.4
17	95.4	85.0
18	**100.0**	99.2
19	70.6	67.2
20	**100.0**	**100.0**
21	91.7	83.0
22	97.8	81.8
23	85.6	83.9
24	**100.0**	70.6
25	**100.0**	88.5
26	**100.0**	79.7
27	87.1	83.5
28	**100.0**	**100.0**
29	**100.0**	**100.0**
30	**100.0**	**100.0**
31	**100.0**	**100.0**
32	91.4	84.6
33	89.3	82.0
34	**100.0**	**100.0**
35	94.4	76.0
36	**100.0**	97.1
37	**100.0**	83.6
38	**100.0**	**100.0**
39	**100.0**	82.3
40	**100.0**	**100.0**
41	95.7	94.6
42	**100.0**	**100.0**
43	**100.0**	87.6
44	**100.0**	96.6
45	**100.0**	81.9
46	**100.0**	98.7
Average	*96.2*	*88.4*

Although it can be concluded that all the models agree that, in general, there are no significant technical inefficiencies, a minimum cost analysis can detect whether cost inefficiencies exist. To that end the minimum cost network DEA model of section 3 has been applied to each DMU. The estimated unit cost coefficients used are 10\$/man·hour for LABORCOST, 20\$/hour gross Ton for TIMECOST and 25\$/hour for SCRANESCOST.

Table 3 Cost Efficiency of Observed DMUs

	Cost		
DMU	Observed	Minimum	Cost Eff. (%)
1	13,666	8,643	63.2
2	22,394	16,451	73.5
3	26,488	12,817	48.4
4	17,195	10,188	59.2
5	14,094	10,930	77.5
6	10,678	10,172	95.3
7	8,934	5,927	66.3
8	11,305	8,478	75.0
9	14,177	13,386	94.4
10	14,681	8,882	60.5
11	26,804	18,122	67.6
12	12,514	8,917	71.3
13	19,890	11,414	57.4
14	18,675	12,126	64.9
15	14,200	11,581	81.6
16	28,155	13,407	47.6
17	14,793	11,361	76.8
18	7,807	7,355	94.2
19	11,479	6,116	53.3
20	11,767	11,155	94.8
21	11,166	8,759	78.4
22	16,881	11,403	67.5
23	22,937	10,817	47.2
24	22,178	12,646	57.0
25	19,717	15,506	78.6
26	19,590	12,577	64.2
27	7,866	5,832	74.1
28	**24,120**	**24,120**	**100.0**
29	22,220	21,531	96.9
30	10,683	10,272	96.2
31	13,027	10,556	81.0
32	11,065	8,397	75.9
33	12,208	8,660	70.9
34	14,604	12,012	82.3
35	28,270	12,661	44.8
36	12,296	9,117	74.1
37	26,668	17,131	64.2
38	23,418	22,566	96.4
39	19,471	14,706	75.5
40	23,638	17,286	73.1
41	24,449	16,559	67.7
42	11,555	10,004	86.6
43	16,913	13,362	79.0
44	11,339	9,998	88.2
45	22,118	13,507	61.1
46	13,316	12,429	93.3
Sum	781,410	559,839	-
Savings = 221,571 *\$*			
Savings = 28.4 *%*			
Savings = 4,817 *\$ per DMU*			
Savings = 15.8 *\$ per TEU*			

Table 3 shows the costs originally incurred (for the given concepts), the minimum cost computed by the proposed network DEA approach and the corresponding cost efficiency. Note that of the 12 DMUs that were labelled technically efficient only DMU 28 is cost efficient. The average cost efficiency is 73.9%.

Note also that not only this minimum cost model but all the other models compute, in addition to the efficiency scores, appropriate target levels for the controllable inputs. Thus, for example, Table 4 shows the value of the targets computed by the minimum cost network DEA model. Unlike the technical efficiency approach, the minimum cost feasibility region is not constrained to those operating points that use less inputs but it can, if it is cost-effective, increase some inputs and reduce others. In addition, the minimum cost approach exhaust all possible slacks that the input-oriented radial efficiency score usually leaves unaccounted for. As shown in the table, the minimum cost efficiency approach could have obtained a 28.4% cost reduction for the DMUs in the sample, with total savings of 221,571 $ which represents 4817 per ship and 15.8 $ per TEU.

Table 4 Cost Efficiency of Observed DMUs

	Targets				
DMU	LABORB	TIMEB	LABORLU	TIMELU	SCRANES
1	28.9	3.7	360.3	8.4	7.6
2	28.3	4.4	407.4	10.5	10.4
3	29.6	4.0	387.1	8.7	7.2
4	20.7	3.8	325.6	8.1	8.0
5	24.8	3.9	337.3	8.2	7.9
6	25.7	3.6	348.4	10.9	7.0
7	20.6	3.8	206.9	14.0	6.4
8	24.8	3.7	330.5	8.1	7.9
9	29.6	3.9	348.4	10.9	7.0
10	20.6	3.8	430.3	8.0	9.5
11	28.3	4.4	390.4	12.9	9.5
12	35.2	3.3	378.7	8.6	7.3
13	30.3	4.1	327.5	8.1	8.0
14	30.4	4.3	373.3	8.6	7.4
15	29.7	3.9	371.1	8.5	7.4
16	30.6	4.5	407.8	8.7	9.1
17	28.1	3.9	362.4	8.5	7.5
18	20.6	3.8	327.2	8.1	8.0
19	20.6	3.8	245.8	11.8	7.0
20	27.8	3.9	325.6	8.1	8.0
21	35.8	3.2	365.8	8.5	7.5
22	29.9	4.2	325.6	8.1	8.0
23	20.6	3.8	349.0	11.0	7.1
24	53.0	4.5	380.8	8.7	7.3
25	20.6	3.8	491.9	11.8	12.3
26	60.9	4.7	367.9	8.5	7.5
27	20.6	3.8	159.8	15.4	6.0
28	**37.7**	**4.3**	**398.3**	**22.1**	**13.0**
29	30.7	3.8	473.8	17.3	15.0
30	20.6	3.8	611.4	6.3	13.0
31	26.5	3.9	325.6	8.1	8.0
32	20.6	3.8	325.6	8.1	8.0
33	35.2	3.3	357.7	8.4	7.6
34	31.5	4.1	379.9	7.7	9.0
35	30.1	3.9	404.4	8.9	7.0
36	25.7	3.6	343.4	8.2	7.8
37	34.5	6.5	350.6	14.2	7.6
38	30.6	4.5	346.2	22.4	8.0
39	28.9	4.1	406.8	11.3	10.6
40	26.6	4.1	352.1	18.5	8.2
41	20.6	3.8	354.9	17.4	8.3
42	24.6	3.9	359.5	8.4	7.6
43	41.3	5.7	365.5	8.5	7.5
44	28.1	3.9	326.0	8.1	8.0
45	31.7	4.1	365.1	10.3	7.8
46	28.4	3.9	405.3	8.9	7.0

The results in Table 2 corresponds to the observed DMUs, i.e. they perform an ex-post analysis and show the potential cost reduction that might have occurred if the processing of the different ships had been as the computed targets indicate instead of being the one observed. Although interesting, this analysis is not too useful because it looks into the past which cannot be changed. Much more useful is to apply the proposed approach to a ship that is to arrive and thus estimate ex-ante the amount of resources to allocate given appropriate upper bounds on the durations of the two stages. Thus, for example, assume that a ship with TONNAGE=25,000 Ton, LENGTH=200 m, DEPTH=10 and that plans to load and unload a total of 400 TEU. Assume also that when the ship arrives the storage are free capacity is AVAILSS=2,500. Formulating and solving the minimum cost network DEA model it can be estimated that the ship can be processed in TIMEB=4.18 hours and TIMELU=8.88 hours (i.e. a total time-in-port of 13 hours approximately) allocating LABORB=30 man·hours, LABORLU=406 man·hours and SCRANES=7.6 with an estimated total cost (due to the concepts considered) of 12,564 $.

5. CONCLUSIONS

In this paper, a DEA approach to assessing the technical and cost efficiency of the processing of ships at a container terminal has been proposed. Unlike conventional DEA that looks at a DMU as a black box consisting in a single, aggregate process, a parallel-processes network DEA approach has been used. The two stages considered have been Berthing and Loading/Unloading. Each stage has inputs and outputs, the latter being non-discretionary in nature. Not only can the technical efficiency of the operations be estimated but also its cost efficiency. A most practical feature of the latter approach is that not just the potential cost reductions of past processing can be measured but the resources to assign for processing an expected ship can be computed and the cost of its processing estimated. The results show the usefulness of the proposed approach in analyzing the historic (i.e.

observed) inefficiencies of the terminal operations as well as estimating minimum cost resource requirements and time-in-port of arriving ships.

Of course, the proposed approach has limitations like its being a static analysis which means that the feasibility of the computed target operating points need to be checked using for example discrete-event simulation. Another major limitation, which the reviewers kindly pointed out, is the deterministic nature of the analysis, which therefore ignores the stochastic variability (e.g. variance) of the processing times of common port operations.

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