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Measuring transport systems efficiency under uncertainty by fuzzy sets theory based Data Envelopment Analysis: theoretical and practical comparison with traditional DEA model

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Abstract

In transportation management the measure of systems efficiency is a key issue in order to verify the performances and propose the best countermeasure to achieve the prefixed goals. Many efforts have been made in this field to provide satisfactory answer to this problem. One of the most used methodologies is the Data Envelopment Analysis (DEA) that has been in many fields. The DEA technique is a useful is non-parametric method that allow to handle many output and input at the same time. In many real world applications, input and output data cannot be precisely measured. Imprecision (or approximation) and vagueness may be originated from indirect measurements, model estimation, subjective interpretation, and expert judgment or available information from different sources. Therefore, methodologies that allow the analyst to explicitly deal with imprecise or approximate data are of great interest, especially in freight transport where available data as well as stakeholders' behavior often suffer from vagueness or ambiguity. This is particularly worrying when assessing efficiency with frontier-type models, such as Data Envelopment Analysis (DEA) models, since they are very sensitive to possible imprecision in the data set. In this paper, we have specified a Fuzzy Theory-based DEA model to assess efficiency of transportation systems and services considering uncertainty in data, as well as in the evaluation result. In particular, we have applied the proposed fuzzy DEA model to evaluate the efficiency of a selected set of international container ports. In particular, we focus on the "delay time" that is an important input data that is usually non easy to measure and then is considered as uncertain. Finally, a comparison of ports efficiency obtained by the proposed fuzzy DEA model and traditional DEA has been carried out in order to evaluate the differences between the two methods.

Keywords: DEA; fuzzy DEA; fuzzy set theory; ports efficiency; comparison

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1. Introduction

In the past two decades the steady growth of seaborne trade has resulted in the increase of container ships, container ports and their terminals. Moreover, the structure of the shipping market is continuously evolving. On the carrier side, shipping companies establish consortia and alliances; on the port side, global terminal operators and dedicated container terminals are emerging. Construction, transportation, and port industry, in particular, play an important role in supporting the country's economy.

Port efficiency is an important factor to foster port competitiveness and boost regional development. With growing international sea traffic and changing technology in the maritime transport industry (containerization, integrated logistic services, etc.), seaports are coping with mounting pressures to upgrade and provide cutting-edge technology. They are also being forced to improve port efficiency to provide comparative advantages that will attract more traffic. Some of the key challenges ports are surmounting to secure traffic flows and prevent diversion to nearby ports include handling containers and goods more rapidly, providing more adequate and performing equipment, reducing berth times and delays, enabling large storage capacity and ensuring multi-modal connections to hinterland. The benefits of port efficiency extend beyond traffic volume: they have direct and indirect effects on related activities, such as maritime insurance, finance, and logistics, because of their strategic position in the transport chain. They create value added and employment, which affect the prospect of regional and urban growth.

Port efficiency is often associated with productivity and performance; however, their focus is narrow, measuring operating technology or total traffic volumes of seaports, which are not the only indicators. There are additional factors that are associated with the more organizational side of production, such as how efficiently ports use inputs to produce current output levels and whether the technologies adopted by ports are the most efficient, that are critical to determining port efficiency. Ports form a vital link in the overall trading chain and, consequently, port efficiency is an important contributor to a nation's international competitiveness (Tongzon, 1989; Chin and Tongzon, 1998).

Thus, monitoring and comparing one to other ports in terms of overall efficiency has become an essential part of many countries' microeconomic reform programs. Port efficiency is an important indicator of port performance; more efficient ports lead to lower transportation costs and then more imports and exports of a country. The aim of this research is to evaluate the efficiency of container ports. Different methods to estimate efficiency are available in literature.

A classification of these methods is:

- parametric methods, based on the assumption that the production function of fully efficient firms is known (Coelli, Rao & Battese, 1998); a method is Stochastic Frontier Analysis (SFA) (Aigner, Lovell, & Schmidt, 1977);
- non-parametric methods, based on the assumption that the production function of fully efficient firms is not known; some methods are Data Envelopment Analysis (DEA) (Charnes, Cooper & Rhodes, 1978) and Free Disposal Hull (FDH) (Deprins, Simar, & Tulkens, 1984; Lovell & Eeckaut, 1993);

In this paper we proposed an innovative approach to transport systems efficiency evaluation based on Fuzzy Theory. In particular, we have specified a Fuzzy Data Envelopment Analysis Model (Fuzzy DEA) that allow to deal with uncertain or approximate input and/or output. The model starts from classical DEA that is properly extended to consider uncertain data where uncertain data became fuzzy constraints to the DEA problem and the problem is formulated as fuzzy optimization problem.

The method can be applied to a wide range of transport services. From the experimental standpoint, in this paper we have applied the Fuzzy-DEA to port efficiency evaluation. Several findings can be derived from these analyses. Significant improvements can be made when the technical efficiency of ports is increased. Among the considered ones, gaps between terminal efficiency mostly reflected gaps in pure technical efficiency.

Over the past three decades Data Envelopment Analysis (DEA) has emerged as a useful tool for business entities and organizations to evaluate their activities. Mathematically, DEA is a linear programming-based methodology for evaluating the relative efficiency of a set of decision making units (DMUs) with multi-inputs and multi-outputs.

DEA evaluates the efficiency of each DMU relative to an estimated production possibility frontier determined by all DMUs. The advantage of using DEA is that it does not require any assumption on the shape of the frontier surface and it makes no assumptions concerning the internal operations of a DMU.

There are some limitations of DEA that have to be considered. Because DEA is a methodology focused on frontiers, small changes in data can change efficient frontiers significantly.

Therefore, to successfully apply DEA, accurate measurement of both the inputs and outputs must be available.

The available data used as input and output in real-world problems are sometimes imprecise or vague. Imprecision and vagueness may result from unquantifiable (such as qualitative information), incomplete and non-obtainable/missed information (for example, for confidential constraints).

In recent years, fuzzy set theory has been proven to be useful tool for to handle imprecise data and also in DEA models. Some researchers have proposed various fuzzy methods for dealing with this impreciseness and ambiguity in DEA (Lertworasirikul, 2002). However, there is no universally accepted approach for solving the fuzzy DEA model. In this paper, we used an original approach to deal with DEA with imprecise data.

We have measured efficiency of sixteen international container ports (four Australian and twelve other international container ports) considering six inputs (number of cranes, number of container berths, number of tugs, terminal area, delay time and labor units) and four outputs (TEUs handled, shipcalls, shiprate, crane productivity). In this work we have used the entire data set of Tongzon (2001) to make a real comparison between the classical DEA model and the Fuzzy DEA model that we have developed. In our Fuzzy-DEA model, we have considered the *delay time* as fuzzy input. Membership functions are of triangular shape. Applying this new approach we solve a Fuzzy Theory-based DEA model by developing an *ad hoc* code in the Matlab™ environment that allows to create, edit, and mathematically handle fuzzy numbers.

In addition, to complete our analysis, we performed a comparison of the efficiency values obtained with the traditional DEA model and those obtained with Fuzzy-DEA model. The comparison was made in order to assess whether the presence of a single fuzzy variable (delay time) has a significant effect on the expected results or we need to consider more than a single fuzzy variable for future application in this transportation field.

The rest of the paper is organized as follows. Section 2 gives a brief review of related studies. Section 3 introduces DEA model and develops the Fuzzy Theory-based DEA model built using MATLAB. Section 4 presents the results of empirical study conducted on 16 international container ports and comparison between efficiencies obtained with the application of traditional DEA and our fuzzy DEA model. Conclusions are reported in the final section.

2. Efficiency measurement: literature review

DEA has been used in several contexts including education systems, health care units, agricultural production, transport and military logistics. The application of the method in the transport sector is wide-spread, especially in the evaluation of airports, ports, railways and urban transport companies as we can see in the work of Markovits and Somogyi (2011a).

Some key characteristics of DEA are summarized as follows:

- DEA is used to measure the efficiency of homogeneous units called decision making units (DMUs)
- DEA is a non parametric approach;
- DEA is a fractional mathematical programming technique. However, it can be converted into a linear programming model and solved by a standard LP solver;
- DEA generalizes the concept of a single-input, single-output technical efficiency measure of Farrell (1957) to the multiple-input and multiple-output to a virtual input;
- DEA is an approach focused on frontiers instead of central tendencies;
- DEA determines the relative efficiency at a time over all other DMUs by finding the most favorable weights from the viewpoint of that, target, DMU;
- Alternative for making each inefficient DMU can be by projecting them onto the efficient frontier.

Many applications of DEA can be found in literature. Chu et al. (1992) use DEA to measure efficiency of selected bus transit systems in the United States.

Most of the applications of DEA refers to ports efficiency analysis. Roll and Hayuth (1993) first tried to use DEA model in analyzing the efficiency of container ports. They evaluated the efficiency of 20 virtual ports through DEA with 3 inputs and 4 outputs. Martinez-Budria et al. (1999) classified 26 container ports in Spain into three groups according to the level of complexity based on data from 1993 to 1997 and then evaluated the efficiency of those ports through DEA-BCC model with 3 inputs and 1 outputs. Tongzon (2001) uses DEA to measure efficiency of four Australian and twelve international ports. Valentine and Gray (2001) also applied the DEA model with 2 inputs and 2 outputs to examine the efficiency of 31 container ports out of the world's top 100 container ports in 1998. Boile (2001) extends previous work by considering variable returns to scale. She uses DEA to measure efficiency of 23 bus transit systems. Park and De (2004) evaluated the efficiency of 11 Korean container ports with 2 inputs and 4 outputs. Park (2005) performed DEA/Window analysis on 11 Korean container terminals during the five years from 1999 to 2002. Song and Sin (2005) also evaluated the efficiency of 53 international major container ports using DEA based on data from 1995 and 2001. Cullinane and Wang (2006) use DEA for measuring the efficiency of 69 container terminals in Europe. Pjevcevic and Vukadinovic (2010) measured efficiency of bulk cargo handling at river port. Applying DEA to estimate the relative efficiency of a sample of Portuguese and Greek seaports is given in Barros and Athanassiou (2004). In Cullinane and Wang (2007), the relevance of DEA was analyzed to estimate the productive efficiency of the container port industry. Available DEA panel data approaches were applied to a sample of 25 leading container ports and evaluated in Cullinane and Wang (2010). In Lin and Tseng (2007), five models of DEA were applied to identify trends in port efficiency of major container ports in the Asia-Pacific region. The impact of different groups on the efficiency of 28 container ports from 12 countries and regions in Asia was studied in Wu, Yan and Liu (2009). The performance of Mediterranean See container terminal using DEA is presented also in Russo & Rindone (2011).

The available data used in real-world problems are often imprecise or vague. Imprecise or vague data may be the result of unquantifiable (say, qualitative measurements, expert judgments), incomplete and non obtainable information (confidential or missed information). Imprecise or vague data is often expressed with bounded intervals, ordinal (rank order) data or fuzzy numbers. In recent years, many researchers have formulated fuzzy DEA models to deal with situations where some of the input and output data are imprecise or vague. There are a relative large number of papers in the fuzzy DEA literature. Fuzzy sets theory has been used widely to model uncertainty in DEA. The applications of fuzzy sets theory in DEA are usually categorized into four groups (Lertworasirikul 2002, Lertworasirikul et al. 2003, Karsak 2008): the tolerance approach, the α-level based approach, the fuzzy ranking approach and the possibility approach. While most of these approaches are powerful, they usually have some theoretical and/or computational limitations and sometimes applicable to a very specific situation (e.g., Soleimani-damaneh et al. (2006)). The tolerance approach was one of the first fuzzy DEA models that was developed by Sengupta (1992a) and further improved by Kahraman and Tolga (1998). In this approach the main idea is to incorporate uncertainty into the DEA models by defining tolerance levels on constraint violations. The α-level approach is perhaps the most popular fuzzy DEA model. This is evident by the number of α-level based papers published in the fuzzy DEA literature. In this approach the main idea is to convert the fuzzy CCR model into a pair of parametric programs in order to find the lower and upper bounds of the α-level of the membership functions of the efficiency scores. The fuzzy ranking approach is also another popular technique that has attracted a great deal of attention in the fuzzy DEA literature. In this approach the main idea is to find the fuzzy efficiency scores of the DMUs using fuzzy linear programs which require ranking fuzzy sets. In this section, we also review a related method, called "defuzzification approach", proposed by Lertworasirikul (2002). In this approach, which is essentially a fuzzy ranking method, fuzzy inputs and fuzzy outputs are first defuzzified into crisp values. These crisp values are then used in a conventional crisp DEA model which can be solved by an LP solver. The fundamental principles of the possibility theory are entrenched in Zadeh's (1978) fuzzy set theory. In fuzzy LP models, fuzzy coefficients can be viewed as fuzzy variables and constraint can be considered to be fuzzy events. Hence, the possibilities of fuzzy events (i.e., fuzzy constraints) can be determined using possibility theory. Dubois and Prade (1988) provide a comprehensive overview of the possibility theory. Lertworasirikul (2002) have proposed two approaches for solving the ranking problem in fuzzy DEA models called the "possibility approach" and the "credibility approach."

The possibility approach deals with the uncertainty in fuzzy objectives and fuzzy constraints through the use of possibility measures. By using the possibility approach, fuzzy DEA models are transformed into well-defined possibility DEA models. The approach can avoid the problem with fuzzy ranking, and provides the flexibility to decision makers to set their own possibility levels in comparing DMUs. By using the credibility approach, fuzzy DEA models are transformed into credibility programming-DEA (CP-DEA) models. In the CP-DEA model fuzzy variables are replaced by "expected credits", which are derived by using credibility measures. The credibility approach provides an efficiency value for each DMU as a representative of its possible range. Mugera (2011) applied fuzzy DEA to compute the technical efficiency scores of 34 DMUs using the α-cut level approach. Nedeljkovic and Drenovac (2008) used fuzzy DEA, credibility approach, to measure efficiency of Serbian post offices. Nedeljković and Drenovac (2012) used fuzzy DEA, possibility approach, to measure efficiency of five Serbian post offices.

Port competitiveness measurement, and consequently ports classification, are very complex because of the uncertainty due to the lack of available data, or to imprecision, and/or vagueness of information; so that traditional mathematical techniques and models could not be the proper approach. In these cases it could be useful to face the problem using soft computing techniques based on fuzzy logic, which have been proved to be more suitable when facing uncertainty. In literature there are few works that explicitly consider the uncertainty lying in freight transportation analysis, especially in measurement of container port efficiency, and even less in Container Terminals (CT) classification (Chou, 2007 and 2010; Huang *et al.*, 2003). Container ports ranking based on uncertain data have been also proposed in Caggiani, *et al.*(2012) where a fuzzy data meta training system for ranking hub container terminals is presented. Fuzzy Logic based methodology is presented in the work by Iannucci *et. al* (2011). In both the works the attention is about the East Mediterranean Terminal Container hubs system.

However it is relevant to notice that Chou (2007 and 2010) e Huang et al. (2003) apply Multi-Criteria Decision Making (MCDM) methods together with fuzzy feature of indicators. In the ports classification, it may be deemed appropriate to focusing upon fuzzy approach as we are going to see in the next section. More recently, Bray et al. (2014) proposed a new Fuzzy-DEA model based on traditional DEA and fuzzy linear programming formulation.

3. Formulation of the proposed methodology

In this section, we investigate the DEA model, the fuzzy number and the Fuzzy Theory-based DEA model that we have developed for the study of ports efficiencies. DEA is a linear programming (LP) based deterministic and non-parametric method for measuring the relative efficiency of DMUs (Decision Making Units) with multiple inputs and outputs. DEA evaluates the efficiency of each DMU relative to an estimated production possibility frontier determined by all DMUs. The advantage of using DEA is that it does not require any assumption on the shape of the frontier surface and it makes no assumptions concerning the internal operations of a DMU.

Since the original DEA study by Charnes *et al.* (1978) there has been a continuous growth in the field. As a result, a considerable amount of published research and bibliographies have appeared in the DEA literature, including those of Seiford (1996), Gattoufi *et al.*(2004), Emrouznejad *et al* (2010) and Cook and Seiford (2009).

Data Envelopment Analysis is a well-known tool for business and organizations to evaluate their activities and to find the opportunities of improvement.

The frequently used DEA models is CCR named after Charnes, Cooper and Rhodes, this model assumes constant returns to scale (CRS). The CCR model has its production frontier spanned by the linear combination of the existing DMU_S. DEA models can be distinguished according to whether they are input-oriented or output-oriented (i.e. either minimizing inputs for a given level of output, or maximizing output for a given level of input). Charnes, Cooper and Rhodes (1978) extended Farrell's (1957) work in the measurement of technical efficiency and first introduced the term data envelopment analysis, known as the CCR model.

Here we give a brief introduction to the model. More formally, assume that there are n DMUs to be evaluated. Each DMU consumes varying amounts of m different inputs to produce s different outputs. Specifically, DMU_j consumes amounts $X_j = [x_{ij}]$ of inputs (i = 1; . . . ;m) and produces amounts $Y_j = [y_{rj}]$ of outputs (r = 1; . . . ; s). The s x n matrix of output measures is denoted by Y, and the m x n matrix of input measures is denoted by X. Also, assume that $x_{ij} > 0$ and $y_{rj} > 0$. Consider the problem of evaluating the relative efficiency for any one of the n DMUs,

which will be identified as DMU$_0$. Relative efficiency for DMU$_0$ is calculated by considering the ratio of a weighted sum of outputs to a weighted sum of inputs, subject to the constraint that no DMU can have a relative efficiency score greater than one.

The DEA model can only deal with accurate measurement of both the inputs and outputs. The available data used as input and output in real-world problems are sometimes imprecise or vague. Imprecise evaluations may be the result of unquantifiable (such as qualitative information), incomplete and non-obtainable/missed information (for example, for confidential constraints). In our model we propose to specify these uncertain data as a fuzzy set (Zadeh, 1965). The concept of fuzzy set theory can incorporate the DEA model, so we can represent input or output data as fuzzy symmetrical triangular number. In fuzzy logic a crisp number belongs to a set (fuzzy set) with a certain degree of membership, named also satisfaction h. The degree of membership is defined by a ''membership function''. If there is no additional specific information, a triangular membership function can be assumed to specify the fuzzy constraint which is analytically defined by the fuzzy set depicted in Fig.1. In fuzzy set theory, the closer to one the degree of membership is, the more the corresponding abscissa value belongs to the respective linguistic variable (fuzzy set). If the membership functions are triangular then all the fuzzy constraints considered can be expressed as inequalities and depend on the satisfaction h (Zimmermann, 1996).
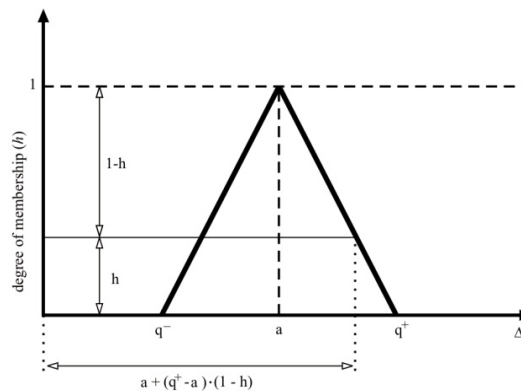

Fig. 1. Fuzzy set $\Delta \cong a$

Where Δ represents the fuzzy input (x_{ij}) or the fuzzy output (y_{rj}) that we are considering. Inequalities representing the fuzzy constraints are:

$$\begin{cases} \Delta \le a + [(q_+ - a)(1 - h)] \\ \Delta \ge a - [(a - q_-)(1 - h)] \end{cases}$$

The closer to one the satisfaction is, the more the constraints are fulfilled. Therefore, in order to find the optimal solution to the classical DEA CCR input-oriented and DEA CCR output-oriented models, it is necessary to maximize the satisfaction h of the fuzzy constraints. In fuzzy optimization, CCR input and output oriented are equivalent to the problems in Eq. (3) and (4), where the objective function to be maximized are the satisfactions h (Fig. 2.). In fact, in this way, the maximization of the weighted sum of outputs (CCR input oriented) and, similarly, the minimization of the weighted sum of inputs (CCR output oriented) became constraints in the fuzzy CCR input and output oriented models (i.e. eqs. (3) and (4)) which have to be satisfied in order to obtain the maximization of the satisfaction *h*, that is now the new objective function.

Moreover, while in eq (3) the variable z is equal to 1, it can be set according to the maximum possible value of the weighted sum of the inputs in model (4).

So, in this way, both the classical models can be specified as fuzzy programming problems as in eqs. 3 and 4, for Fuzzy CCR model input-oriented and Fuzzy CCR model output-oriented, respectively:

Fuzzy CCR model input-oriented

$Max\ h$

Subject to:

$$\sum_r u_r y_{r0} \geq h$$
$$\sum_i v_i x_{i0} = 1$$
$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0 \tag{3}$$
$$u_r, v_i \geq 0$$

for $j = 1, \dots, n; \ r = 1, \dots, s \ and \ i = 1, \dots, m$

$$\begin{cases} \Delta \leq a + [(q_+ - b)(1 - h)] \\ \Delta \geq a - [(a - q_-)(1 - h)] \end{cases}$$

Similarly, the fuzzy CCR model output-oriented can be written as follows:

$Max\ h$

Subject to:

$$\sum_i v_i x_{i0} \leq 1 + z(1 - h)$$
$$\sum_r u_r y_{r0} = 1$$
$$\sum_i v_i x_{ij} - \sum_r u_r y_{rj} \geq 0 \tag{4}$$
$$u_r, v_i \geq 0$$

for $j = 1, \dots, n; \ r = 1, \dots, s \ and \ i = 1, \dots, m$

$$\begin{cases} \Delta \leq a + [(q_+ - b)(1 - h)] \\ \Delta \geq a - [(a - q_-)(1 - h)] \end{cases}$$

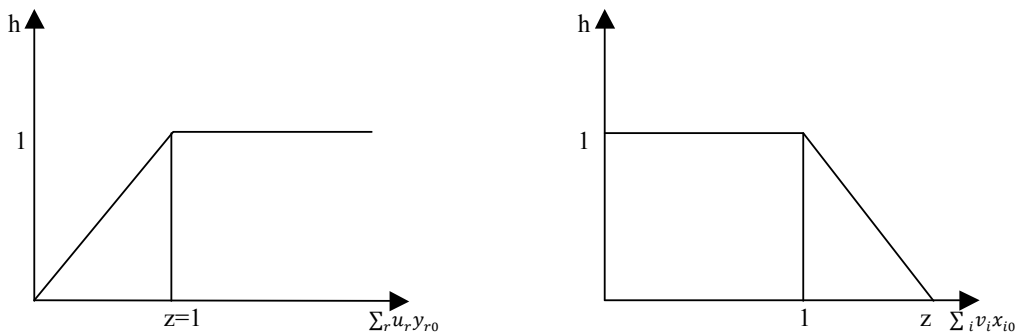Fig. 2. Fuzzy set representing the expression ''satisfactory maximization'' (fuzzy CCR in. and out. oriented)

The formulation given in eqs. 3 and 4 can be applied to a wide range of efficiency analysis of transport systems. In the next section we have applied the proposed Fuzzy CCR input oriented model to a specific case study. The model has been developed with an *ad hoc* code written in MATLAB[TM] environment.

Specifically, the model has been applied to the evaluation of efficiency of 16 container ports worldwide. The dataset used for this purpose includes a given number of input and output variables properly selected, one of which is assumed uncertain and was modelled as fuzzy number.

In conclusion, an analysis has been performed to compare the values of the efficiency of the ports obtained using the classical DEA (CCR input-oriented) and by the proposed fuzzy DEA model (CCR- fuzzy input oriented).
In this way, it will be possible to highlight the effects produced by considering uncertain input variables that have been modelled by fuzzy numbers.

4. Numerical application

Following the previous sections, the case study examines efficiency with respect to containerized cargoes across ports recognized for their high level performance (in terms of throughput) in Asia and Europe for which data were available.

Data availability is particularly important since many of the ports surveyed for data via questionnaires refused to reveal information on some aspects of operations due to confidentiality.

Thus, apart from the data obtained from the survey, the study has to depend on secondary sources. The following are the secondary sources of data for this study: the Australian Bureau of Transport and Communications Economics (1996) survey data on four Australian ports and selected Asian and European ports for data on reliability and speed; Containerization International Yearbook (1998) and Lloyd's Ports of the World (1998) for data on port infrastructure. The Australian Bureau of Transport and Communications Economics data on reliability and speed should be quite reliable and unbiased since these were obtained from the same shipping lines calling at the selected ports, rather than from their various port authorities or terminal operators.

In this application, the fuzzy DEA is applied to four Australian and twelve other international container ports.
We consider four output variables:

- *TEUs handled* (the number of twenty foot container equivalent units handled),
- *shipcalls* (number of ship visits);
- *shiprate* (ship working rate which measures the number of containers moved per working hour);
- *crane prod.* (crane productivity which measures the number of containers moved per crane per working hour).

The input variables are six:

- *nocranes* (number of cranes),
- *noberths* (number of container berths),
- *notugs* (number of tugs),
- *termiarea* (terminal area),
- *delaytime* (delay time)
- *labor* (proxied by the number of port authority employees).

Obviously, both DEA and Fuzzy DEA are non-parametric techniques that allows us to measure the relative efficiency of similar Decision-making units (the sixteen ports in this numerical application).

The relative efficiency is independent of the unit of measurement of inputs and outputs.

An important input influencing port outputs is the amount of *delay time* which is the difference between total berth time plus time waiting to berth and the time between the start and finish of ship working, and is an indicator of how well working time is being used. These delays could be due to labor disputes, work practices such as meal breaks, equipment breakdown, port congestion, perceived ship problems or bad weather.

To illustrate the application of the fuzzy DEA, uncertainty is introduced in the data by representing one input (delay time) as symmetric triangular fuzzy number for five ports. The data are reported in Table 1.

As we can see in the last column of Table 1, with the term 'spread delay time' we have actually defined the quantities q_- and q_+ (see Fig. 1 and Eq. 3 and 4) as percentage of the central value "a" of the fuzzy number, where

"a" is the value of the delay time available from data for the considered port and given in the column "delay time" . If the "spread delay time" is "crisp" than it is assumed to be certain value.

Table 1. Port data

International Port	TEUs	Ship calls	Ship rate	Crane prod	N. of cranes	N. of cont. berths	N. of tugs	Term. area (m^2)	Labor (UNITS)	Delay time (h)	Spread Delay time
Melbourne	904618	823	20,8	14,8	16	12	6	1184100	829	8	30%
Hong kong	13460343	12880	45	45	64	18	24	2198300	800	5	CRISP
Hamburg	3054320	4178	37,2	19,6	52	14	25	3030000	1168	0,2	CRISP
Rotterdam	4935616	5544	32	16	66	18	15	4158000	981	1,7	CRISP
Felixstowe	2042423	2677	56,4	23,5	29	13	3	1432000	1824	0,6	CRISP
Yokohama	3911927	11908	47	47	41	20	34	1823250	472	6	CRISP
Singapore	12943900	24015	40	39,3	95	17	12	2979211	978	2,3	40%
Keelung	2320397	3144	24	24	23	14	9	339000	690	13	20%
Sydney	695312	759	22,8	13,4	14	11	3	1124500	635	9,5	CRISP
Fremantle	202680	692	13,3	12,9	5	7	5	273000	498	9	CRISP
Brisbane	249439	556	21	12,5	6	3	5	474000	200	5,5	CRISP
Tilbury	394772	347	32,8	18,2	11	4	2	519000	750	4,5	CRISP
Zeebrugge	553175	1608	36,7	26,2	16	9	5	2311100	21	1	20%
La Spezia	871100	1045	23,9	17,1	8	7	8	270000	177	3,7	CRISP
Tanjung Priok	1421693	3239	18	18	10	6	11	310000	1513	50	CRISP
Osaka	987948	2375	32	32	24	13	10	1154000	1070	4	30%

The efficiency values obtained by the proposed method for all the sixteen container ports are reported in Table 2.

The computing was performed by coding the fuzzy programming problem in eq. 3 in MATLAB language and using the data as reported in Table 1.

From Table 2, Hong Kong, Felixstowe, Yokohama, Singapore, Keelung, Fremantle, Brisbane, Tilbury, Zeebrugge, La Spezia, Tanjung Priok and Osaka are efficient while Melbourne, Hamburg, Rotterdam and Sydney are inefficient. Interpreting the results of Table 2 depends on the heterogeneity of the ports (the exogenous factors such as size, facilities and function).

The port of Melbourne is quite small relative to Rotterdam. The port of Rotterdam is a hub port in Western Europe while the ports of Melbourne, generate most of their cargo-for his close hinterland serving mainly through traffic and not transshipment. Like the port of Melbourne, the ports of Sydney have an enormous slack in the terminal area and labor input.

Furthermore, if on one hand we give an interpretation of the results based on the characteristics of the ports (different values of inputs and outputs), on the other hand we can't fully clarify how the delay time, treated as a fuzzy variable only for a small number of ports, has influenced the final values of efficiencies.

In order to provide a fully comprehensive answer to this question, in the next subsection two different analysis of efficiency for the same set of ports were carried out: one with the application of traditional DEA model and another with the application of our fuzzy DEA model.

In this way, we were able to observe closely if the delay time, treated as a fuzzy variable, affected the final values of efficiency compared to a classical DEA analysis where it is regarded as crisp value.

Table 2. Relative efficiency measures using the fuzzy DEA (CCR input oriented)

Ports	Efficiency Fuzzy DEA
Melbourne	0.6003
Hong Kong	1
Hamburg	0.5114
Rotterdam	0.6795
Felixstowe	1
Yokohama	1
Singapore	1
Keelung	1
Sydney	0.6823
Fremantle	1
Brisbane	1
Tilbury	1
Zeebrugge	1
La Spezia	1
Tanjung Priok	1
Osaka	1

4.1. Comparison between DEA and proposed fuzzy DEA

This subsection will set out the results of the efficiency analysis obtained with the application of classical DEA model, which involves only the use of crisp data, and the application of the fuzzy DEA model developed by the authors where the delay time is the fuzzy variable.

As can be seen from Table 3, it was considered the same set of ports used in the previous analysis: sixteen international container ports (four Australians and twelve international). For what concern the outputs/inputs dataset we have considered the same number of inputs and outputs used by Tongzon (2001) in his study.

We consider one output variable:

- *TEUs handled* (the number of twenty foot container equivalent units handled).

The input variables are six:

- *nocranes* (number of cranes),
- *noberths* (number of container berths),
- *notugs* (number of tugs),
- *termiarea* (terminal area),
- *delaytime* (delay time)
- *labor* (proxied by the number of port authority employees).

This choice was made in order to make a real and proper comparison analysis between the classical DEA analysis carried out by Tongzon in his study and our fuzzy DEA analysis. The only difference in the application of these two models is about the delay time.

In fact, in the study of Tongzon (2001) the delay time has been considered as crisp number while in our analysis has been considered as fuzzy number because it is difficult to determine the true value and therefore it suffers from enormous uncertainty also because of confidential issue. Specifically, in the last column of the Table 3 it can be seen

that the delay time has been modelled as a symmetric triangular fuzzy number with a spread of the central value of 30% for all ports.

The choice of this spread value is due to the numerous tests carried out with the fuzzy DEA model, where we have considered different level of uncertainty (20%, 30%, 40%). It was shown that, among all the analyzes conducted only one, where the delay time had spread to 30%, converged to the solution and hence led to satisfactory efficiency results comparable with the results obtained with a classical DEA analysis.

Once obtained efficiency values from both models, the results of the two analyses are reported in Table 4.

Table 3. Port data used for comparison analysis.

International Ports	TEUs	N. of cranes	N. of cont. berths	N. of tugs	Term. area (m^2)	Labor (UNITS)	Delay time (h)	Spread Delay time
Melbourne	904618	16	12	6	1184100	829	8	30%
Hong kong	13460343	64	18	24	2198300	800	5	30%
Hamburg	3054320	52	14	25	3030000	1168	0,2	30%
Rotterdam	4935616	66	18	15	4158000	981	1,7	30%
Felixstowe	2042423	29	13	3	1432000	1824	0,6	30%
Yokohama	3911927	41	20	34	1823250	472	6	30%
Singapore	12943900	95	17	12	2979211	978	2,3	30%
Keelung	2320397	23	14	9	339000	690	13	30%
Sydney	695312	14	11	3	1124500	635	9,5	30%
Fremantle	202680	5	7	5	273000	498	9	30%
Brisbane	249439	6	3	5	474000	200	5,5	30%
Tilbury	394772	11	4	2	519000	750	4,5	30%
Zeebrugge	553175	16	9	5	2311100	21	1	30%
La Spezia	871100	8	7	8	270000	177	3,7	30%
Tanjung Priok	1421693	10	6	11	310000	1513	50	30%
Osaka	987948	24	13	10	1154000	1070	4	30%

Discussing the results of Table 4, it can be observed that the values of efficiencies obtained through the application of the fuzzy DEA model does not differ much from the results obtained by the traditional DEA model except for six ports (Rotterdam, Felixstowe, Fremantle, Tilbury, La Spezia, Tanjung Priok) out of sixteen.

Moreover, we can observe that among these six ports only one, Tanjung Priok highlighted in the table, is inefficient with the fuzzy DEA model while it is fully efficient with the traditional DEA model.

Beyond the discrepancies found for the other five ports, our attention will focus on the port of Tanjung Priok because it is the only one judge to be inefficient Fuzzy DEA and efficient with classical DEA.

It has to be observed that the classic DEA returns the port of Tanjung Priok be efficient even if it has the highest delay time (i.e. 50hours). Assuming that that value was not certain (in the best case it is an average value on yearly base) we consider such possible uncertainty level assuming a 'spread delay time' for all the ports. Differently from the classic DEA, the Fuzzy-DEA shows that, under these assumptions, the port of Tanjung Priok is inefficient and the efficiency of other ports is different. In one hand, these results highlight the usefulness of considering the uncertainty lying in available data (in this case the "delay time") and the consequent effects on the efficiency estimation.

In the other hand, we can see that applying classic DEA, the port of Sydney is more efficient than Fremantle even if its delay time is higher. Also in Fuzzy DEA (assuming a spread delay time equal to 30%) both the ports are inefficient and the port of Sydney is more efficient than Freemantle. Thus, the delay time not the main is source of relative inefficiency between the two ports. In fact, they have very different characteristics in terms of size and

function.

Table 4. Efficiency measures using the fuzzy DEA (CCR input oriented) and traditional DEA model (CCR input-oriented)

Port	Efficiency Fuzzy.DEA (Spread-30%)	Efficiency DEA (Tongzon,2001)
Melbourne	0.27	0.27
Hong Kong	1	1
Hamburg	1	1
Rotterdam	0.59	0.54
Felixstowe	0.57	0.63
Yokohama	0.49	0.49
Singapore	1	1
Keelung	1	1
Sydney	0.31	0.31
Fremantle	0.18	0.19
Brisbane	0.20	0.20
Tilbury	0.23	0.17
Zeebrugge	1	1
La Spezia	0.52	0.53
Tanjung Priok	**0.74**	**1**
Osaka	0.20	0.20

Through the comparison between the results obtained from the two models, we can conclude by saying that we have tested closer our fuzzy DEA model. From one side, we can underlined that the delay time is certainly a data that affects the value of efficiency. From the other side, when two ports of the sixteen ports have similar value of delay time, the final value of efficiency with Fuzzy DEA model is the same of that one determinate with classical DEA model. In conclusion, the strength of the fuzzy DEA model in comparison with the traditional DEA will be investigated more deeply and with more precision in the future. Certainly, with our model uncertain data are treated in the right way (fuzzy numbers) by making efficiency values very closed to reality.

In addition, we have to highlight that the considered input and output variables are the same assumed in the study by Tongzon (2001) in order to achieve the comparison. Actually, the selection of the input variables is another important issue that some authors solve out with bootstrap techniques (see for ex. Button & Neiva, 2014).

In the next section we have reported the final considerations on the study carried out about the efficiency analysis applied to terminals for freight transport (container ports), also considering possible future developments of the research.

5. Conclusions

This study proposes a Fuzzy DEA model for evaluate transport services efficiency. In particular, the proposed model aims at providing a satisfactory answer to the problem of making efficiency comparisons among a set of international container ports. This paper is employing the fuzzy set theory in the original DEA model, supporting it with the ability to offer more objective evaluation in vague environment. Fuzzy DEA has recently been successfully applied to a number of different economic efficiency measurement situations. The technique offers a significant alternative to classical econometric approaches to extracting efficiency information from sample observations.

Important features of fuzzy DEA are that the technique is non-parametric and that more than one output measure can be specified. In the case of port efficiency, the ability to handle more than one output is particularly appealing

because a number of different measures of port output are available, depending on which features of port operation are being evaluated. Although this study has shown the suitability of fuzzy DEA for port efficiency evaluation and produced useful findings for certain ports, there is still more scope for future investigation. The lack of access to stevedoring employment data for most of the sampled ports has constrained the fuzzy DEA analysis. It will be interesting to see how port efficiency can be attributed to stevedoring labor once complete data for this particular variable are available and this variable is incorporated into the analysis.

With availability of more port data and inclusion of more ports, applying the fuzzy DEA analysis to similar ports based on a larger sample size is another interesting area for future research. Ports can be classified into various clusters in terms of size, facilities and function (i.e., whether hub or feeder ports), and only ports belonging to the same clusters are included in the port efficiency analysis (Tongzon and Ganesalingam, 1994). Fuzzy DEA models allow us to evaluate the current level of efficiency of each port and to identify the strength and weakness of each of them and eventually to suggest an efficient way of benchmarking to inefficient container ports. Evaluating the port efficiency helps port's management understand the comparative level of their overall service quality in terms of manageable service attributes, thus identifying service areas to be improved where the index serves as a service benchmarking and management tool for ports. The proposed model allows the analyst to explicitly consider the eventual uncertainty embedded available data and then in the variables used in the DEA analysis. With respect to the use of the results from the analysis, it is the same of the traditional and widely used DEA analysis. For example, to improve the delay time the manager could decide to increase the number of cranes (that is crisp), but he/she does not know exactly how much the delay time will be reduced. Thus, an uncertain value of the delay time could be assumed as input.

Despite of the above implication, we still need to conduct further studies as follows. Firstly, to measure the operational efficiency of the container ports, in our fuzzy DEA model we just used just one input (delay time) as symmetric triangular fuzzy number for five ports. This is a very restrictive model and it is therefore required to conduct various studies for models with various inputs and outputs as fuzzy variables.

Secondly, it is also required to perform, as a future research, the use of a parametric approach (Stochastic Frontier Analysis) or a semi-nonparametric approach as the StoNED model (STOchastic semi-nonparametric Envelopment of Data) proposed by Kuosmanen & Kortelainen (2012). The StoNED model allows handling with multiple outputs and inputs as the traditional DEA models. The use of a stochastic approach could be interesting in the context of this paper as it accounts for the noise that are present in the imprecise data.

About the comparison made between the two models, Fuzzy-DEA and DEA, we observed that treating uncertain data in fuzzy environment makes the efficiency estimation much more accurate and realistic.

Nevertheless, it is necessary to carry on further analysis to have a much more complete picture of the range of application of the fuzzy DEA model. More precisely, for the future we can increase the number of data to be processed in fuzzy environment in order to observe how they, together, affect the values of efficiency. For example, we can think about using data on emissions or energy consumption of container ports. In fact, these data, considered as fuzzy data, could give the efficiency results which would lead to a more detailed assessment of the operating state of the port. Another step to be addressed for the future is definitely considering trapezoidal fuzzy data in order to obtain a representation even closer to reality in the treatment of uncertain data.

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