

## EFFICIENCY AND PRODUCTIVITY ANALYSIS OF THE INTERSTATE BUS TRANSPORTATION INDUSTRY IN BRAZIL

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### Abstract

Productivity analysis is an important policy making and managerial control tool for assessing the degree to which inputs are utilized in the process of obtaining desired outputs. Data Envelopment Analysis (*DEA*) is a non-parametric method based on piecewise linear frontiers estimated with the aid of mathematical programming techniques and used, in this paper, to investigate technical, scale and managerial efficiencies associated with interstate bus companies in Brazil (*ISBT*). Data has been obtained from the web-site of the Brazilian National Agency of Land Transportation (*ANTT*). Since production factors in the application are constrained by technical and operational reasons, weight restrictions were introduced into the *DEA* models. The analysis has shown three groups of non-efficient bus firms, with clear differences in productivity. The relative managerial efficiencies of the firms in the non-efficient groups were also computed and analyzed. Finally, an example of benchmarking a non-efficient firm with *DEA* is presented.

**Keywords:** regional bus transportation; *DEA*; efficiency and productivity.

### Resumo

A análise de produtividade é ferramenta importante para a tomada de decisão e para a gestão de organizações, possibilitando avaliar os efeitos dos inputs na obtenção de níveis desejados de outputs. A Análise Envoltória de Dados (*DEA*) é um método não paramétrico baseado em fronteiras lineares por partes ajustadas através de programação matemática e utilizada para analisar as eficiências técnica, de escala e de gestão de empresas de ônibus que operam nas ligações interestaduais no Brasil (*ISBT*). Os dados foram obtidos no *web-site* da Agência Nacional de Transportes Terrestres (*ANTT*). Como os fatores de produção são restritos por razões técnicas e operacionais, restrições de pesos foram introduzidas nos modelos. A análise mostrou três grupos de empresas não eficientes, com claras diferenças de produtividade. Também são calculadas as eficiências de gestão relativas a esses três grupos. Finalmente é apresentado um exemplo de *benchmarking* de uma empresa não eficiente através de *DEA*.

**Palavras-chave:** transporte interestadual em ônibus; *DEA*; eficiência e produtividade.

## 1. Introduction

There is an extensive literature on the formulation and estimation of productivity measures for the transportation industries (Oum *et al.*, 1992). Productivity analysis is an important policy making and managerial control tool for assessing the degree to which inputs are utilized in the process of obtaining desired outputs. Currently, there are two fundamental approaches or paradigms used for the estimation of frontiers of maximum productivity. The parametric approach is probably the most common. Its distinguishing characteristic is the assumption of an explicit functional form to represent the production function frontier. The stochastic frontier production function (Coelli *et al.*, 1998) is an important example of parametric modeling. Data Envelopment Analysis (*DEA*), on the other hand, is a non-parametric approach based on piecewise linear frontiers estimated with the aid of mathematical programming techniques (Cooper *et al.*, 2000).

Performance evaluation of organizations, such as business firms and governmental agencies, usually starts with the definition of a production function, which describes the technical relationship between the outputs and the inputs of a production process. A production function defines the maximum output(s) obtainable from a given vector of inputs. Under the parametric approach, production functions are generally estimated by first adjusting a cost function to the sample data. Least square estimation of such cost functions involving a reasonable number of inputs and/or outputs is likely to suffer from degrees of freedom and multicollinearity problems, resulting in inefficient estimates (Coelli *et al.*, 1998). After an appropriate cost function is fitted to the data, the corresponding production function parameters can be obtained making use of the Shephard's duality lemma (Beattie & Taylor, 1985; Coelli *et al.*, 1998). However, the Shephard's duality concept implies that, in order to define a maximum production frontier, the firms or organizations under analysis must strive to minimize costs. In practice, cost minimization is not, in fact, a clear objective of regulated transport firms, and the estimated cost function parameters are likely to be biased due to misspecification of the model. Furthermore, since the direct fitting of least-square econometric production functions through the middle of the data is not in accordance with the production function concept, more elaborate estimation methods such as the stochastic frontier production function has to be adopted. The performance of regional bus transportation firms in Italy was analyzed from an economic point of view by Cambini & Filippini (2003). In Switzerland, Farsi *et al.* (2005) studied the productivity of 94 regional bus properties, applying four stochastic frontier models to the data. Gonçalves *et al.* (2007) applied econometric methods to forecast interstate bus transportation demand in Brazil. Castro (2003) and Brasileiro *et al.* (2001) discussed aspects of the interstate passenger bus transportation regulation in Brazil.

Due to the difficulty in parametrically fitting a production function, Farrel (1957) suggested that it can be estimated from the sample data using a non-parametric piece-wise linear technology. This suggestion was further developed by Charnes, Cooper and others, leading to Data Envelopment Analysis (*DEA*). Today, *DEA* is applied to a large list of topics, and the number of papers on *DEA* theory and applications has increased sharply in the literature. *Pesquisa Operacional*, for instance, has published 26 papers on the subject in the period 2001-2009.

A number of researchers have recently applied *DEA* to investigate the productivity of diverse transportation systems. Among others, Chu *et al.* (1992), and Karlaftis (2003) applied *DEA* to analyze transit systems, Forsund & Hemaes (1994) investigated the efficiency of

Norwegian ferry services, Oum *et al.* (1999) and Yu & Lin (2008) studied the efficiency of railways, Cowie & Asenova (1999) analyzed the British urban bus industry, Novaes (2001) studied the efficiency of rapid-transit properties, Tongzon (2001) and Cullinane *et al.* (2006) applied *DEA* to investigate the efficiency of container ports, Mello *et al.* (2003) and Yoshida & Fujimoto (2004) used *DEA* in air-transportation applications, Barnum *et al.* (2007) analyzed public transportation with the *DEA* approach. *DEA* models have also been used as a tool to perform benchmarking analysis of non-efficient firms and organizations (Post & Spronk, 1999; Hinton *et al.*, 2000; Novaes, 2001; Kyrö, 2003; Yoshida & Fujimoto, 2004; Vasconcellos *et al.*, 2006). In this paper we utilize the *DEA* approach to investigate technical, scale, and managerial efficiencies associated with interstate bus lines in Brazil. An example of benchmarking a non-efficient firm with *DEA* is also presented. This paper is a revised and enlarged version of a preliminary draft presented at the XV Pan-American Conference of Traffic and Transportation Engineering, (Novaes & Silveira, 2008).

The remainder of this paper is organized as follows. Section 2 presents a summary of how the *ISBT* is regulated and operated in Brazil. Section 3 describes the basic *DEA* methods and variations utilized in the paper. Section 4 deals with the *DEA* application to the Brazilian *ISBT*, followed by Section 5 with the analysis of results. In Section 6 it is presented a benchmarking analysis of one non-efficient bus firm. Finally, concluding remarks are given in Section 7.

## 2. Background

Interstate Bus Transportation (*ISBT*) in Brazil is regulated and controlled by the National Agency of Land Transportation (*ANTT*), created in 2001 by the Federal Government. The *ISBT* also includes international lines, representing 10% of the total movement in passenger-kilometers, and with links to six South American countries. The *ANTT* website ([www.antt.gov.br](http://www.antt.gov.br)) registers 222 bus companies enrolled in the *ISBT* in 2006, with a total of 15,616 busses, 25,101 bus drivers, and performing about 4.2 million trips. Total production reached 28.5 billion passenger-kilometers in 2006, the market being heavily concentrated: 20% of the bus companies are responsible for 84% of the total production. The largest bus company, Viação Itapemirim, produced a total of 3.5 billion passenger-kilometers in 2006. The *ISBT* data also include the so called “semi-urban” lines, which are short-distance links connecting two or more towns, and crossing the border of two states. A typical example is the city of Brasília, located in the small Federal District, and having bus lines connecting the Capital to nearby suburban places located in the state of Goiás. These lines are typically of a commuting nature. Since the objective of our study is to analyze typical non-commuting interstate passenger connections, “semi-urban” lines were eliminated from the sample.

The concession of *ISBT* services in Brazil by *ANTT* is done through line tendering. The bids are based on least price per passenger-km, and the competing bus companies offer to operate (without subsidy) a specific line linking two end locations and serving some intermediate towns, over a given itinerary, and offering a number of weekly frequencies. Because of the tendering process, all *ANTT* data on *ISBT* is based on bus lines. But market competition is performed at the company level. Thus, data on bus lines were preliminary aggregated into company level in order to further apply *DEA*.

### 3. The DEA method

#### 3.1 The basic DEA models

In this paper, the *DEA* method is used to measure the efficiencies (technical, scale and managerial) of the *ISBT* in Brazil. The inefficiency of a *DMU* (*Decision Making Units*) is measured by the distance from the point representing its observed input and output values to the corresponding reference point on the production frontier. *DEA* models allow for multiple inputs and multiple outputs and do not require strong *a priori* assumptions regarding production technology or error structure (Oum *et al.*, 1992). Two basic *DEA* models are generally used in the applications. The first, called the *ratio form model* and named *CCR* after its authors Charnes, Cooper & Rhodes (1978), has an input orientation and assumes constant returns to scale (*CRS*). It evaluates overall efficiencies, identifies the efficient and non-efficient *DMUs*, and determines how far from the efficient frontier are the non-efficient units. One has an *input oriented model* when the technical upgrading of a non-efficient *DMU* is attained by performing a movement from its corresponding point toward the efficient frontier through proportional reduction of inputs, but maintaining the output levels constant. Conversely, in an *output oriented model* one keeps the input levels constant and moving to the efficient frontier via proportional augmentation of outputs (Cooper *et al.*, 2000). Let  $y_k = \{y_{1k}, y_{2k}, \dots, y_{Sk}\}$  and  $x_k = \{x_{1k}, x_{2k}, \dots, x_{Mk}\}$  be the vectors of outputs and inputs for *DMU*  $k$  ( $k = 1, 2, \dots, n$ ), where  $S$  and  $M$  are respectively the number of outputs and inputs considered in the analysis. Outputs and inputs are transformed into single virtual entities by weighting the values of the production factors. The single virtual output, for *DMU*  $k$ , is

$$Y_k = u_1 y_{1k} + u_2 y_{2k} + \dots + u_S y_{Sk}, \quad (1)$$

and the single virtual input for *DMU*  $k$  is

$$X_k = v_1 x_{1k} + v_2 x_{2k} + \dots + v_M x_{Mk}. \quad (2)$$

The basic *CCR* model is a fractional programming problem (Bitran & Novaes, 1973), whose solution yields, for each *DMU*  $k$  separately, the values of the variables represented by the input “weights”  $v_i$  ( $i = 1, 2, \dots, M$ ) and by the output “weights”  $u_j$  ( $j = 1, 2, \dots, S$ ). The definition of efficiency in *DEA* is based on the concept of total factor productivity and is specified as the ratio of the weighted sum of outputs to the weight sum of inputs for an individual *DMU*  $k$  (Cooper *et al.*, 2000)

$$\text{Max } \theta_k = \frac{u_1 y_{1k} + u_2 y_{2k} + \dots + u_S y_{Sk}}{v_1 x_{1k} + v_2 x_{2k} + \dots + v_M x_{Mk}}, \quad (3)$$

Subject to

$$\frac{u_1 y_{1j} + u_2 y_{2j} + \dots + u_S y_{Sj}}{v_1 x_{1j} + v_2 x_{2j} + \dots + v_M x_{Mj}} \leq 1, \quad (j = 1, 2, \dots, n) \quad (4)$$

$$v_1, v_2, \dots, v_M \geq 0 \quad (5)$$

$$u_1, u_2, \dots, u_S \geq 0, \quad (6)$$

where  $k$  is a generic *DMU* and  $\theta_k$  its efficiency. Solving this fractional problem for each *DMU*, one gets the efficiency scores  $0 \leq \theta_k \leq 1$ , ( $k = 1, 2, \dots, n$ ). The *DMUs* with  $\theta_k = 1$  are considered efficient, and the ones with  $\theta_k < 1$  are non-efficient.

The *BCC* model, named after its authors Banker, Charnes & Cooper (1984), has an input orientation and assumes variable returns to scale (*VRS*). It evaluates the efficiency of *DMU*  $k$  ( $k = 1, 2, \dots, n$ ) by solving the following (envelopment form) linear program ( $j = 1, 2, \dots, S$ ) (Cooper *et al.*, 2000):

$$\min \theta_k \tag{7}$$

subject to

$$\theta_k x_{ik} - \sum_{\ell=1}^n x_{i\ell} \lambda_{\ell} \geq 0, \quad i = 1, 2, \dots, M \tag{8}$$

$$\sum_{\ell=1}^n y_{j\ell} \lambda_{\ell} \geq y_{jk}, \quad j = 1, 2, \dots, S \tag{9}$$

$$\sum_{\ell=1}^n \lambda_{\ell} = 1 \tag{10}$$

with  $\lambda_{\ell} \geq 0$ . Cooper *et al.* (2000) show that  $\theta_k^*$ , the resulting efficiency of *DMU*  $k$ , satisfies the relation  $0 \leq \theta_k^* \leq 1$ .

By suppressing constraint (10) in the above *BCC* model, one gets the *CCR* model in the envelopment form (Seiford & Thrall, 1990). The efficiency score  $\theta_k^{(CCR)}$  ( $k = 1, 2, \dots, n$ ) obtained with the *CCR* model represents the overall efficiency of *DMU*  $k$ . Following Cooper *et al.* (2000), we employ the sign (\*) to identify the *DMUs* that are *BCC*-efficient. Let  $\theta_{BCC}^*$  and  $\theta_{CCR}^*$  be the efficiencies obtained with models *BCC* and *CCR* respectively, for a *BCC*-efficient *DMU*. Dividing  $\theta_{CCR}^*$  by  $\theta_{BCC}^*$ , one gets the scale efficiency of a *BCC*-efficient *DMU* (Cooper *et al.*, 2000)

$$\theta^{(sc)} = \frac{\theta_{CCR}^*}{\theta_{BCC}^*}, \tag{11}$$

### 3.2 Outlier identification and removal

In the literature, an outlier does not have a generally accepted, precise definition. Often it is referred to as an observation which appears to be inconsistent with the remainder of the data (Simar, 2003). There are many reasons why an observation may be atypical. Sometimes it is because it contains a specific error, or because it came from a different data generating process than the others. Or it might simply be an observation with low probability of being drawn from the same data generating process. Most of the standard geometrical methods for detecting outliers are very computer intensive in multivariate set-ups and do not take the frontier aspects of the problem into account (Simar, 2003). Among a number of methods

proposed to detect and remove outliers in *DEA*, the *super-efficiency model* (Andersen & Petersen, 1993; Banker & Chang, 2006) is well accepted in the literature.

As indicated in Section 3.1, *DEA* assigns an efficiency score less than one to inefficient units. A score less than one means that a linear combination of efficient units from the sample could produce the same vector of outputs, but using smaller values of inputs. The score reflects the radial distance from the production frontier of the *DMU* under evaluation. Efficient *DMUs*, on the other hand, all have an efficiency score of one and, thus, no ranking of efficient units can be inferred from the results of the basic *DEA* model. Although Banker & Chang (2006) argue against the use of the super-efficiency model for ranking efficient units, they recommend it for screening out possible outliers, thus obtaining more reliable efficiency estimates. The basic idea of the super-efficiency model is to compare the efficient *DMU* under evaluation with a linear combination of all other units, which is done excluding the *DMU* itself from the sample (Banker & Chang, 2006). Taking the basic *BCC* model (radial, input oriented, VRS), the equivalent super-efficiency model is obtained by not including the observation “*k*” under evaluation in the reference set for the constraints (8 – 10)

$$\min \theta_k \tag{12}$$

subject to

$$\theta_k x_{ik} - \sum_{\substack{\ell=1 \\ \ell \neq k}}^n x_{i\ell} \lambda_{\ell} \geq 0, \quad i=1,2\dots M \tag{13}$$

$$\sum_{\substack{\ell=1 \\ \ell \neq k}}^n y_{j\ell} \lambda_{\ell} \geq y_{jk}, \quad j=1,2\dots S \tag{14}$$

$$\sum_{\substack{\ell=1 \\ \ell \neq k}}^n \lambda_{\ell} = 1, \tag{15}$$

with  $\lambda_{\ell} \geq 0$ . Under this condition, an efficient *DMU* may increase its input vector proportionally, while preserving efficiency. The *DMU* assumes in such a case an efficiency score above one. This score reflects the radial distance from the *DMU* under evaluation to the production frontier estimated with that *DMU* excluded from the sample. In other words, the *DMU* is subject of maximum proportional increase in inputs while preserving efficiency (Andersen & Petersen, 1993). Banker & Chang (2006) suggested the use of a screen based on the super-efficiency score to identify those observations that are more likely to be contaminated with noise. To do this, those observations with super-efficiency scores higher than a pre-selected screen level are eliminated from the sample. Banker & Chang (2006) technique was applied to the data of the application to be described later in this paper (Section 4).

### 3.3 Weight restrictions

*DEA* assumes that the output weights  $u_1, u_2, \dots, u_S$  and the input weights  $v_1, v_2, \dots, v_M$  are the variables of the model. In other words, the *DEA* model may assume any non-negative value for each weight. This assumption is a basic conceptual characteristic of *DEA*

(Cooper *et al.*, 2000). This complete flexibility in the selection of weights is important in the identification of inefficient *DMUs*. The weights estimated by *DEA* can, however, prove to be inconsistent with prior knowledge or accepted views on the relative values of the inputs and outputs (Allen *et al.*, 1997). Among a number of possible situations (Allen *et al.*, 1997; Pedraja-Chaparro, 1997), there are cases in which the production factors are constrained by technical or operational reasons (Novaes, 2001). For instance, when analyzing the *ISBT*, it makes no sense in adopting a positive weight to bus drivers, and at same time allocating a zero weight to the number of busses in the fleet. In order to cope with these situations, the initial development of *DEA* was followed by a rapid evolution of *value judgments* in the assessment of efficiency followed as a natural by-product of real life applications (Allen *et al.*, 1997). As a consequence, a great number of articles on *DEA* weight restrictions have appeared in the literature (Roll & Golany, 1993; Allen *et al.*, 1997; Pedraja-Chaparro, 1997; Podnovski & Athanassopoulos, 1998; Cooper *et al.*, 2000; Angulo-Meza & Lins, 2002).

The most commonly used weight restrictions are bounds on the ratios of weights. This approach has been named the *assurance region method* by Cooper *et al.* (2000). Assurance region restrictions were introduced into our *DEA* model since most of the production factors of the problem are constrained to certain relative limits. The assurance region method imposes constraints to the *DEA* model on the relative magnitude of the weights for special items (Cooper *et al.*, 2000). For example, one may add a constraint on the ratio of weights for input *i* and input *j*, as follows:

$$L_{i,j} \leq \frac{v_j}{v_i} \leq U_{i,j}, \tag{16}$$

where  $L_{i,j}$  and  $U_{i,j}$  are lower and upper bounds that the ratio  $v_j/v_i$  may assume. The assurance region method is formulated for a *DEA* model by adding constraints of type (16). For example, constraint (16) is split into two constraints:

$$v_j - v_i L_{i,j} \geq 0, \quad \text{and} \quad v_i U_{i,j} - v_j \geq 0. \tag{17}$$

For a more detailed discussion on this topic and for additional information on other types of weight restrictions in *DEA*, the reader is referred to Cooper *et al.* (2000) and Pedraja-Chaparro *et al.* (1997).

### 3.4 Returns to scale

In *DEA* the technology is expressed by the variable returns to scale (*IRS*) alternative, namely the *BCC* model. As explained in Section 3.1, the *CCR* model assumes constant returns to scale (*CRS*), and yields the overall efficiency. The scale efficiency  $\theta_k^{(sc)}$ , on the other hand, is given by (11). One shortcoming of this scale measure is that its sole value does not indicate whether the *DMU* is in a range of increasing or decreasing returns to scale. In order to check this important characteristic one runs an additional *DEA* problem imposing non-increasing returns to scale (*NIRS*). To do this the *BCC* model (7-10) is altered by substituting

restriction (10) with  $\sum_{\ell=1}^n \lambda_{\ell} \leq 1$ . Thus, the *NIRS* model is (Coelli *et al.*, 1998)

$$\min \theta_k \tag{18}$$

subject to

$$\theta_k x_{ik} - \sum_{\ell=1}^n \lambda_{\ell} x_{i\ell} \geq 0, \quad i = 1, 2, \dots, M \tag{19}$$

$$\sum_{\ell=1}^n \lambda_{\ell} y_{j\ell} \geq y_{jk}, \quad j = 1, 2, \dots, S \tag{20}$$

$$\sum_{\ell=1}^n \lambda_{\ell} \leq 1, \tag{21}$$

with  $\lambda_{\ell} \geq 0$ . Figure 1 shows the typical plotting of the *NIRS* frontier together with the *CRS* and *VRS* frontiers, obtained with *DEA* models *CCR* and *BCC* respectively. Let  $\theta_k^{(NIRS)}$  be the efficiency of *DMU* *k* obtained with the *NIRS* model. One then compares the value of  $\theta_k^{(NIRS)}$  with the value of  $\theta_k^{(BCC)}$ :

- a) If  $\theta_k^{(NIRS)} = \theta_k^{(BCC)}$ , as in the case of point *Q* in Figure 1, then decreasing returns to scale exist for *DMU* *k*;
- b) If  $\theta_k^{(NIRS)} \neq \theta_k^{(BCC)}$ , as in the case of point *P* in Figure 1, then increasing returns to scale apply to *DMU* *k*.

Note that, if  $\theta_k^{(CCR)} = \theta_k^{(BCC)}$  occurs then, by definition, the *DMU* is operating under constant return to scale (Coelli *et al.*, 1998). This method can be applied in order do check whether a firm is operating in a region of increasing, decreasing or constant returns to scale.

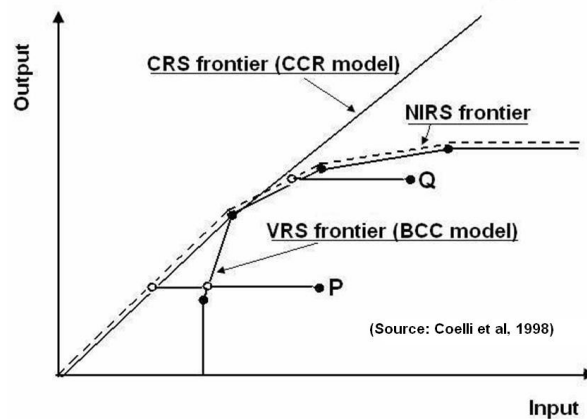


Figure 1 – Frontiers of the CCR, BCC and NIRS models.



### 3.5 Managerial efficiency

Sometimes, a subset of *DMUs* shows clear productivity discrepancies when compared with the remaining more-efficient *DMUs*. This situation may be attributed to technological and/or organizational drawbacks encountered in the former group. This discrepancy can be measured through the managerial efficiency of the *DMUs* in the less productive subset (Charnes *et al.*, 1981; Cowie & Asenova, 1999). Let *FS* represent the full set of *DMUs*, and let *SS* be the subset of the less efficient *DMUs* under analysis. We admit that *DMU* managers are able to improve efficiency levels acting only on technical efficiency, since increasing returns to scale are obtainable only on a long term basis. Accordingly, the *DEA* model to be used is the *BCC* model.

Figure 2 shows the efficiency frontier (input orientation) for the hypothetical *VRS* models related to the sets *FS* and *SS*. Since part of the *FS* points have been removed to form the *SS* set, the  $VRS_{SS}$  frontier must lie either on or below the  $VRS_{FS}$  frontier. In simple terms, the ratio of the distances *AB* and *AC* for *DMU k*, in Figure 2, represents the level of inefficiency attributed to its organizational structure (Cowie & Asenova, 1999). In practice, the managerial efficiency of the *DMUs* in the *SS* set is equal to the ratio of the technical efficiencies obtained with the *BCC* model for sets *FS* and *SS* respectively

$$\theta_k^{(mg)} = \frac{\theta_k^{(BCC, FS)}}{\theta_k^{(BCC, SS)}}, \quad (k \in SS). \quad (22)$$

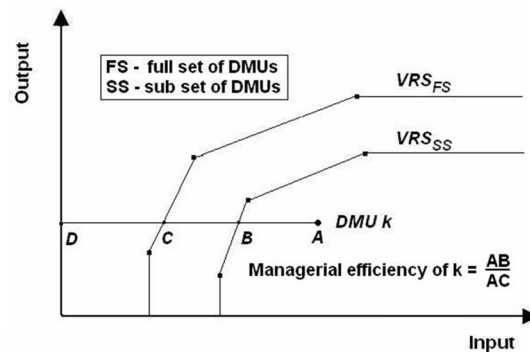


Figure 2 – Managerial efficiency estimate under variable returns to scale.

## 4. The DEA application framework

In this work, *DEA* models were solved with the software *EMS* – Efficiency Measurement System, Version 1.3, by Holger Scheel, Dortmund University, Germany.

### 4.1 Data and input/output factors

Bus companies operating in the *ISBT* are required to periodically report operational data to *ANTT*. But data inconsistency is a common fact. Some reports lack important figures, and since *DEA* requires data completeness, these firms had to be eliminated from the sample.

Because a number of bus companies also perform intra-state or even municipal bus services (returns to scope), some types of information are sometimes misleading. For example, one company showed a ratio of 40 bus drivers per vehicle, a figure much higher than the average of about 2-3 drivers/bus observed in the sample. Drivers assigned to other services were probably reported in the data. As a consequence that firm had to be eliminated from the sample. After the necessary eliminations, the final sample was formed by 89 bus companies. We have used *ANTT* statistics covering the year 2006, the latest full set available when this analysis was performed.

The choice of inputs and outputs was limited by *ANTT* data availability. One of the outcomes of the study is, in fact, a recommendation to *ANTT* to modify its data structure in order to improve the analysis and to get a better model fitting. Two outputs were adopted in the *DEA* models (Table 1). First, a *revenue output measure (PKM)* expressed in passenger-kilometers and indicating the level of production consumed by users. This output was chosen because tariffs are strongly related to passenger-kilometers in the *ISBT*. Oun & Yu (1994) discussed, in general terms, the alternative use of *available output measures* (such as seat-kilometers, for example) and *revenue output measures* (such as passenger-kilometers). The use of available output measures may be justified in measuring managerial efficiency when the government controls the service, in terms of what to supply (price, frequency of service, and so on). However, it is preferable to use the revenue output measures when public policy analysis is the main purpose of the study (Oun & Yu, 1994), as it is the case of this application. The second output (*PMA*) is an important evaluation figure normally used to check the performance of a bus fleet. It represents the average annual mileage of a vehicle and, in this study, it is obtained by dividing the total distance traveled by the number of busses in the fleet. Although this definition of outputs is not totally in accordance with traditional transportation production theory, it must be remembered that the *DEA* approach aims to reflect the actual *DMU*'s decision process through the selection, by the model, of appropriate weights assigned to inputs and outputs. Therefore, the selected outputs must appropriately convey the real objectives of the participants, even if their behavior does not entirely follow the standard transportation production theory. In the Brazilian *ISBT*, external rules are imposed by the controlling agency to all companies. As a consequence, the bus firm strives to (a) increase its revenue, by increasing *PKM*; (b) increase the *PMA* in order to reduce fleet cost, and consequently increase profits. Consequently, these two outputs seem to reflect reasonably well the firm's decision process in the Brazilian *ISBT*.

The four input production factors assumed in the analysis are indicated in Table 1. Input  $x_1$ , the number of busses in the fleet, reflects capital cost. The number of bus drivers (input  $x_2$ ) is directly related to labor cost. As long as the number of interstate bus lines (input  $x_3$ ) increases, the operator has to apply more effort in terms of additional depots, increasing labor deployment and higher labor costs, higher marketing and sales costs, etc. So, this input factor is intended to reflect these additional costs. As the relative number of bus trips increases (input  $x_4$ ), the average idle time between successive bus departures tends to increase, thus increasing vehicle and labor costs. The four input factors are related to important operating costs of the bus firm, which the operator tries to reduce in order to obtain a larger profit margin, since revenue levels are somewhat fixed due to external tariff control.

**Table 1** – Output and input factors adopted in the *DEA* models.

Output/ Input	$x_i$	$y_j$	Symbol	Production factor
Output	-	$y_1$	<i>PKM</i>	Annual production (passenger-kilometers)
Output	-	$y_2$	<i>PMA</i>	Average mileage covered by a bus in one year (km)
Input	$x_1$	-	<i>FLT</i>	Bus fleet (n° of busses assigned to the <i>ISBT</i> )
Input	$x_2$	-	<i>DRV</i>	N° of bus drivers
Input	$x_3$	-	<i>LIN</i>	N° of interstate lines operated by the bus firm
Input	$x_4$	-	<i>TRIP</i>	Number of bus trips performed per year

#### 4.2 Outlier identification and removal

The super-efficiency model described in Section 3.2 was preliminary applied to the sample of 89 bus companies in order to identify outliers. From the 89 *DMUs*, fifteen units were considered efficient. We adopted a screen level of 1.30 for outlier identification (Banker & Chang, 2006). Five *BCC*-efficient units showed higher super-efficiency scores (outliers), and were eliminated from the sample, thus remaining 84 *DMUs*. One of outliers is the bus firm Viação Itapemirim, with the largest production per year (3.48 billion passenger-kilometers), showing a super-efficiency score of 2.25.

#### 4.3 Weight restrictions

Let  $x_i$  represent the input weights, with  $i = 1, 2, \dots, 4$  as indicated in Table 1, and let  $y_j$  ( $j = 1, 2$ ) represent the output weights. As defined in Section 3.1, we assign the symbol  $v_i$  to represent the *DEA* weights associated with the inputs, and  $u_j$  the ones associated with the outputs. As explained in Section 3.3, there are situations in which not all the weights of the production factors can vary freely, since they are constrained by technical or operational reasons. That is what happens in this application.

Setting restrictions on the weights implies the formulation of value judgments about the relative importance of the different inputs and outputs and this may be criticized on the grounds of losing some notion of objectivity implicit in *DEA* (Pedraja-Chaparro, 1997). But this approach is well justified in the literature, as indicated in Section 3.2. Moreover, all bounds introduced in the paper, as for example the ones depicted in Figures 3 and 4, reflect the limits of weight relations actually observed in the sample data. Thus, no external bounds are imposed into the *DEA* model. Figure 3, for instance, shows the variation of the number of bus drivers (*DRV*) as a function of the fleet size (*FLT*). From Figure 3 the following constraint has been defined

$$1.12 \leq \frac{v_2}{v_1} \leq 3.0, \quad (23)$$

where  $v_2$  and  $v_1$  are the weights of inputs *DRV* and *FLT* respectively. Another restriction has been defined by analyzing the variation of *PKM* as a function of *FLT* (Figure 4), yielding

$$1.35 \times 10^{-3} \leq \frac{u_1}{v_1} \leq 3.45 \times 10^{-3}, \quad (24)$$

where  $u_1$  and  $v_1$  are the weights of output  $PKM$  and input  $FLT$  respectively, defined in Table 1.

A third relation (Figure 5) reflects the relative limits between the number of bus trips ( $TRIP$ ) and the number of interstate lines operated by the company ( $LIN$ )

$$0.35 \leq \frac{v_4}{v_3} \leq 2.4 \quad (25)$$

Since  $PMA$  is considered a secondary output, no restriction was imposed to its variation, letting it free. The three restrictions (23-25) are of the assurance-region type (Cooper *et al.*, 2000).

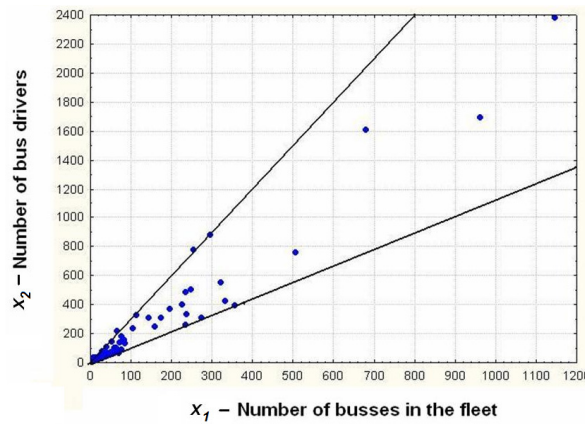


Figure 3 – Relationship between n° of drivers and n° of busses.

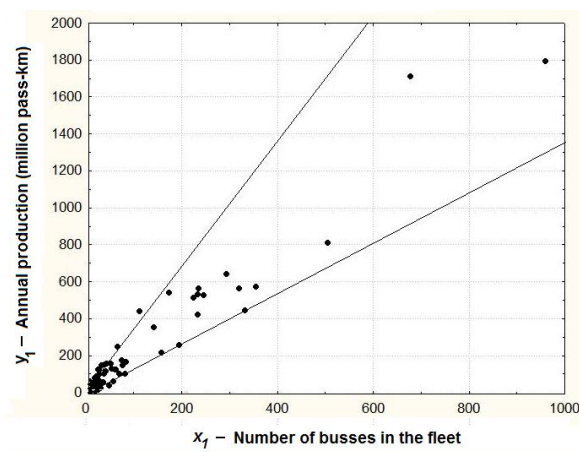


Figure 4 – Relationship between annual production and the fleet size.

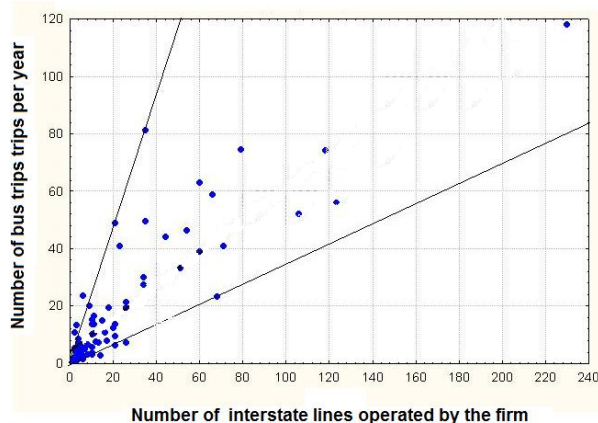


Figure 5 – Relationship between number of bus trips and interstate lines.

## 5. Analysis of results

### 5.1 Technical efficiency

As explained in Section 3.1, technical *DMU* efficiency scores  $\theta_k^{(BCC)}$  are obtained with the *BCC* model (*VRS*). We assume input orientation and radial efficiency throughout the paper (Cooper *et al.*, 2000). Input orientation has been adopted because the *ISBT* is a regulated industry in Brazil, with operators having more freedom of changing input factors of production than of changing outputs. Fifteen *DMUs*, among the 84 of the sample (17.8%), are in the efficient frontier, with  $\theta_k^{(BCC)} = 1$ .

Figure 6 shows the variation of technical efficiency as a function of cumulative production, expressed in percentage. As in Forsund (1994), the sample data was submitted to a crescent classification on the technical efficiency  $\theta_k^{(BCC)}$ . On the *x* axis, the cumulative values of the annual production are plotted, with its values taken as a percentage of the total production of the sample. The *DMUs* of the sample were classified into three groups (Figure 6). Group I, containing 22 small *DMUs* and representing only 6% of the total production, has shown low technical efficiency levels, ranging from 0.12 to 0.55. Group II, containing 47 *DMUs* and representing 75% of the total annual production, has shown crescent technical efficiency scores ranging from 0.55 to 0.99. Finally Group III, containing the 15 technically efficient *DMUs*, corresponds to 19% of the total production. The managerial efficiencies of the *DMUs* in groups I and II, to be analyzed in Section 5.3, will bring additional information on this matter.

The average technical efficiency score of the *BCC*-inefficient *DMUs* is 0.65. This low figure indicates a high level of inefficiency within the industry. Low technical efficiency figures denote a low level of competition, since, in a highly competitive market, inefficient operators would be driven out of business through the competitive process (Cowie & Asenova, 1999). Possibly, a good part of the technical inefficiency observed in the Brazilian *ISBT* may be attributed to large variation in returns to density, which considers production growth within a fixed-size transport network, while returns to scale also involve network growth

(Basso & Jara-Diaz, 2006). In order to measure such an effect it would be necessary to include, in the data, an indicator of the size of the bus-firm network as, for example, the total network extension (route-kilometers) or the number of boarding stops (Cambini & Filippini, 2003). This kind of information, however, is not presently available from the *ANTT* data base.

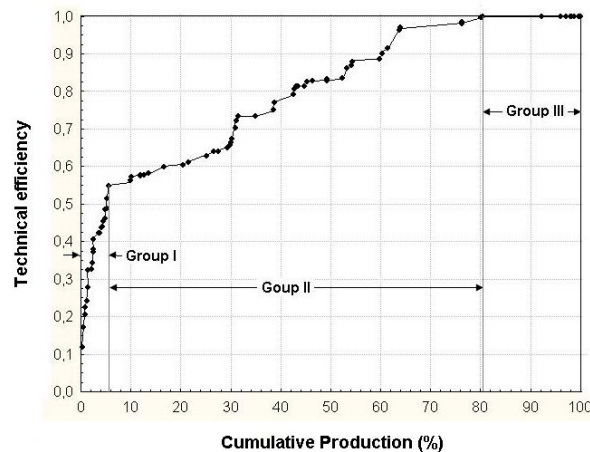


Figure 6 – Technical efficiency versus cumulative annual output (%).

## 5.2 Scale efficiency and returns to scale

Scale efficiency scores ( $\theta_k^{(sc)}$ ) are obtained running the models *CCR* and *BCC* and dividing the efficiency scores  $\theta_k^{(CCR)}$  by the corresponding  $\theta_k^{(BCC)}$  values ( $k = 1, 2, \dots, n$ ), as indicated in Section 3.1 and shown in Figure 7. As discussed in Section 3.1, scale efficiency should be measured for the *BCC*-efficient *DMUs* only, although some authors compute it for all the *DMUs* of the sample. Figure 6 shows the variation of scale efficiency as a function of annual production. The results for the efficient *DMUs* are depicted in a different format to distinguish them from the non-efficient units. It is also plotted the polynomial curve that fits the *BCC*-efficient values, obtained with the *Statistica* package. Clearly, scale efficiency attains its maximum (the unit value) for firms with annual production around 100 million passenger-km per year. The average value of  $\theta_k^{(sc)}$  is 0.804, but a great number of firms present low values, starting from 0.27.

A more precise way of analyzing returns to scale is to apply the *NIRS* model, as discussed in Section 3.3. Applying the *NIRS* model, it resulted that bus companies with annual production greater than 100 million passenger-kilometers tend to show decreasing returns to scale, whereas firms with annual production not greater than 100 million passenger-kilometers present increasing returns to scale. It is interesting to observe that 73.4% of the total production is represented by firms showing decreasing returns to scale.

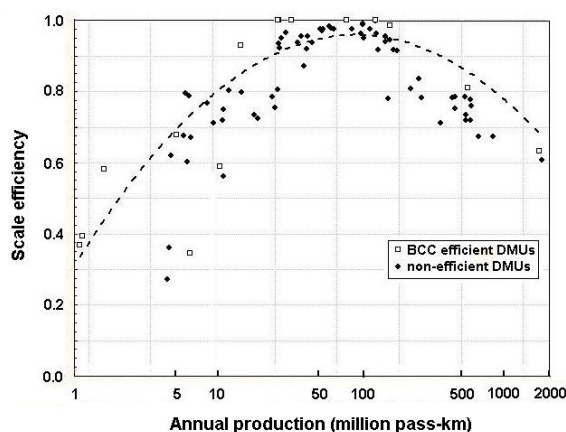


Figure 7 – Scale efficiency as a function of annual production.

### 5.3 Managerial efficiency

Managerial efficiency scores are computed for each non-efficient *DMU* group defined in Section 5.1. According to Section 3.4, a subset *SS* is formed with the *DMUs* of one of the groups I and II described in Section 5.1. The full set *FS* is formed by all 84 *DMUs* of the sample. Applying the *BCC* model (*VRS*) separately to both subsets, the managerial efficiency scores of the *DMUs* in the group are given by (22). The results are shown in Table 2.

Each one of the two groups of non-efficient *DMUs* has to be treated separately when performing upgrading measures and benchmarking analysis (Post & Spronk, 1999; Novaes, 2001). For example, part of the *DMUs* in Group II show managerial efficiencies close to unit, meaning they can be projected to the efficient frontier, in a benchmarking process, with more confidence. Firms in Group I, on the other hand, with low efficiency scores, could be seen as lacking size to perform the services contemplated in the *ISBT*. But care must be taken since such small and non-efficient bus firms may be the only ones to cover remote areas of the country, thus performing important social services.

Table 2 – Managerial efficiencies of the non-efficient *DMU* groups.

	<i>DMUs</i>	Managerial Efficiency		
		Minimum	Average	Maximum
Group I	22	0,37	0,44	0,55
Group II	47	0,66	0,88	0,99

## 6. Benchmarking

The literature on organizational decision-making indicates that many decisions fail because of poor management actions or inappropriate analysis tools. This situation can be improved through the benchmarking approach, which basically involves the process of evaluating and applying best practices to improve the performance of less efficient organizations (Ross & Droge, 2002; Kyrö, 2003). *DEA* provides a method of identifying the *DMUs* that

represent the “best practice”, which are those on the efficient frontier (Post & Spronk, 1999; Hinton *et al.*, 2000; Ross & Droge, 2002).

Suppose that, by applying the *BCC* model, *DMU k* has been found to be inefficient. Associated with this inefficient *DMU*, there is an optimal virtual point on the envelopment surface that may be expressed as a convex linear combination of the efficient *DMUs* (Cooper *et al.*, 2000). The efficient *DMUs*, obtained by applying the *BCC* model (7-10) to *DMU k*, have  $\lambda > 0$  and form the peer group that can be used as reference to benchmark unit *k*. For the inefficient *DMU k*, the input-oriented *BCC* model seeks to radially contract the input vector  $X_k$  as much as possible, while still remaining within the feasible input set. The radial contraction of the input vector  $X_k$  produces a projected point on the surface of the efficient frontier (Coelli *et al.*, 1998). The original point representing *DMU k*, however, may be relatively distant from the efficient frontier, and the radial contraction of the input set may lead, in practice, to a non-realistic configuration. Because of that, instead of applying the radial contraction to get the virtual efficient configuration for *DMU k*, one could use the peer group data to perform a direct benchmarking analysis of *DMU k*, through interviews, gathering of additional data (quantitative as well as qualitative), and professional judgment. A benchmarking analysis, restricted only to the *DEA* context, has been done for a particular non-efficient *DMU* of the sample, the bus company Auto Viação Catarinense.

Auto Viação Catarinense headquarters are located in the state of Santa Catarina, south of Brazil, and its busses serve localities in that state, as well as part of the state of Paraná, and farther reaching the state of São Paulo (the city of São Paulo and whereabouts). The *DEA* models indicated a technical efficiency  $\theta_k^{(BCC)} = 0.603$  and an overall efficiency  $\theta_k^{(CCR)} = 0.469$ , leading to a scale efficiency  $\theta_k^{(sc)} = 0.75$  for Auto Viação Catarinense. It belongs to group II of non-efficient *DMUs* (Section 5.1). Applying the *BCC* model, two efficient *DMUs* were selected as benchmarking peers to Auto Viação Catarinense. But one of them, the bus firm Viação Motta, showed a participation weight of  $\lambda = 0.98$  as a benchmarking peer to Auto Viação Catarinense. Thus, due to this high score, Viação Motta was the only peer considered in the *DEA* benchmarking analysis of Viação Catarinense. Table 3 shows the relevant information on both companies.

Both bus companies show almost the same annual production and their fleets travel almost the same average distance per year. But Viação Catarinense carries 60% more passengers per year, due, in part, to the shorter average distance travelled by its passengers. On the other hand, Viação Catarinense presents a technical efficiency equal to 0.60, as against full technical efficiency for its benchmarking peer, Viação Motta. Both firms show similar values for the scale efficiency. This index is related to the size of the firms, which is almost the same for both companies. Furthermore, Viação Catarinense shows a managerial efficiency equal to 0.81, meaning it should apply efforts in order to reach a full-efficiency status.

The average bus mileage (*PMA*) presented by Auto Viação Catarinense is only 53% of the *PMA* of Viação Motta. This indicates that the former company should apply efforts in order to utilize its fleet more intensively. The shorter bus-trip length explains in part such drawback. The average bus trip length of Viação Catarinense is only 47% of Viação Motta's. Shorter trips imply longer turnaround times, thus reducing effective vehicle usage. Of course, the geographic coverage of an interstate bus company depends on a number of other factors, some of them of a strategic nature, and therefore the extension of the network may not be an immediate decision to be taken by the company's executives. But it is



important to know whether such a restriction is, in fact, a drawback when comparing the firm with other operators.

Viação Motta shows a ratio of 1.79 drivers per bus, 4% higher than the value presented by Auto Viação Catarinense, but one should observe that the former presents trip lengths more than twice the ones shown by the latter. Longer distances means more bases, more crew turnaround, etc., leading to the necessity of more drivers. Perhaps this situation would explain the need of Viação Motta for more drivers per bus, but this hypothesis should be checked with more operational information.

Although *DEA* is a powerful tool to perform the benchmarking analysis of firms and organizations, this process should not be restricted merely to the comparison of quantitative data, but include the examination of the underlying causal factors (Hinton *et al.*, 2000). A thorough analysis of other kinds of information, considering the two firms and other similar ones, should be performed in order to reach a reliable benchmarking diagnosis. But undoubtedly *DEA* helps to concentrate the benchmarking analysis on a set of *DMUs* more likely to be operationally related to the unit in question.

**Table 3** – Data for benchmarking Auto Viação Catarinense.

Item	<i>DMU to be benchmarked</i>	Benchmarking Reference
• DMU name	Auto Viação Catarinense	Viação Motta
• $\lambda$	not applicable	0.98
• Production factors		
• Annual production – <i>PKM</i>	560,998,922	538,443,726
• Pass. carried per year – <i>PAX</i>	2,169,012	1,356,759
• Fleet (n° of busses) – <i>FLT</i>	321	174
• N° of bus drivers – <i>DRV</i>	551	311
• N° of lines – <i>LIN</i>	60	44
• N° of trips per year – <i>TRIP</i>	63,084	29,980
• ( <i>D</i> ) Total distance traveled annually by the fleet (km)	25,216,781	25,587,430
• Technical indexes		
• Technical efficiency	0.60	1.000
• Scale efficiency	0.75	0.81
• Managerial efficiency	0.81	1.00
• <i>PMA</i> (km/bus/year)	78,557	147,054
• Average n° of drivers per bus	1.72	1.79
• Average bus trip length (km) = $D / TRIP$	399.7	853.5
• Average passenger trip length (km) = $PKM / PAX$	258.5	396.9

## 7. Conclusions

In this paper we have performed a productivity and efficiency analysis of the bus firms that operate in the Brazilian interstate passenger transportation system (*ISBT*). This market is heavily concentrated, with 20% of the bus companies being responsible for 84% of the total volume, expressed in passenger-kilometers. Technical, scale and managerial efficiency scores were computed with the *CCR* and the *BCC DEA* models. In the paper, weight restrictions have been introduced based on trade-offs among the production factors. This was done following recent *DEA* developments aimed to refine the analysis with the inclusion of value judgments.

Scale efficiencies ranged from 0.27 to 1.000, with an overall average value of 0.80. Increasing returns to scale have been detected for firms with production not greater than 100 million passenger-kilometers per year. A small number of firms have shown a constant return to scale.

On the other hand, firms presenting production levels greater than 100 million passenger-kilometers per year have shown decreasing returns to scale. These operators represent about 73% of the total production. This means that preference should be given by the regulatory agency to medium size operators, preferably in the production range around 100 million passenger-km per year.

With regard to technical efficiency, the analysis has detected three groups of bus firms. Group I contains 22 small *DMUs*, representing only 6% of the total production and showing low efficiency scores, in the 0.12 – 0.55 range. Group II comprises 47 firms, totaling 75% of the production, and showing efficiency levels in the 0.55 – 0.99 range. Finally group III is formed by 15 efficient firms, representing 19% of the total production of the sample.

In general, technical efficiency scores are low, indicating a high level of inefficiency within the industry. Low technical efficiency figures denote a low level of competition, since, in a highly competitive market, inefficient operators would be driven out of business through the competitive process. Possibly, a good part of the technical inefficiency observed in the Brazilian *ISBT* may be attributable to large variation in returns to density. In order to measure such an effect it would be necessary to include in the data an indicator of the size of the bus-firm network as, for example, the total network extension (route-kilometers) or the number of boarding stops. This kind of information, however, is not presently available from the *ANTT* web-site.

It is suggested that a deeper analysis be performed in order to identify the causes of the low efficiency levels presented by firms in group I and part of group II. It is also suggested that a reasonable sample of non-efficient bus firms in groups II and III be submitted to a benchmarking process, using *DEA* as a part of the evaluation process. The quality of data is another important subject to be approached by *ANTT*. Since interstate bus operators are required to periodically report operational data, it would be highly desirable that such information be prepared and submitted with more accuracy.

## Acknowledgements

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