Pontifícia Universidade Católica
do Rio de Janeiro

Bianca Brandão de Paula Antunes

ICU efficiency assessment using Data Envelopment Analysis

Dissertação de Mestrado

Dissertation presented to the Programa de Pós-Graduação em Engenharia de Produção of PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Engenharia de Produção.

Advisor: Silvio Hamacher
Co-Advisor: Fernando Augusto Bozza

Rio de Janeiro
July 2020

Bianca Brandão de Paula Antunes

ICU efficiency assessment using Data Envelopment Analysis

Dissertation presented to the Programa de Pós-Graduação em Engenharia de Produção of PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Engenharia de Produção. Approved by the Examination Committee.

Silvio Hamacher
Advisor
Departamento de Engenharia Industrial - PUC-Rio

Fernando Augusto Bozza
Co-Advisor
Fundação Oswaldo Cruz - FIOCRUZ

Julia Lima Fleck
Departamento de Engenharia Industrial - PUC-Rio

Marcio Soares
Instituto D'Or de Pesquisa e Ensino

Rio de Janeiro, July 16th, 2020

Bianca Brandão de Paula Antunes

The author graduated in Production Engineering at the Instituto Ibmec/RJ. She has experience with management and data analysis and has participated in projects in healthcare operations management at the Instituto Tecgraf (PUC-Rio).

Bibliographic data

Antunes, Bianca Brandão de Paula

ICU efficiency assessment using Data Envelopment Analysis / Bianca Brandão de Paula Antunes ; advisor: Silvio Hamacher ; co-Advisor: Fernando Augusto Bozza. – 2020.
92 f. : il. color. ; 30 cm

Dissertação (mestrado)–Pontifícia Universidade Católica do Rio de Janeiro, Departamento de Engenharia Industrial, 2020.
Inclui bibliografia

1. Engenharia Industrial – Teses. 2. UTI. 3. DEA. 4. Eficiência. 5. Saúde. I. Hamacher, Silvio. II. Bozza, Fernando Augusto. III. Pontifícia Universidade Católica do Rio de Janeiro. Departamento de Engenharia Industrial. IV. Título.

CDD: 658.5

Acknowledgements

To CNPq, CAPES, and PUC-Rio for providing the resources needed to this work.

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

Abstract

Antunes, Bianca Brandão de Paula; Hamacher, Silvio (Advisor); Bozza, Fernando Augusto (Co-Advisor). **ICU efficiency assessment using Data Envelopment Analysis.** Rio de Janeiro. 2020. 92p. Dissertação de Mestrado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

Healthcare performance assessment is especially relevant for Intensive Care Units (ICUs), which deal with high complexity cases. This work evaluates 93 ICUs using Data Envelopment Analysis (DEA). Three models are proposed to broaden the analysis from different perspectives: staffing, structure, and capacity. It uses patient-level data to adjust outcomes to the ICU's case-mix, which results in two outputs: Standardized Mortality Rate (SMR) and Standardized Resource Use (SRU). Statistical analyses are also performed to show the relation of the variables. Average DEA efficiency scores are calculated for categorical non-discretionary variables, assessing that private for-profit hospitals, in general, have better efficiency results and that large ICUs have lower SMR and SRU.

Keywords

ICU; DEA; efficiency; healthcare

Resumo

Antunes, Bianca Brandão de Paula; Hamacher, Silvio (Orientador); Bozza, Fernando Augusto (Co-Orientador). **Avaliação de eficiência de UTIs com uso de Análise Envoltória de Dados**. Rio de Janeiro. 2020. 92p. Dissertação de Mestrado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

A avaliação de desempenho no contexto da saúde é especialmente importante para Unidades de Terapia Intensiva (UTIs), que lidam com casos de alta complexidade. Este trabalho avalia 93 UTIs com uso de Análise Envoltória de Dados (DEA). Três modelos são propostos para aprofundar a análise em diferentes perspectivas: equipe médica, estrutura e capacidade. Este trabalho usa dados a nível de paciente para ajustar os resultados pelo case-mix da UTI, o que resulta em dois outputs: taxa de mortalidade ajustada (SMR) e taxa de uso de recurso ajustada (SRU). Análises estatísticas também são realizadas para mostrar a relação entre as variáveis. Médias dos valores de eficiência obtidos pelo DEA são calculados para variáveis categóricas não-discricionárias, mostrando que hospitais privados com fins lucrativos, em geral, têm melhores resultados de eficiência, e que grandes UTIs têm menores valores de SMR e SRU.

Palavras-chave

UTI; DEA; eficiência; saúde

Table of Contents

List of Figures

List of Tables

List of Abbreviations

BOR	Bed Occupancy Rate
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
ICU	Intensive Care Unit
ICU_Bed	Number of ICU beds
LOS	Length of Stay
MD_Bed10	Number of physicians per 10 beds
MD_hours	Total hours worked by physicians per week
Nur_Bed10	Number of nurses per 10 beds
Nur_hours	Total hours worked by nurses per week
NurTec_Bed10	Number of nursing technicians per 10 beds
Physio_Bed10	Number of physiotherapists per 10 beds
SMR	Standardized Mortality Rate
SRU	Standardized Resource Use
VRS	Variable Returns to Scale

1
Introduction

The purpose of measuring quality is to know when performance is out of standards and to detect and correct deviations (Donabedian, 1978). The sole measure of quality, however, does not comprise the use of resources, which might lead to high costs. At the same time, reducing costs without accounting for the quality missed can lead to false savings and ineffective results (Porter, 2010). Therefore, efficiency measures can be useful, as they balance both quality and use of resources.

In the healthcare scenario, the pursuit of better outcomes can be decisive to whether a patient lives or dies, or to their quality of life after a certain procedure. Therefore, studies that address the measurement of efficiency are important and applicable to different countries and scenarios, thus relevant on a global level.

Determination of hospital performance, specifically, can be used as benchmarking, resulting in motivation for managers in the pursuit of best practices. For patients, it means having access to better quality treatment, as well as being able to choose care based on scientific analyses. In some settings, the price of hospital services is also set based on their efficiency.

Some papers measure the efficiency of the hospitals as a whole (Alam, 2018), while others focus on specific departments or diagnostics (Cohen-Kadosh & Sinuany-Stern, 2020; Huang, Liu & Lu, 2010). Within the hospitals, performance assessment is especially relevant for Intensive Care Units (ICUs) as they deal with high costs and high complexity cases (Garland, 2005). Besides, they are helpful in understanding the course of diseases and plan ahead of time (Ray et al., 2009).

The definition of the parameters that will be used in the assessment, however, is challenging since they have to be useful not only for patients but also for hospitals and the society (Garland, 2005). Besides, measuring ICU efficiency is complex since its outcomes are highly dependent on the type of patients treated in that unit (case-mix). For that reason, a few severity scores have been created, providing means to compare ICU outcomes with a reference population (Breslow; Badawi, 2012).

Data Envelopment Analysis (DEA) has been the basis to most studies in the hospital efficiency field, mainly because it can deal with multiple inputs and outputs, which is especially important to the healthcare environment (Hollingsworth, Dawson & Maniadakis, 1999), leading to more accurate results (Porter, 2010).

Also, DEA is a good starting point for decisions regarding hospital management (Kohl et al., 2019). When dealing with ICU efficiency specifically, however, only a few studies have used frontier analysis such as DEA, as most of the works conduct statistical analysis.

The main objective of this research is to compare the efficiency of ICUs applying frontier analysis, specifically DEA, on a database that contains information on the hospitals, the ICUs, and the patients. Secondary objectives include:

- Perform a literature review to understand the main metrics and models used in this problem;
- Define which metrics and indicators are useful to the comparison;
- Obtain and analyze ICUs' efficiencies, considering the specifications of the DEA model;

This study aims to contribute to the existing literature by performing an ICU efficiency analysis using DEA with patient-level variables adjusted to their severity. Besides, it will provide extensive review and discussion of parameters and methods.

The next section of this work presents a review of the literature on this subject; Section 3 structures the methodology used; Section 4 performs descriptive analyses on the database used; Section 5 discusses the DEA results; Section 6 presents other analyses using the results obtained with the DEA model, and Section 7 concludes the research.

2
Literature Review

To understand what fits best to this work and which are the techniques and tools most useful to this research, the literature review was based mainly on five aspects: what it is and how to perform a DEA analysis; how efficiency is seen in the healthcare environment; which were the inputs and outputs used in other models, and how they were selected; which are the tools and models used to assess healthcare performance; and how other works have used DEA to evaluate ICU efficiency. As only a few studies have used DEA for ICU performance assessment, works that deal with hospitals, in general, were also considered in this review.

2.1. Data Envelopment Analysis (DEA)

In general, frontier methods consist of studying the efficiency of a Decision-Making Unit (DMU) in comparison to the other units. The analysis is performed by defining an efficient frontier, which is composed of the "best-practice" DMUs since the true theoretical frontier is unknown (Cooper, Seiford & Zhu, 2004). DMUs that are not located in the frontier are considered inefficient. Therefore, these methods consider a relative frontier, which has to be achieved by at least one unit (Adler, Friedman & Sinuany-Stern, 2002).

Hollingsworth, Dawson & Maniadakis (1999) classify frontier methods using two aspects: whether they are deterministic or stochastic, and parametric or non-parametric (Table 1). Deterministic models assume that the distance between a hospital and the frontier is explained by the lack of efficiency, while stochastic models consider that a part of it is also due to other factors. The difference between a parametric and a non-parametric model is that the first one assumes a specific production function (or frontier). That is, the frontier is previously defined by the user, while the non-parametric model defines the frontier according to the best-practice DMUs.

Table 1 – Methods of frontier analysis

	Parametric	Non-parametric
Deterministic	- Parametric mathematical programming - Deterministic frontier analysis	- Data Envelopment Analysis (DEA)
Stochastic	- Stochastic frontier analysis	- Stochastic data envelopment analysis

Source: adapted from Hollingsworth, Dawson & Maniadakis (1999)

One of the main advantages of using DEA, therefore, is that there is no need to specify a production function (Kohl et al., 2019). DEA was first introduced by Charnes, Cooper & Rhodes (1978). Since then, several new methodologies and extensions to the basic DEA model were suggested and applied in different scenarios.

Basically, in a DEA model, efficiency is calculated as the ratio of the weighted sum of outputs (outcomes) to the weighted sum of inputs (resources). The weights are defined by maximizing the efficiency of a determined DMU (Eq. 1), with the constraint that each DMU cannot have an efficiency greater than 1 (Eq. 2). Also, the weights have to be non-negative (Eq. 3) (M1) (Charnes, Cooper & Rhodes, 1978).

(M1)

$$\max \frac{\sum_r u_r * y_{r0}}{\sum_i v_i * x_{i0}} \quad (1)$$

$s.t.$

$$\frac{\sum_r u_r * y_{rj}}{\sum_i v_i * x_{ij}} \leq 1 \qquad \forall j \quad (2)$$

$$u_r, v_i \geq 0 \qquad \forall r, i \quad (3)$$

Where:

u_r: weight of each output r

v_i: weight of each input i

y_{rj}: amount of each output r in each DMU j

x_{ij}: amount of each input i in each DMU j

The model presented will result in the relative efficiency of one unit (DMU 0). By changing the indices in the objective function, it is possible to analyze the efficiency of each DMU in relation to the rest of the set. Therefore, to obtain the efficiency scores of all units, it is necessary to run the model j times, with j being the number of units in the set.

To linearize the model and to avoid multiple solutions, the denominator of the objective function is set to be equal to one, and the constraints in (2) are also adjusted (the weighted sum of the inputs passes to the right-hand side). This model is known as "multiplier," as there are weights multiplying the input and output values. As it is now a linear programming problem, it has a dual that results in the same value of efficiency (objective function). It is called "envelope," and it is represented by the following equations in model 2 (M2).

(M2)

$$\min h \quad (4)$$

$s.t.$

$$hx_{i0} \geq \sum_j \mu_j x_{ij} \qquad \forall \boldsymbol{i} \quad (5)$$

$$y_{r0} \leq \sum_j \mu_j y_{rj} \qquad \forall \mathrm{r} \quad (6)$$

$$\mu_j \geq 0 \ \ \forall j \quad (7)$$

Where:

h: efficiency score of DMU 0

μ_j: weight of each DMU j

y_{rj}: amount of each output r in each DMU j

x_{ij}: amount of each input i in each DMU j

In the model above (M2), the maximum efficiency is obtained by reducing the use of inputs and maintaining the outputs constant, defined as input-oriented. The objective function (eq. 4) minimizes the efficiency score, which multiplies the inputs of DMU 0. If the efficiency score is equal to one (the maximum value possible), it means that there is no need to minimize the inputs, which indicates that the unit is efficient.

The output-oriented model focus on maximizing the use of outputs while maintaining the same level of inputs. A third possibility is the Additive model, which combines input and output-oriented, both minimizing inputs and maximizing outputs at the same time.

Also, (M2), named CCR model (in reference to its creators, Charnes, Cooper & Rhodes (1978)), assumes Constant Returns to Scale (CRS), which means that any variation on inputs causes a proportional change in outputs. Another possibility is to consider Variable Returns to Scale (VRS), as proposed by Banker, Charnes, & Cooper (BCC) (1984), that assumes that returns to scale can be increasing, constant, or decreasing, forcing the frontier to be convex (Mello et al., 2005).

A DMU considered efficient using the CRS model will also be efficient if the VRS model is used. However, the opposite is not always true. Mathematically, the difference is that in the VRS envelope model, there is one more constraint that states that the sum of the weights has to be equal to one (Eq. 8).

$$\sum_j \mu_j = 1 \qquad (8)$$

Graphically, the difference can be seen in

. D is the only DMU that is not considered efficient in either model. A and C are only efficient when the VRS model is applied. Unit B is efficient in the CRS model and, therefore, also efficient using the VRS equations.

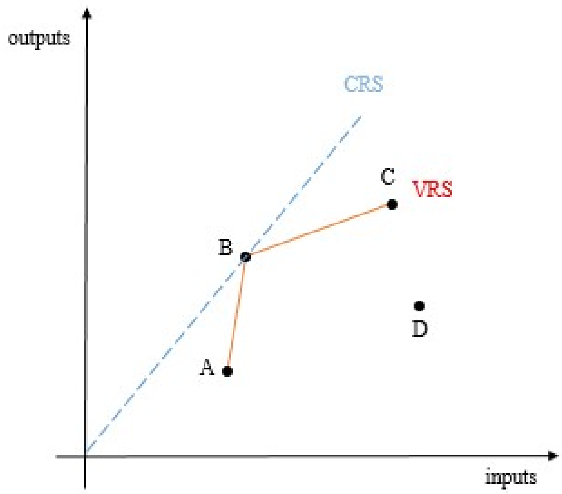

Figure 1 – Example of the difference between the CRS and the VRS frontiers
Source: Adapted from (Mello et al., 2005)

As the returns to scale are defined by the user based on the characteristics of the business being analyzed, it is important to make the decision carefully. If the nature of the business is of constant returns to scale and the VRS model is used instead, inefficient units might end being part of the frontier, being wrongly classified (Dyson et al., 2001).

The flexibility given to the weights in DEA models (that change accordingly to the DMU being analyzed) may be seen in two ways: if the DMU is considered efficient, then it might be said that the choice of the weights was accountable for the result. However, if the DMU is inefficient even with adequate weights, then the result of inefficiency is clear (Boussofiane, Dyson & Thanassoulis, 1991).

Also, due to the flexibility given to the weights, the number of inputs and outputs should be small compared to the number of units in the set, so that there is effective discrimination between units (Boussofiane, Dyson & Thanassoulis, 1991). Considering that a unit can allocate all possible weight in a single input and in a single output, the number of units that can easily appear efficient will be the product of inputs and outputs. For that reason, Dyson et al. (2001) specify that the number of DMUs should always be bigger than two times the number of inputs multiplied by the number of outputs (Eq. 8).

$$\#DMUs \geq 2 * \#inputs * \#outputs \tag{8}$$

Dyson et al. (2001) also list common mistakes when using DEA. They include comparing units that are not homoge1nous and ignoring environmental differences that may influence the results. Another point of attention regards omitting a variable only because it is highly correlated to another variable already present in the model. This should be avoided, as the regression shows a correlation on the aggregate level, but differences on an individual level might be significant to the efficiency analysis.

One of the critics regarding the use of DEA is the visualization of the results. The DMU might be efficient when the weights are favorable but inefficient with all other possible weights (when the model is trying to maximize the other DMUs' efficiencies). One possible way to overcome this problem is to use a cross-efficiency matrix (Sexton, Silkman & Hogan, 1986).

It lists the efficiency results that each DMU had with each of the possible weights (Table 2). The columns represent the efficiency of that DMU when using the most favorable weights to the DMU in the row. The last row is the average of the results obtained for that DMU across all weights, which is known as peer-appraisal. The rows, thereby, are the results of all efficiency scores using the best weights to the DMU in the row. The last column is the average of the efficiency scores given to the other DMUs with those specific weights, known as "averaged appraisal of peers." The diagonal is composed of the actual value of efficiency scores of each DMU with its best weights, named self-appraisal (Doyle & Green, 1994).

Table 2 – Cross-efficiency matrix representation

	Reference		
Results	**DMU 1**	**DMU 2**	**Average**
DMU 1	Best DMU 1 efficiency (self-appraisal)	Efficiency of DMU 2 with DMU 1's best weights	Appraisal of peers (DMU 1)
DMU 2	Efficiency of DMU 1 with DMU 2's best weights	Best DMU 2 efficiency (self-appraisal)	Appraisal of peers (DMU 2)
Average	Peer-appraisal (DMU 1)	Peer-appraisal (DMU 2)	

Source: elaborated by the author

2.2. Efficiency in healthcare

Donabedian (1966) considers three approaches to quality assessment in healthcare: outcome, process, and structure. The outcome of healthcare is defined as the change in health status that can be associated with specific care, and it might include factors such as quality and duration of life, sociological function, and social performance (Donabedian, 1978).

Process indicators are the second approach mentioned by Donabedian (1966), and they measure the means instead of the ends. Conclusions are drawn not from the final result, but from the process itself. The main objective is to determine if proper medical care has been applied.

The last approach regards the structure in which the care has taken place, as well as its administrative processes. It includes information such as the quality of the establishment and its equipment, and the physicians' qualifications (Donabedian, 1966).

In another work, Donabedian (1978) considers two factors as the most relevant to influence results of health outcomes, and they are included in the "structure approach": the nature of the hospital, since the size and the type of the hospital might affect its results; and the physician specialization, since specialists usually present better outcomes than generalists.

Regarding outcome assessment, the quality of life after a health intervention can be valued by asking patients to answer questionnaires. This information is not only for understanding people's satisfaction with the service provided but also to get information about their health status and perceived quality of life (Black, 2013).

However, there might be logistical difficulties in obtaining these answers (Garratt et al., 2002). Besides, they are usually not standardized, and the information is not completely trustable as it is reported by the patient and thus, subjective (Gutacker et al., 2013). For that reason, some authors choose to use more objective data, such as the length of stay (LOS), and the number of patients treated.

The sole measure of quality, however, might not be useful to managers, as there are other considerations relevant when making decisions. In any setting, having a goal that is interesting to all stakeholders is, at the same time, a challenge and essential to improving performance.

Increasing the quality of outcomes per dollar spent can be an objective that unites all stakeholders (Porter, 2010). Efficiency assessment usually leads to benchmarking, which can provide clearer views of targets for hospital staffing and managers (Salluh, Soares & Keegan, 2017).

According to Kohl et al. (2019), the first study regarding health efficiency measurement was by Nunamaker (1983), which evaluated nurse performance. One year after that, a research on hospital efficiency was published by Sherman (1984). Since then, many papers have been published regarding the assessment of hospital efficiency, using different models, data, and parameters.

2.3. Choice of measures

In the literature, there are different choices of inputs and outputs, according to the study purpose, the level of specificity, and the available data. The main choices for inputs can be categorized into three types: capital investment (i.e., beds and service-mix), labor (i.e., number of physicians), and operating expenses (OZCAN, 2014). The possible outputs can be divided into intermediate (or process) indicators (i.e., waiting line, number of patients treated), and final (or outcome) indicators (i.e., mortality, quality of life), being the last the best measure for economic evaluations (Mant, 2001; Palmer & Torgerson, 1999).

Each of these groups has strengths and weaknesses in the study of healthcare performance. The wider the perspective, the better it is to use outcome indicators. Therefore, when looking at healthcare performance in different countries, outcome measures might be more useful. For example, Retzlaff-Roberts, Chang & Rubin (2004) compare countries using two outputs: infant mortality and life expectancy. On the contrary, when analyzing hospital or physician performance, process indicators are usually more accurate, as they are less sensitive to variations (Mant, 2001). However, measuring process indicators in ICUs is not straightforward, which makes using these data more complicated.

The main aspects that can influence these variations, cited by Mant (2001), are differences in the type of patients (e.g., age, co-morbidity, severity), differences in measures, chance (random variation) and the actual difference in the quality of care. For that reason, outcome indicators should be used with case-mix adjustment and standardization of data. The characteristics of each type of indicator are presented in Table 3.

Table 3 - Differences between process and outcome indicators

Process indicators	**Outcome indicators**
More sensitive to actual differences in quality	Less sensitive to actual differences in quality
Easy to interpret; straightforward	More difficult to draw conclusions
Reflect one aspect at a time	Reflect all aspects of the process
Data is usually less accessible	Data is usually more accessible

Source: adapted from Mant (2001)

Kohl et al. (2019) emphasize that inputs should include all resources needed, while outputs should reflect the hospital's main managerial objectives. They rank the main inputs and outputs that appeared in their literature review (Table 4).

Table 4 – Ranking of most used inputs' and outputs' categories

Inputs	Used at least once	Outputs	Used at least once
Beds	184	Outpatients	120
Medical staff	149	Other/total cases	118
Nurses	114	Inpatients	103
Non-medical staff	93	Surgery	62
Overall staff	65	Services	48
Supplies	60	Performance/quality	41
Equipment & infrastructure	40	Others	37
Total costs	37	Revenue	13
Service & performance	29	Case-mix	5
Other costs	27	-	
Socio-economic	16	-	
Other	5	-	

Source: adapted from (Kohl et al., 2019)

Most studies found in the “hospital efficiency” field use only aggregate data, usually on the hospital level, as the number of patients treated, and the number of beds (Mehrtak, Yusefzadeh & Jaafaripooyan, 2014; Walker, 2018; Giménez, Keith & Prior, 2019; Xenos et al., 2017). Only a few use only patient-level data (Cohen-Kadosh & Sinuany-Stern, 2020; Gyrd-Hansen, Olsen & Sørensen, 2012; Laudicella, Olsen & Street, 2010) such as expected costs of each patient, number of procedures performed and presence of comorbidities. This difference can be decisive to the choice of indicators used.

Laudicella, Olsen & Street (2010) argue that hospital-level data has limitations. Firstly, it usually assumes that different hospitals and sectors within a hospital have the same production function, which can bias the analysis. Secondly, the sample size is sometimes a problem if the comparison includes different types of hospitals. Thirdly, when considering the entire hospital, it is harder to find the reason and source of the inefficiency. Finally, patient-level data allows for better adjustments, considering the characteristics of patients on an individual level.

According to Gyrd-Hansen, Olsen & Sørensen (2012), one common benchmarking output measure is the ratio between expected and observed costs. However, if patient-level data is used, there could be problems in the analysis. Firstly, because of hospital differences in the method of costing, secondly, costs that are not directly associated with patients’ care are sometimes distributed to individual patients. To overcome these difficulties, the authors use LOS as a performance measure to analyze if hospital efficiency models should be adjusted to the patient’s socio-demographic characteristics. They conclude that these attributes are not critical to the model.

However, regressing costs instead of LOS, Laudicella, Olsen & Street (2010) found that some of the patients’ characteristics are significant to explain differences in costs in obstetric departments. They include socio-demographic factors, such as income deprivation of the area where the patient lives. Other significant characteristics include the number of babies delivered, and the number of diagnoses recorded.

2.4. Efficiency models in healthcare

Most works regarding hospital efficiency use DEA or closely related models. A few other studies, however, have not used frontier analysis. Goshtasebi et al. (2009) used the Pabon Lasso method, in which three indicators (LOS, bed turn over, and occupancy rate) for each hospital are plotted in a graph that is divided into four areas, as represented in Figure 2. Depending on the quadrant the hospital is in, it can be considered efficient, not efficient, or in between (Mehrtak, Yusefzadeh & Jaafaripooyan, 2014).

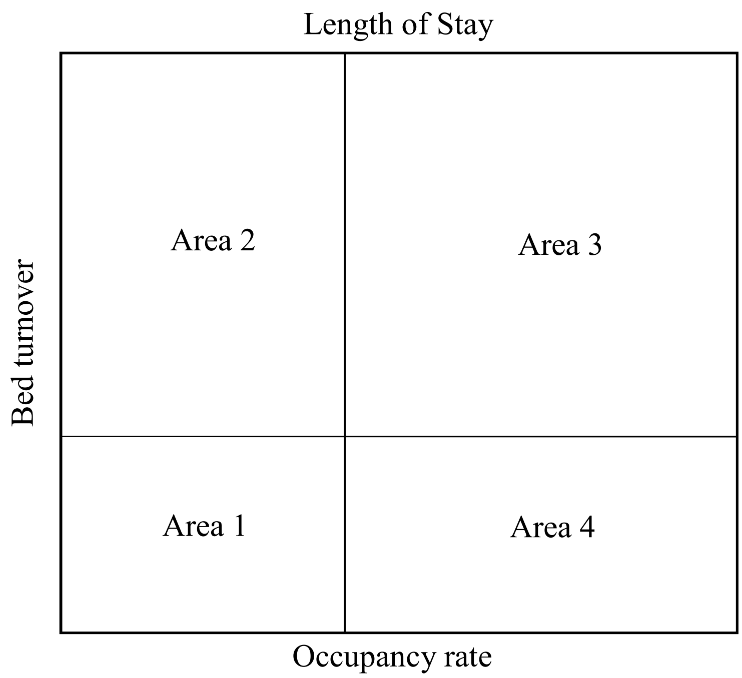

Figure 2 – Pabon Lasso method used by Goshtasebi et al. (2009)

Source: Adapted from (Goshtasebi et al., 2009)

A similar analysis was performed by Rhodes et al. (1997), but using LOS and administrative price as indicators, divided by the Diagnostic Related Group. Laudicella, Olsen & Street (2010) compare costs after removing the bias from patients' and departments' characteristics.

Kohl et al. (2019) explore the use of DEA in healthcare, especially in hospitals, by reviewing 262 papers that cover twelve years of research (2005-2016). The papers are divided into four areas: pure DEA analysis, development and application of new DEA-based methodologies, specific management questions, and surveys on the impacts of determined reforms.

The authors highlight that DEA is mostly performed in theory and that few studies result in actual decision-making guidance, even though there is a positive trend in the number of articles involving DEA in hospitals over these twelve years.

Trends regarding the geographical focus of publications were also performed. However, only the four continents with a significant number of publications were represented, which excluded South America from the analysis. Three of the regions (North America, Europe, and Asia) had positive trends, and Africa had a slight negative trend. Other descriptive statistics performed include the top contributing authors and journals, the most used inputs and outputs (Table 4 – section 2.3), and a ranking of the models used more than once (Table 5).

Table 5 – Most used DEA models

Model	**Number of applications**
VRS	144
CRS	112
Super Efficiency	14
Distance Functions	11
ADD/SBM	10
Congestion	8
Assurance Region	7
Fuzzy DEA	4
Network DEA	2
Others	18

Source: adapted from (Kohl et al., 2019)

The main drawback of the classic models (VRS and CRS) is making it possible to have only one of the inputs' (and outputs') weights different than zero (Kohl et al., 2019), which means that some of the parameters might be ignored. One way to overcome this issue is to use Assurance Region models. It assumes a value (fixed or variable) to the weights to make sure inputs or outputs are not wrongfully discarded (weights = 0).

The ADD (Additive model) and the SBM (Slacks-Based measure) differ from others because the user does not need to specify an orientation. They minimize inputs while maximizing outputs by maximizing the slacks (input excess and output shortfall). In that case, a DMU will only be efficient if all of its slacks are equal to zero (Tone, 2011).

The Super Efficiency model allows efficiency to be greater than one by comparing the unit under evaluation with a linear combination of all other units, thus removing the unit from the analysis, which creates an efficiency ranking and raises the discrimination between units (Andersen & Petersen, 1993).

Kohl et al. (2019) also mention the subsequent techniques used jointly with the DEA models to deepen the analyses (Table 6).

Table 6 – Techniques used with DEA

Technique	Number of publications
Regression	76
Bootstrapping	48
Malmquist Index	47
Window Analysis	5
Others	4
Total	180

Source: adapted from (Kohl et al., 2019)

The most used technique is regressing DEA scores on environmental variables to understand which of these characteristics are significant to hospital efficiency. The Bootstrapping technique reduces the possibility of the frontier obtained not being the actual most efficient frontier. It resamples data repeatedly in order to obtain theoretical efficiency values. The final scores are then inferred from these data. Malmquist Index and Windows Analysis are ways of measuring how efficiency changes over time by revealing time trends. The Malmquist Index is used to compare the results of a unit in a given period of time with the efficient frontier of the other periods. The Windows Analysis is performed by considering that a unit in different periods is actually different DMUs. This means that one unit is evaluated against itself (and others) in different periods (Charnes et al., 1984).

2.5. ICU performance assessment using DEA

Although DEA has been widely used for hospital performance, only a few studies approached ICUs specifically, which is the objective of this work. Of the ones that did, some had different objectives compared to this research, as analyzing the efficiency of ICU nurses (Osman et al., 2011), or the performance of neurotrauma patients (Nathanson et al., 2003). There was also a work that analyzed ICU efficiency comparing the ICUs both among them and between other hospital departments, that is, each department in each hospital was considered as a different DMU (Migdadi; Al-Momani, 2018).

There were also some studies that calculated ICUs efficiencies using other frontier methods, such as SFA (Stochastic Frontier Analysis) (Bahrampour; Goodarzi; Tohidi, 2013) and RFDH (Robust Free Disposable Hull) (Dervaux et al., 2009).

Works that applied DEA to evaluate ICU performance specifically were also found in the literature. Their metrics vary according to their objectives, and they can be generally divided into categories: finance (costs and revenues), structure (equipment, number of beds), staffing patterns (nurse hour per patient day), patient condition (falls, infections), capacity (bed occupancy rate), and outcome (discharges, mortality rate).

The variables (inputs and outputs) selected by six of the works found in the literature, as well as the models' orientations and returns to scale are summarized in Table 7.

Table 7 – Works that use DEA for ICU performance assessment

(Authors, year)	**Inputs**	**Outputs**	**Orientation**	**Returns to scale**
(Ferreira; Marques, 2018)	Expenditures with external services, expenditures with staff, expenditures with technological asset investments, hospital days	Inpatient discharges	Output	VRS
(Lacko; Hajduová; Hurný, 2018)	Number of beds, number of doctors, number of nurses, material costs, operational costs	Number of inpatients, number of inpatient days, and total revenues	Output	CRS
(Tsekouras et al., 2010)	Equipment, number of beds, number of doctors, number of nurses	Days of treatment	Output	VRS and CRS

(Min et al., 2018, 2019)	(registered nurse, licensed practical nurse, and unlicensed assistive personnel) hour per patient day	Patient falls per 1000 patient days, percent of patients with hospital-acquired pressure ulcers, (central line catheter-associated bloodstream infections, catheter-associated urinary tract infections, and ventilator-associated events) per 1000 days, percent of patients with physical restraints	Input	CRS
(Bahrami et al., 2018)	Number of physicians, nurses, active beds and equipment	Bed occupancy rate, number of discharged patients, bed price and physicians' fees	NA	VRS
(Azadeh et al., 2016)	Number of physicians, number of operating rooms, number of ICU beds, and number of nurses	Mortality rate, waiting days for operation, cerebral hospitalization time, spinal hospitalization time, postponed surgery plans, and number of patients with bedsore	Input	NA

Source: elaborated by the author

The relations between the inputs and outputs chosen for each model indicate the objectives and perspectives of each work. Ferreira & Marques (2018), for example, are interested in the effects that different expenditures have on the number of patients who were discharged (not dead); Azadeh et al. (2016), on the other side, want to understand how the structure of an ICU affects patient outcomes in different ICUs.

The inputs, which are usually defined as the resources used by the unit to get to the outputs, are frequently associated with medical staffing, either in volume of professionals (Azadeh et al., 2016; Bahrami et al., 2018; Lacko; Hajduová; Hurný, 2018; Tsekouras et al., 2010) or in proportion of hours worked related to the number of beds (Min et al., 2018). One of the works used the expenditures as resources (Ferreira; Marques, 2018), however, these values are commonly hard to access (Rothen; Takala, 2008).

The outputs chosen varied more than the inputs. The metrics related to patient volume were the most used (discharges, inpatients, and inpatient days), but there were also economic variables (revenue, bed price and physicians' fees), rates such as mortality and bed occupancy, and even more detailed patient-level aspects: falls, physical restraints, and bedsores.

3
Methods

This research compared Brazilian ICUs using DEA. It first explored the literature to find the best practices in frontier analysis and healthcare efficiency. After that, the model was applied using the database from the ORCHESTRA study (Zampieri et al., 2019), which comprises information of 129,680 patients admitted to 93 ICUs at 55 Brazilian hospitals, in 2014 and 2015.

The dataset was filtered to contain only adults (≥ 16 years old). Readmissions and patients missing core data (such as age, main diagnosis, and LOS) were excluded (Zampieri et al., 2019). The data can be divided into three levels: patients, hospitals, and ICUs. The main categories and examples of variables are listed in Table 8.

Table 8 – Description of the analyzed dataset

Level	**Categories (variables)**
Patient	• Demographic (age, gender); • Hospitalization (diagnostic, comorbidity, LOS, admission source, SAPS 3); • Outcome (date of discharge/death, destination, LOS).
Hospital	• Infrastructure (hospital number of beds, number of ICUs, type of hospital); • Accreditation
ICU	• Infrastructure (ICU number of beds, type of ICU); • Staffing patterns (number of physicians, nurses, and intensivists, empowerment score); • Organizational aspects (professionals in clinical rounds, use of checklists, implemented protocols)

Source: elaborated by the author

The analyses were performed using R software version 1.1.456 and the packages *tidyverse* for database operations and plotting, and *deaR* for DEA modeling. Additional DEA results were computed with the use of AIMMS 4.70.3.4.

The steps of this study are listed in the following:

a) Descriptive Analyses

To understand the data and its specificities, descriptive analyses were performed. They present information regarding the differences in each of the levels (patient, hospital, and ICU) using absolute numbers and percentages, as well as mean and standard deviations.

b) Calculated indicators

Using the data provided, two indicators commonly used to assess ICU efficiency (Rothen et al., 2007; Soares et al., 2016) were calculated. The Standardized Mortality Rate (SMR) and the Standardized Resource Use (SRU) are used to adjust mortality and LOS, respectively, by patients' severity.

SMR is the ratio between observed and expected deaths of patients treated in the ICU (Siegel et al., 2015), as shown in Equation 9. Therefore, if SMR < 1, it means that the actual number of deaths was less than what was expected, which is a positive result for the unit.

$$SMR = \frac{\#\, observed\ deaths}{\#\, expected\ deaths} \tag{9}$$

The expected deaths were estimated using the Simplified Acute Physiology Score 3 (SAPS 3), which is one of the main severity scores used worldwide (Keegan & Soares, 2016). Moreno et al. (2005) proposed a general equation as well as customized equations at the regional level, allowing ICUs to be evaluated under a global or local reference. Therefore, the score is inserted in one of the equations, which will provide, as a result, the probability of death. The predictive model was developed with the use of data from 16,784 patients treated in 303 ICUs in 35 countries (Moreno et al., 2005).

A potential metric to calculate resource use is cost. However, it is usually hard to access, and it also depends on the conversions of different currencies if data from various countries is used (Rothen & Takala, 2008). To overcome this problem, another proxy used is the ICU Length of Stay (LOS), which is the duration in days that the patient was in the ICU. As LOS also varies according to the case-mix, SRU is calculated using SAPS 3 to adjust the data to the severity of patients. It is defined as the average observed-to-expected ratio use of resources (estimated using the LOS) per surviving patient (Rothen. et al., 2007), as shown in Equation 10.

$$SRU = \frac{\sum observed\ Resource\ Use}{\sum expected\ Resource\ Use} \tag{10}$$

The expected LOS used in SRU calculation is the average LOS observed in the SAPS 3 study for that specific stratum. It is calculated as the sum of the LOS for all patients in SAPS 3 categorized in that specific stratum, divided by the number of surviving patients in that stratum (Rothen et al., 2007).

c) Model Specifications

Golany & Roll (1989) suggested three steps to select the inputs and outputs of the DEA model. The last step, reducing the number of variables using DEA analysis, was not needed in this work because of the low number of variables selected. The first two steps are described below.

i. Judgemental screening

It is the selection of relevant factors by field experts. At this stage, it is important to account for the availability and quality of the information. The variables selected to this research were divided into four groups: staffing, structure, outcome, and strain. The distribution is shown in Table 9.

Table 9 – Selected variables for the DEA model

Staffing

Variable	Description
MD_Bed10	Average number of physicians per 10 beds
Nur_Bed10	Average number of nurses per 10 beds
NurTec_Bed10	Average number of nursing technicians per 10 beds
Physio_Bed10	Average number of physiotherapists per 10 beds

Structure

Variable	Description
ICU_Bed	Number of ICU beds
MD_Hours	Total physicians' hours per week
Nur_Hours	Total nurses' hours per week

Strain

Variable	Description
BOR	Bed Occupancy Rate

Outcome

Variable	Description
SMR	Standardized Mortality Rate
SRU	Standardized Resource Use

Source: elaborated by the author

The staffing variables represent the load of work of the medical team. It is the proportion of professionals (physicians, nurses, nursing technicians, and physiotherapists) per 10 ICU beds. They are calculated based on the number of professionals in each shift.

The structure variables are volume metrics that represent the size of the ICU, such as the number of beds and hours worked by the professionals in the medical team. They are the absolute values, as opposed to the staffing variables, that are measures of their proportion in relation to the number of beds. Both groups (structure and staffing) are representative of the resources used by the ICU to reduce mortality; thereby, they were chosen as inputs to the DEA model.

The strain variables are used to reflect the strained capacity of the ICU, that is, the difference between what it can offer in terms of resources and what is demanded by the patients (Rewa et al., 2018). In this work, the Bed Occupancy Rate (BOR) was used to represent this group of variables. It was collected in each ICU, resulting in a real measure instead of an estimate using calculated occupancy.

ii. Non-DEA quantitative methods

This step corresponds to the treatment of the variables, and it includes deciding whether to aggregate variables (to reduce the number of inputs and outputs) and how to handle not available (NA) values and categorical variables. Only one variable (that represents the function of checklists in clinical rounds) had NA values in the database. As it was not considered essential to the model, it was discarded.

At this stage, it is also important to classify if a variable should be considered as an input or an output. Golany & Roll (1989) recommended that this decision could be backed up in regression analyses. If a factor shows high relation with outputs rather than with inputs, it is an indicator that it should also be considered an output. However, if the relationship is too strong, the information might be redundant and, therefore, should be deleted.

Considering that quality in healthcare means better chances of patient survival and that mortality is the main metric used to evaluate ICU performance, SMR was the first output chosen to enter this analysis. The other outcome measure, SRU, is also an output candidate, as it also measures the results adjusted by severity, but using the length of stay instead of mortality.

The strain variable shows the use of the ICU's capacity (bed occupancy rate). However, its interpretation as input or output is not straightforward. Therefore, the correlations between SMR, SRU, and BOR were analyzed to differentiate between inputs and outputs. The Spearman's rank correlation test was performed, and the results are shown in Table 10.

Table 10 – Correlation between variables

	SMR	SRU	BOR
SMR	-		
SRU	0.61	-	
BOR	0.06	0.32	-

Source: elaborated by the author

The hypothesis is that SRU is also indicative of the quality of the treatment received, which would make it an output candidate. The high correlation between SMR and SRU reinforces this idea. BOR had low correlations with SMR and SRU and, therefore, was selected as an input.

Three models were established considering the different groups of variables in order to understand their relations. As described above, the outcome variables (SMR and SRU) were used as outputs in all the models. First, because they are outputs commonly measured in the context of ICU efficiency. Secondly, because, as described by Laudicella, Olsen & Street (2010), patient-level data allows for better adjustments, which reduces the possible effects of sample size variation and, in this case, of case-mix differences.

Model A used the staffing variables as inputs. The main idea was to understand the use of resources: given certain outcome results, the model shows how high (or low) was the proportion of medical professionals, compared to the other units. Therefore, in this case, the model was input-oriented: it minimizes the inputs, maintaining the outputs constant.

Model B has a different perspective since it uses the structure variables as inputs: given a certain ICU structure, it shows how well the ICU performed. The hypothesis, as shown by other works, such as (Donabedian, 1978), is that larger hospitals have better results. For that reason, ICUs with more beds, physician hours, and nursing hours are expected to have better results of SMR and SRU. It uses the output orientation since the structure variables are fixed, and the outcomes are maximized.

A third model was formed to understand how the strained capacity of the ICU relates to the results. Model C uses BOR as an input. Both orientations would fit this model. The input orientation was chosen to show if the ICU could increase its occupancy, given its results.

There is one particularity common to all these models, which is the use of undesirable outputs. The basic idea under traditional DEA is that an increase in inputs generates an increase in outputs. However, in some scenarios, an increase in inputs should result in a decrease in outputs, which are the cases of SMR and SRU.

There are different methods to handle these variables in DEA models. One of them is to work with the opposite sign (-output), but this transformation might make the values negative, which is also not straightforward to work with (Halkos & Petrou, 2019). A second approach is to use the inverse of the values (1/output), which can be used as long as there are no zero values for any DMU (Halkos & Petrou, 2019).

Given that in our case, there are no zeros, neither in SMR or SRU, the inverse of these values was used in the models. This was also the case for the input BOR because, in theory, low occupancy rates are easier for the ICU to handle and, therefore, should result in better outcomes.

The VRS model was chosen in the three cases because none of the inputs seem to have a proportional impact on the outputs. Besides, the CRS model is considered to achieve better results for small sample sizes (up to 50 DMUs), while the VRS model is better for larger samples (Banker, Chang & Cooper, 1996). The specifications of the three models are summarized in Table 11.

Table 11 – Specifications of the DEA models

Model	Focus	Inputs	Outputs	Orientation
A	Staffing	- Number of physicians per 10 beds; - Number of nurses per 10 beds; - Number of nursing technicians per 10 beds; - Number of physiotherapists per 10 beds.	- SMR - SRU	Input
B	Structure	- Number of ICU beds; - Total physicians' hours per week; - Total nurses' hours per week.	- SMR - SRU	Output
C	Capacity	- Bed Occupancy Rate (BOR)	- SMR - SRU	Input

Source: elaborated by the author

d) Analysis of the DEA results

The main DEA result is the efficiency score of each DMU. The units are usually grouped as efficient (score of one), and non-efficient (score different than one). However, this is a simplistic view, as there are other relevant factors involved in the analysis. Two metrics were used in this research to differentiate between efficient DMUs: their slacks and being in reference sets.

If an efficient unit has a slack in some input or output, it means that even though they had a result of one, they could have had the same results using less of an input (input surplus) or more of an output (output shortfall), which can be interpreted as "less efficient." Mathematically, the slack is the difference between the left-hand side and the right-hand side of each input/output constraint in the envelope model (Eqs. 5 and 6, page 12).

The analysis of the reference set is also relevant to differentiate among efficient DMUs. One unit can be efficient and a reference to many others, while the other can be efficient and not a reference to any DMU. The reference sets will depend highly on the model orientation. A graphic representation with one input and one output is shown in Figure 3.

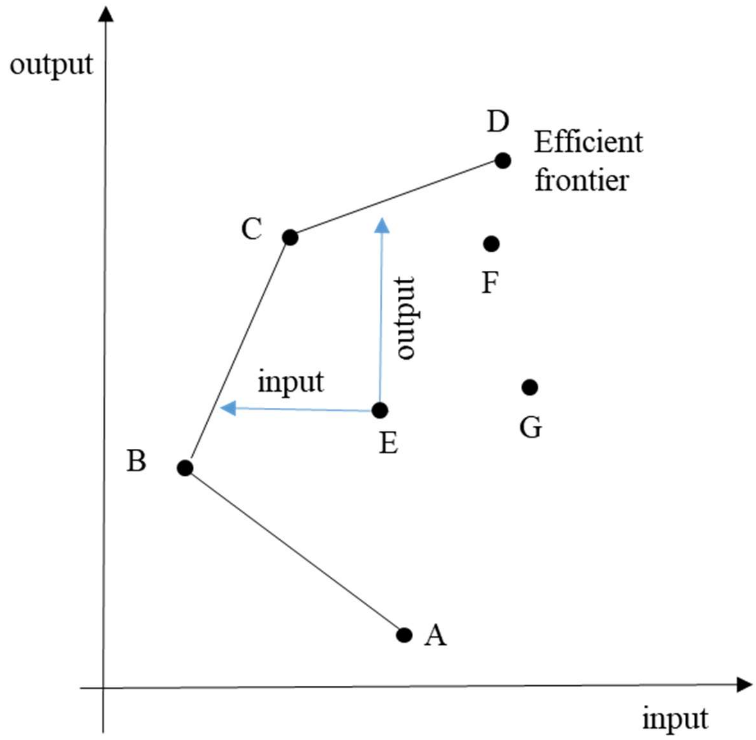

Figure 3 – Representation of the reference set

Source: elaborated by the author

In the example above, DMU E is not efficient, and, in an input-oriented model, its references would be DMUs B and C, as the model maintains outputs constant and reduces the inputs. In an output-oriented model, however, the outputs would be maximized while the inputs would stay constant. In that case, the reference set of DMU E would be composed of DMUs C and D.

Mathematically, the reference set is composed by the DMUs j that have weights different than zero in the envelope model ($\mu_j \neq 0$). In the VRS model, as the sum of the weights have to be equal to one, the value of μ_j represents how much (in percentage) of DMU j is a reference to the DMU being analyzed in that model. With these weight values, it is possible to define targets to the analyzed DMU as the weighted sum of the input/output values of the reference DMUs, with the weights being the results of μ_j.

e) Post-DEA analysis

After the interpretation of efficiency scores, slacks, and reference sets, other analyses were performed to understand the patterns among efficient and non-efficient DMUs. Categorical non-discretionary variables that do not directly affect the outputs were selected to enter the analysis after the efficiency scores were calculated.

For each category (in each variable), the mean score obtained by the DMUs was calculated to check if there were differences among units with that specific characteristic. The variables selected to this analyses were the type of hospital (public, private philanthropic, and private for-profit), the type of ICU (mixed, general, surgical, medical, neurological, and others), the size of the hospital (small – less than 100 beds; medium – between 100 and 200 beds; and large – more than 200 beds, as in (El-Jardali et al., 2008), and the proportion of ICU beds.

This last variable was calculated as the ratio between the number of beds in each ICU to the total of beds in its hospital. It was then categorized into terciles: a low proportion was considered between 0 and 4.70%, a medium proportion was between 4.80% and 9.56%, and a high proportion was composed of ICUs with more than 9.57% of ICU beds in relation to the total of hospital beds.

4
Descriptive Analyses

The descriptive analysis performed in the ORCHESTRA database was divided into two perspectives: hospital and patient characteristics. Most ICUs are in private for-profit hospitals (61%), are of mixed type (81%), and have less than 30 ICU beds (88%). The main results of the ICU analysis are shown in Table 12.

Table 12 – Descriptive statistics (hospital characteristics)

Characteristics	n (%)
Total ICUs	93
Hospital Type	
Public	17 (18)
Philanthropic	19 (20)
Private for-profit	57 (61)
Hospital certified by an Accreditation Organization	
No	24 (26)
Yes, nationally	32 (34)
Yes, internationally	37 (40)
Is there an emergency room?	
No	6 (6)
Yes, open	83 (89)
Yes, reference	4 (4)
Training programs in Intensive Care	
For Physicians	47 (51)
For Nurses	5 (5)
For Other professionals	7 (8)
ICU Type	
Mixed	75 (81)
Surgical	8 (9)
Medical	1 (1)
Neurological	5 (5)
Other	4 (4)
ICU beds, ICU No (%)	
<10	37 (40)
11 - 30	45 (48)
31 - 50	10 (11)
> 50	1 (1)

Source: elaborated by the author

Most patients in the ORCHESTRA database have health insurance (73%), and 68% had non-surgical admissions. They are almost evenly distributed between the genders (50.6% are female). The information is presented in Table 13.

Table 13 - Descriptive statistics (patient characteristics)

Characteristics	n (%)
Patients, No	129,680
Gender (female)	65,662 (50)
Type of admission	
Medical	88,034 (68)
Elective Surgery	32,378 (25)
Urgent Surgery	9,268 (7)
Destination	
Home	101,048 (78)
Dead	23,563 (18)
Other hospital	2,839 (2)
Unkwown	1,201 (1)
Home-care	959 (1)
Hospice	70 (0)
Payment	
Health Insurance	94,883 (73)
Public (SUS)	12,392 (10)
Private	3,267 (2)
NA	19,138 (15)

Source: elaborated by the author

The numerical variables that could be relevant to the efficiency analysis are presented with their median and interquartile values in Table 14. The staffing metrics were also calculated as proportions in relation to the number of ICU beds to adjust for the difference between ICUs structure.

Table 14 – Descriptive statistics (selected variables)

Variables	**Median [IQR]**
SMR	1 [0.79 - 1.21]
SRU	1.15 [0.95 - 1.56]
Hospital Beds	202 [153 - 290]
ICU Beds	13 [10 - 20]
No. of ICUs	3 [2 - 5]
Total Physicians' hours	372 [276 - 504]
Total Nurses' hours	396 [336 – 648]
Physician per 10 Beds ratio	1.67 [1.36 - 2]
Nurse per 10 Beds ratio	1.71 [1.41 - 2.39]
Nurse Technician per 10 Beds ratio	5 [4.55 - 5.56]
Physiotherapist per 10 Beds ratio	1 [0.83 - 1.25]
BOR	0.83 [0.75 - 0.87]

IQR - Interquartile Range

Source: elaborated by the author

Some variables were also regressed against the two chosen outputs (SMR and SRU) using a negative binomial regression to understand if and how they affect the outcomes (Table 15).

Table 15 – Regression results

Variables	SMR RR (95% CI)	p	SRU RR (95% CI)	p
Hospital Beds	1 [0.999 - 1]	0.43	1 [1 - 1.001]	0.49
ICU Beds	0.994 [0.989 - 1]	0.06	0.994 [0.985 - 1.002]	0.16
Physicians' hours	0.999 [0.999 - 1]	0.30	0.999 [0.999 - 1]	0.52
Nurses' hours	0.999 [0.999 - 1]	**0.00**	0.999 [0.999 - 1]	0.08
Physician per 10 Beds	0.961 [0.843 - 1.096]	0.56	0.976 [0.802 - 1.186]	0.81
Nurse per 10 Beds	0.924 [0.844 - 1.01]	0.08	0.926 [0.81 - 1.058]	0.26
Nurse Technician per 10 Beds	0.999 [0.956 - 1.045]	0.98	1 [0.935 - 1.07]	0.99
Physiotherapist per 10 Beds	0.882 [0.739 - 1.053]	0.17	0.941 [0.721 - 1.227]	0.65
% of certified Physicians	0.997 [0.995 - 0.999]	**0.01**	0.999 [0.996 - 1.002]	0.47
% of certified Nurses	0.996 [0.994 - 0.998]	**0.00**	0.997 [0.994 - 1.001]	0.15
Nurse Empowerment Score	1.003 [0.985 - 1.021]	0.75	1.017 [0.991 - 1.044]	0.21
Physiotherapist Empowerment Score	1.015 [0.997 - 1.033]	0.10	1.027 [1.001 - 1.055]	**0.04**
No. of other exclusive professionals	0.982 [0.93 - 1.037]	0.51	1.023 [0.943 - 1.11]	0.58
No. of Professionals in clinical rounds	1.018 [0.971 - 1.066]	0.46	1.052 [0.982 - 1.126]	0.15
No. of implemented care protocols	0.948 [0.927 - 0.969]	**0.00**	0.951 [0.919 - 0.986]	**0.01**
BOR	1.348 [0.732 - 2.484]	0.34	3.223 [1.346 - 7.717]	**0.00**

IQR - Interquartile Range

RR - Rate ratio from Negative Binomial Regression - Bold: $p < 0.05$; Underscore: $p < 0.15$

Source: elaborated by the author

The variable that represents the bed occupancy rate had a significant association with SRU, showing that an increase in BOR results in an increase in SRU. Other significant variable was the number of implemented protocols, with a negative influence both on SMR and SRU (as the inputs increase, the outputs decrease). The physiotherapist empowerment score also had significant p-values with both indicators, however, the rate ratios were very close to one. Although the physicians' hours did not show significant regression results, the nurses' hours were significant with both indicators.

The relations between variables can be useful to define the inputs, outputs, and the orientation used in the DEA models, as well as to interpret the results. In general, the inputs chosen to all three models have the expected effect: an increase of the inputs generate a decrease in the outputs (SMR and SRU). That statement is also true for the Bed Occupancy Rate, as we use its inverse as an input.

5
DEA results

The results of the DEA models were described in four sub-sections, one for each model and one for the overall results. The first model is composed of staffing variables; the second model contains information on the structure of the ICU, and the third model analyses ICU capacity. The values used in the DEA models are presented in Table 16. It shows the inputs divided by each model and the outputs in the last two columns.

Table 16 – Values of inputs and outputs of models A, B, and C

ICU	A				B			C	Outputs	
	MD_ Bed10	**Nur_ Bed10**	**NurTec_ Bed10**	**Physio_ Bed10**	**ICU_ Bed**	**MD_ hours**	**Nur_ hours**	**BOR**	**SMR**	**SRU**
1	1.64	1.55	4.79	1.25	24	660	624	0.94	1.26	1.73
2	1.76	1.81	5.00	1.54	13	384	396	0.91	1.27	1.28
3	1.64	1.36	5.00	1.00	10	276	228	0.87	1.23	1.00
4	1.36	2.36	5.00	0.00	10	228	396	0.75	0.71	0.95
5	1.76	2.39	4.71	1.55	17	504	684	0.87	1.42	2.50
6	2.05	1.70	6.88	1.25	8	276	228	0.91	1.64	1.82
7	2.00	2.71	6.50	1.36	10	336	456	0.97	1.09	2.01
8	1.67	2.80	5.00	0.83	12	336	564	0.74	0.89	0.93
9	2.54	2.62	4.44	1.11	9	384	396	0.83	0.79	0.97
10	2.71	2.00	4.00	2.00	5	228	168	0.75	1.20	1.00
11	2.86	3.37	5.00	1.43	7	336	396	0.74	0.93	0.89
12	2.36	2.36	4.00	1.00	10	396	396	0.68	0.99	0.78
13	2.50	2.95	5.00	1.25	8	336	396	0.79	0.87	0.79
14	1.82	2.47	4.55	0.91	11	336	456	0.70	1.01	0.61
15	1.18	0.68	4.50	0.68	20	420	228	0.87	0.97	0.92
16	1.23	3.07	4.09	0.69	33	684	1704	0.96	0.70	1.27
17	1.86	1.54	4.00	0.82	20	624	516	0.75	1.16	0.78
18	1.24	3.18	14.21	1.13	38	816	2052	0.84	0.64	0.58
19	1.45	2.43	5.95	1.60	37	924	1536	0.83	0.68	0.60
20	1.23	2.14	5.45	1.23	11	228	396	0.87	2.23	2.13
21	1.43	2.67	5.33	1.45	30	744	1368	0.79	0.85	0.76
22	1.36	1.18	5.00	1.00	20	456	396	1.04	1.21	1.21
23	2.29	2.36	4.00	1.00	10	384	396	0.75	0.80	0.62

24	2.05	2.50	5.00	1.25	8	276	336	0.74	0.57	0.56
25	2.05	2.50	5.00	1.25	8	276	336	0.89	0.64	0.73
26	2.05	2.50	5.00	1.25	8	276	336	0.90	0.72	0.72
27	2.00	2.00	4.00	1.00	10	336	336	0.89	0.67	0.82
28	2.05	2.50	5.00	1.25	8	276	336	0.90	0.69	0.82
29	1.96	2.50	5.00	0.83	12	396	504	0.69	0.81	0.71
30	1.28	1.58	5.59	1.28	34	756	924	0.83	0.89	1.16
31	2.00	2.36	5.00	0.50	20	672	792	0.78	0.66	0.95
34	2.10	1.69	5.00	1.36	30	1056	852	0.83	0.93	0.85
35	1.18	1.71	5.25	1.18	20	396	576	0.92	1.06	1.60
36	1.51	2.22	3.89	1.11	18	456	672	0.84	0.91	1.07
37	1.65	1.47	5.00	0.40	16	444	396	0.76	1.04	1.07
38	1.47	1.25	5.00	0.85	16	396	336	0.73	1.10	1.33
39	1.43	3.83	1.43	0.97	14	336	900	0.54	0.85	1.23
40	1.70	1.70	5.62	1.25	8	228	228	0.85	1.00	1.20
41	1.70	2.14	5.62	1.25	8	228	288	0.86	1.28	1.25
42	1.70	2.14	5.62	1.25	8	228	288	0.84	1.28	1.27
43	1.36	1.71	5.50	1.00	10	228	288	0.89	1.54	3.06
44	1.00	1.18	5.00	1.00	20	360	396	0.78	1.08	1.56
45	1.67	1.67	3.33	1.67	6	168	168	0.73	1.29	4.48
46	1.05	1.05	5.26	1.05	19	336	336	0.78	1.11	1.31
47	0.97	1.43	5.00	0.71	14	228	336	0.76	1.09	1.15
48	1.43	1.43	2.86	0.71	28	672	672	0.75	1.76	1.94
49	2.14	1.82	4.55	0.58	11	396	336	1.04	1.81	3.58
50	2.00	2.71	5.00	0.64	10	336	456	1.01	1.98	4.77
51	0.86	1.35	3.71	0.86	35	504	816	0.88	0.58	1.31
52	1.89	1.68	3.57	0.71	14	444	396	0.80	1.04	1.70
53	2.03	1.54	3.85	0.77	13	444	336	0.83	1.15	0.95
54	1.89	1.43	3.57	0.71	14	444	336	0.79	1.25	1.79
55	1.09	1.25	5.50	0.91	40	732	840	0.78	1.11	1.20
56	2.05	2.50	4.06	0.85	16	552	672	0.98	0.88	1.21
57	1.83	2.22	4.44	1.11	9	276	336	0.98	0.75	1.11
58	2.74	3.33	5.00	1.67	6	276	336	0.71	0.52	0.77
59	1.64	2.71	5.00	1.36	10	276	456	0.65	1.07	1.02
60	1.64	2.00	4.00	1.00	10	276	336	0.52	0.84	1.14
61	1.00	1.12	5.33	0.88	30	504	564	0.79	0.71	1.17
62	1.64	1.36	5.00	1.00	10	276	228	0.87	1.13	2.12
63	1.83	1.51	5.56	1.11	9	276	228	0.86	0.98	1.31
64	1.88	1.47	5.62	1.25	16	504	396	0.75	0.86	1.07
65	2.26	2.74	7.08	1.67	12	480	552	0.84	1.18	2.03
66	1.24	1.43	5.26	0.53	19	396	456	0.78	1.68	1.08
67	1.51	1.11	7.22	0.71	9	228	168	0.85	1.25	2.43
68	1.51	1.11	7.22	0.71	9	228	168	0.85	1.42	2.22
69	1.23	1.56	5.91	0.58	11	228	288	0.85	1.29	2.39
70	2.46	1.11	5.56	1.11	9	372	168	0.87	0.66	0.99
71	2.46	1.11	5.56	1.11	9	372	168	0.85	0.79	0.67
72	1.85	0.83	5.00	0.83	12	372	168	0.83	0.96	1.07
74	2.00	3.14	6.00	1.00	10	360	528	0.84	1.07	1.50

75	1.43	1.43	6.43	0.97	14	360	336	0.88	1.17	1.07
76	1.82	1.82	7.73	0.91	11	360	336	0.88	1.24	1.50
77	1.21	1.45	5.33	1.00	30	612	732	0.82	0.65	1.00
78	1.63	1.14	4.00	0.94	35	984	672	0.82	1.13	0.99
79	1.03	1.25	5.00	0.00	16	276	336	0.85	1.05	1.31
80	0.62	0.62	2.81	0.00	16	168	168	0.62	1.41	1.15
81	1.36	1.36	5.00	1.00	10	228	228	0.95	0.91	0.89
82	1.55	1.68	5.88	0.78	34	888	984	0.79	0.58	0.80
83	0.99	1.41	4.61	0.84	64	1068	1512	0.86	0.55	1.19
84	1.70	0.80	5.00	1.25	8	252	108	0.96	0.57	1.64
85	1.07	0.88	4.55	1.07	22	420	324	0.85	0.80	1.36
86	1.33	1.81	5.33	1.57	15	360	456	0.95	0.68	0.98
87	0.78	1.60	5.88	0.80	34	444	912	0.65	1.22	1.09
88	2.69	2.20	6.86	1.04	35	1584	1296	0.90	1.31	2.33
89	2.07	1.97	6.90	1.03	29	1008	960	0.54	1.38	2.35
90	1.31	1.71	5.40	1.06	25	552	720	0.86	0.83	1.40
91	1.46	1.71	5.40	1.06	25	636	720	0.85	0.95	1.48
92	1.64	2.00	5.50	1.00	10	276	336	0.79	0.79	1.61
93	1.70	2.05	5.62	1.25	8	228	276	0.66	0.64	0.98
95	1.18	1.18	6.00	1.00	20	396	396	0.78	1.04	0.68
96	2.26	3.33	5.00	1.07	6	252	336	0.67	1.08	1.03
97	1.88	1.25	5.62	1.47	16	504	336	0.94	0.97	1.56

Source: elaborated by the author

These values can be indicative of some of the DEA results. The DMUs that have the minimum values of outputs, for example, have high chances of being considered efficient in all models and of being a reference many times in output-oriented models. This is the case of DMU 58 (minimum SMR: 0.52), and DMU 24 (minimum SRU: 0.56).

Maximum output values can also give an idea of which units will be considered inefficient. Unit 20 has a SMR of 2.23 and a SRU of 2.13. Unless it presents very low values of inputs, it will not be considered efficient in any models. A low level of inputs, however, makes it easier for a unit to be considered efficient, which is the case of DMU 45 in model B, which has all three inputs with low values.

The efficiency results of all DMUs in the three models are summarized in Appendix I. The first column shows if the DMU had or not slacks in any variables, the second column represents how many times the unit was considered a reference to others, and the third column is the efficiency score of each unit (using its best weights). The three columns are repeated to each one of the three models. The results in gray indicate the efficient units (efficiency score equal to one).

5.1. Model A (staffing)

Model A is focused on staffing patterns and how they relate to the outcomes. The variables used as inputs were the number of professionals (physicians, nurses, nursing technicians, and physiotherapists) per 10 ICU beds.

A summary of the DEA results of model A is presented in Figure 4. It shows the number of efficient DMUs and the distribution of the efficiency scores of the non-efficient units in each model.

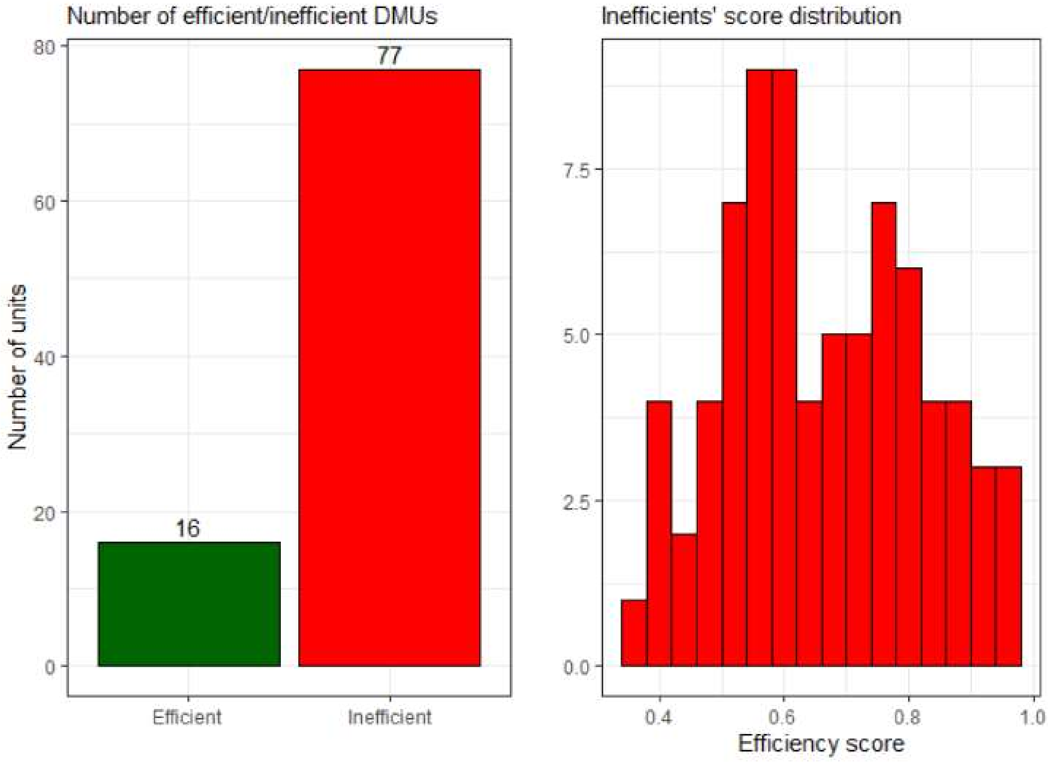

Figure 4 – Number of efficient DMUs and efficiency distribution (Model A)
Source: elaborated by the author

In the input-oriented model, the efficiency scores vary between zero and one, and one is the target. However, it should not be considered that all DMUs with an efficiency score of one had the same results. Slacks and reference sets can be analyzed to differ between efficient units. In the case of model A, there were four efficient units with slacks (ICUs 14, 58, 83, 84).

In all the cases of this model, the slacks of efficient DMUs were small, almost zero. For inefficient units, however, some slacks were significant. For example, ICU 87 has 5.88 nursing technicians per 10 ICU beds and slack of 1.49 in this input in model A. If it had fewer professionals per 10 beds and it maintained the other inputs and outputs constant, the same results of efficiency (for all DMUs) would be obtained by the DEA model. The number of nursing technicians that could be subtracted without resulting in any changes in the efficiency score can be calculated as the slack (1.49) divided by the efficiency score (0.8636), which equals 1.73. Therefore, if DMU 87 had any value between 4.15 (5.88 – 1.73) and 5.88 of nursing technicians, it would still have the same efficiency score, given that all other variables would stay constant. The slacks of all DMUs are in Appendix II (model A), III (model B), and IV (model C).

Another point of attention regarding the analysis of efficient DMUs concerns the set of reference units. A bar graph showing the number of times each efficient unit appeared as a reference to others is shown in Figure 5.

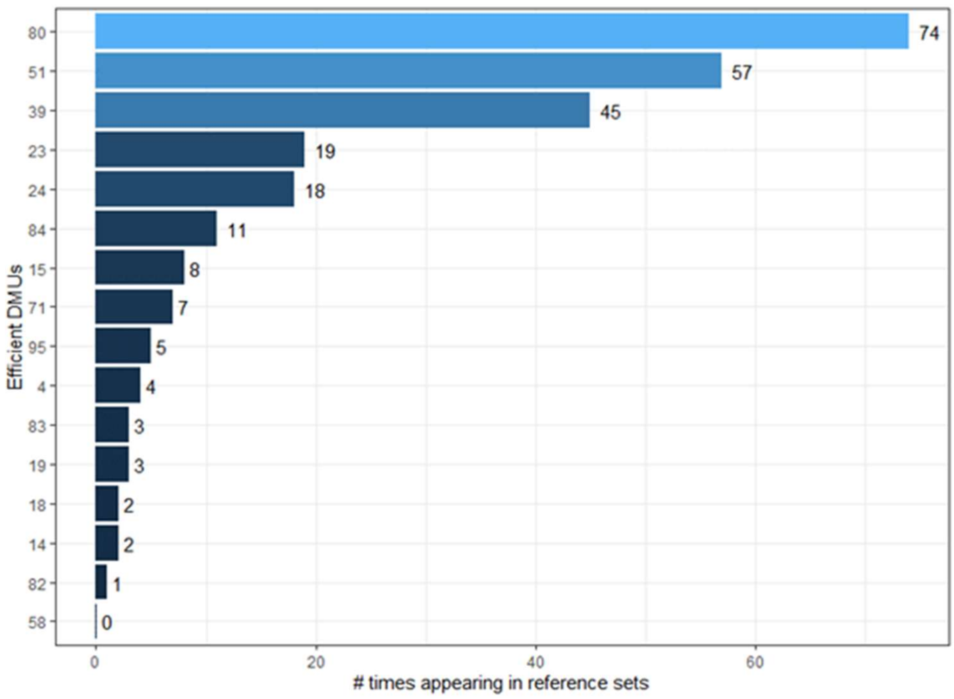

Figure 5 – Number of times each unit was in the reference set (Model A)

Source: elaborated by the author

In this case, ICU 80 was a reference for 74 DMUs, while ICU 58, even with an efficiency score of one, was not a reference to any DMUs. This situation can be better understood by looking at the values they had as inputs and outputs and comparing them with the variables' medians for the whole dataset (Table 17).

Table 17 – Inputs and outputs of ICUs 58 and 80 in model A

ICU	MD_ Bed10	Nur_ Bed10	NurTec_ Bed10	Physio_ Bed10	SMR	SRU
58	2.74	3.33	5.00	1.67	0.52	0.77
80	0.62	0.62	2.81	0.00	1.41	1.15
Median	1.67	1.71	5.00	1.00	1.00	1.15

Source: elaborated by the author

Unit 58 has a higher use of inputs and better results of outputs (lower SMR and SRU) when compared to the dataset's median. The positive results were enough to compensate for the high use of inputs and make it an efficient DMU. However, it was not considered a reference to other DMUs due to the high level of the inputs, as it was an input-oriented model. The opposite happened to DMU 80, which had higher outputs and lower inputs in relation to the median and, for that reason, was a reference 74 times.

The reference units are also useful for the definition of targets, which can be the basis for the managers to define goals. For unit 87, for example, since its reference units were DMUs 18 (6,33%), 51 (6,01%), and 80 (87,66%), the targets will be the weighted sum of these DMUs' values. These percentages are the results of the weights in the envelope model. The value of each variable of each reference DMU will be multiplied by the DMU's percentage. The sum of these values of all reference DMUs will result in the target for that variable.

The number of physicians per 10 beds will then be 0.0633*1.24 + 0.0601*0.86 + 0.8766*0.62, which equals 0.67. Table 18 shows the actual values of DMUs 18, 51, 80, and 87 and Table 19 shows the calculated targets of inputs and outputs for ICU 87.

Table 18 – Inputs and outputs of ICUs 18, 51, 80, and 87

ICU	MD_Bed 10	Nur_Bed 10	NurTec_Bed 10	Physio_Bed 10	SMR	SRU
18	1.24	3.18	14.21	1.13	0.64	0.58
51	0.86	1.35	3.71	0.86	0.58	1.31
80	0.62	0.62	2.81	0.00	1.41	1.15
87	0.78	1.60	5.88	0.80	1.22	1.09

Source: elaborated by the author

Table 19 – Targets of ICU 87

ICU	MD_Bed 10	Nur_Bed 10	NurTec_Bed 10	Physio_Bed 10	SMR	SRU
87	0.67	0.83	3.59	0.12	1.22	1.09

Source: elaborated by the author

If ICU 87 maintained its outputs constant, it would have to reduce all its inputs to become efficient. Given its output results, the unit is consuming more resources than what is expected, based on what is consumed by the efficient units. For example, it would have to reduce the number of physicians per 10 beds from 0.78 to 0.67, the number of nurses from 1.60 to 0.83, the number of nursing technicians from 5.88 to 0.80, and it would have to maintain the same levels of SMR and SRU. Three tables containing all of the targets for all the models are represented in Appendix V, VI, and VII.

A graphic representation is useful in interpreting the results. However, as there are many inputs and outputs in the model, the illustration is not straightforward. In the case of this research, as there are only two outputs, Figure 6 is useful to interpret the data. SRU and SMR are represented in the horizontal and vertical axis, respectively, while the size of the point represents how many times the DMU appeared as a reference to others in the model.

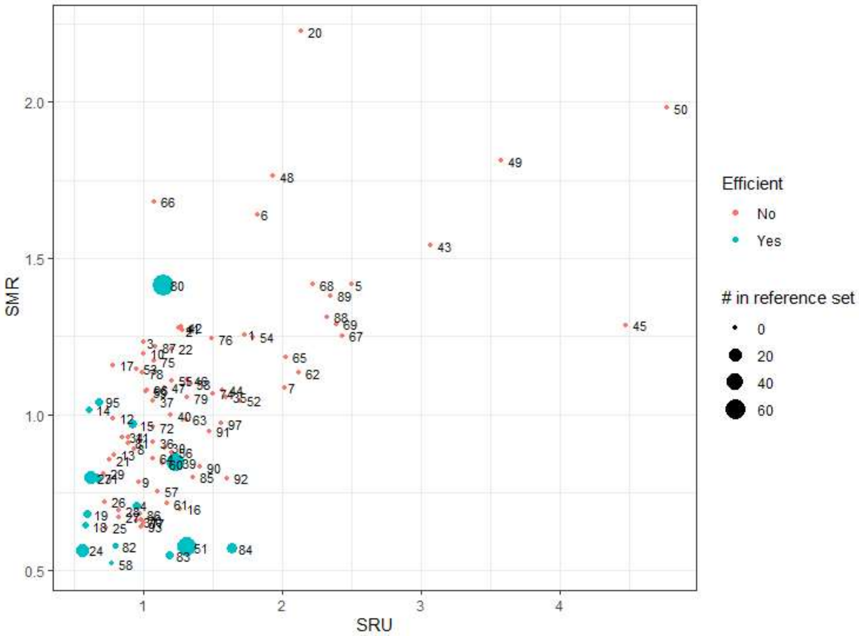

Figure 6 – SMR x SRU scatter plot (Model A)

Source: elaborated by the author

As this graph shows both outputs used in the models, the position of the efficient DMUs is a good sign of the overall values of inputs. Unit 58, for example, is considered efficient, and it is in the bottom left-hand corner of the graph (low SMR and low SRU). As it has not been a reference to many DMUs and it was an input-oriented model, it likely had high values of inputs. As seen in Table 17, aside from the nursing technicians per 10 beds variable, all the other inputs had higher values than the median.

A cross-efficiency matrix is also useful to overcome a common criticism regarding DEA results, which is that efficiency scores are obtained using the best weights for each DMU. It is a j x j matrix (with j being the number of DMUs in the set), that results in the efficiency scores that would be obtained by each DMU if they used the others' best weights. With these values, it is easier to understand if the unit was considered efficient only because its weights were chosen in a way that would increase the impact of one variable that had a satisfactory result, or if it could have also been efficient with other weights.

Figure 7 shows the variation in efficiency scores in model A depending on the weights used. As variable returns to scale were used, some of the cross-efficiency scores were negative because the model adds a constraint in the envelope model that becomes an unconstrained variable in its dual problem (the multiplier model) (Lim and Zhu, 2015). Although interpreting negative scores can be more difficult, they are still useful to understand how wide is the efficiency range. A DMU that has a small range of scores has more consistent results when compared to a DMU with a wide range. Two efficient units, therefore, can have different results in terms of variability and consistency.

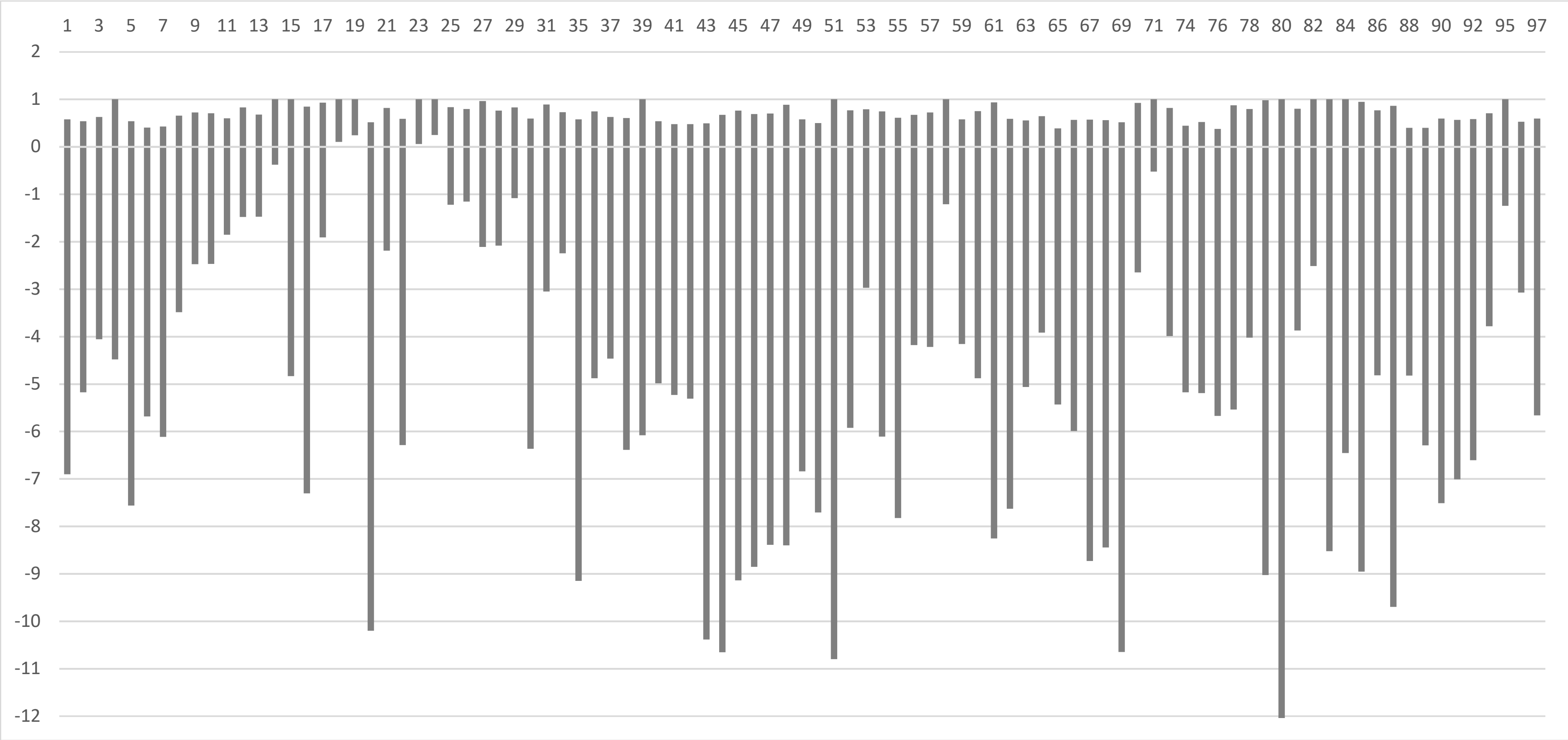

Figure 7 – Cross-efficiency results (model A)

Source: elaborated by the author

Unit 24, for example, had a range of 0.75, with a minimum score of 0.25, being efficient 18 times. Unit 51 was efficient in more rounds (57); however, it had a range of 11.80 (minimum efficiency score of -10.8). These metrics can indicate that unit 24 has more solid results, being efficient (or almost efficient) regardless of the variable that is intensified by the weights. Unit 51's minimum result (-10.8) was obtained using unit 18's best weights, which were very high for SRU. As unit 51 had a relatively high SRU (1.31, and the dataset median was 1.15), it had a poor performance with these weights.

Although Figure 7 showed the efficiency score range for all DMUs, it could still be misleading, as only one very low (or high) result in a specific round could drastically increase the variation range. Therefore, a boxplot of the efficient units' results could be an even better representation, especially because it can show the outliers (Figure 8).

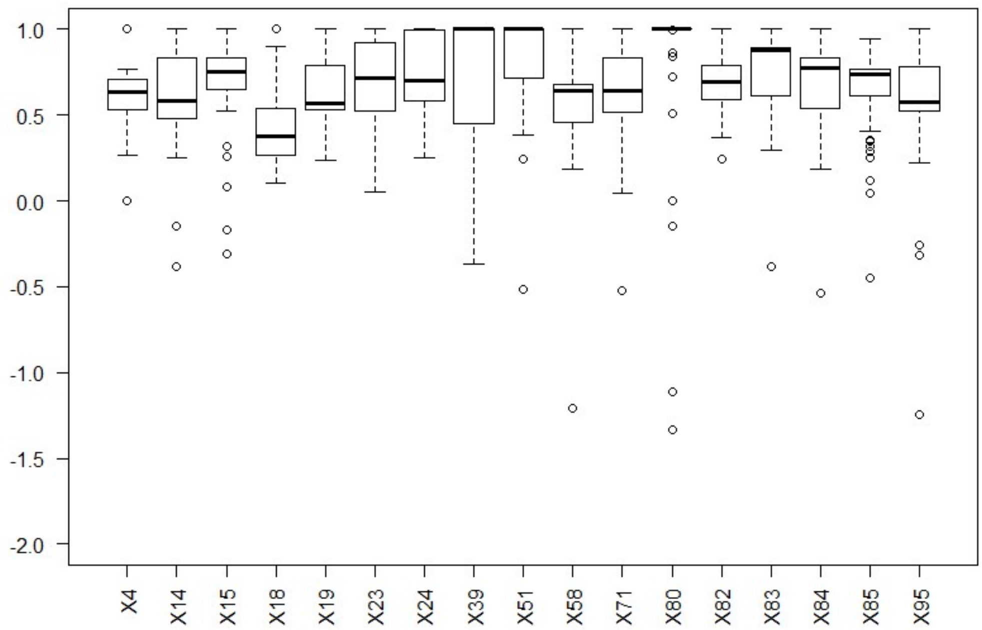

Figure 8 - Cross-efficiency boxplot for the efficient units (Model A)

Source: elaborated by the author

As model A has some very low values of efficiency, the graph was limited to only show scores between -2 and 1, which resulted in suppressing nine outliers from nine different DMUs. DMU 80, besides being in reference sets in more rounds, also had a smaller range of efficiency scores when compared to DMU 58, if outliers are not considered. This is mostly because DMU 80 was considered efficient when using the best weights of 82 other units. Therefore, it can be considered "more efficient" in model A, considering an input-oriented model. It is the efficient unit with the smallest range (not considering outliers) and it is a reference to more units. Besides, it does not have any slacks.

5.2. Model B (structure)

Model B has the primary objective of comparing units with a similar structure. It maintains constant the level of inputs (number of ICU beds, total hours of physicians, and total hours of nurses) while it maximizes the levels of the inverse of SMR and SRU.

In an output-oriented model, as model B, the scores of the non-efficient DMUs are harder to interpret as they do not have a maximum value, as in the input-oriented models. In this case, the objective is to have the smallest score, with the values varying between one and infinity. In model B, most units had efficiency scores between one and 2, with a maximum value of 3.80, as shown in Figure 9.

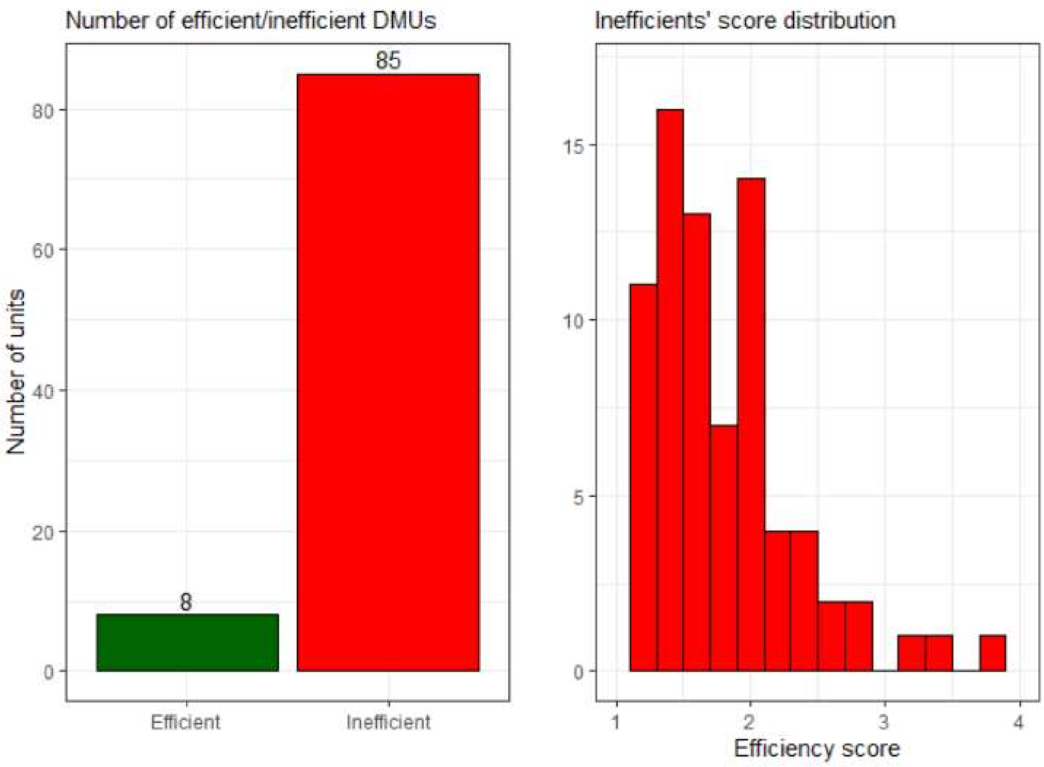

Figure 9 - Number of efficient DMUs and efficiency distribution (Model B)

Source: elaborated by the author

Unit 24 was a reference to 63 other DMUs and all of the efficient units were in reference sets at least 4 times, as shown in Figure 10. Besides, units 58 and 80, which were considered efficient in model A, also had an efficiency score of one in model B. However, regarding the reference sets, the results were different. As model B is output-oriented, unit 58 was more times in reference sets when compared to DMU 80, since it has very low values of SMR and SRU.

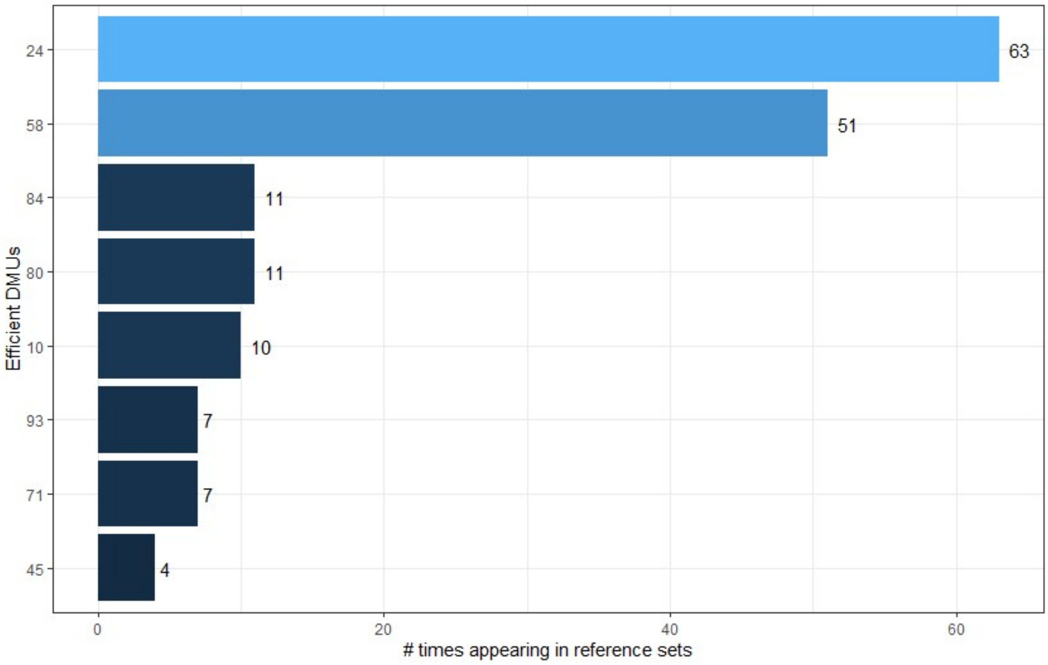

Figure 10 - Number of times each unit was in the reference set (Model B)

Source: elaborated by the author

The results can be better understood by analyzing the input and output values of some DMUs and the dataset median in Table 20.

Table 20 - Inputs and outputs of ICUs 24, 45, and 80 in model B

ICU	ICU_Bed	MD_hours	Nur_hours	SMR	SRU
24	8	276	336	0.57	0.56
45	6	168	168	1.29	4.48
80	16	168	168	1.41	1.15
Median	13	372	396	1.00	1.15

Source: elaborated by the author

Unit 24 is a reference 63 times because it had positive output results (lower SMR and SRU than the median) in an output-oriented model. It also had low use of resources. Unit 45, on the other hand, had low values of inputs and high values of outputs, which is why it was efficient, but it was not in reference sets as many times.

Unit 80 had high values of ICU beds (in comparison to the median), but it had very low values of physician and nursing hours. Given the flexibility given to the weights in the DEA model, the number of beds was not considered for this unit, as shown in Table 21, that represents the value of the weights chosen by the model. Also, as unit 45 had a very high value of SRU, its weight was also set to zero.

Table 21 – Weights of DMUs 45 and 80 (Model B)

DMU	ICU_Beds	MD_Hours	Nur_Hours	SMR_inv	SRU_inv
45	0.000	0.017	0.000	1.286	0.000
80	0.000	0.010	0.000	0.000	1.148

Source: elaborated by the author

DMU 80 puts all the weights in one input and in one output in which it has low values (physician hours and SRU). For that reason, it is a reference to units that have similar patterns, that is, relatively low number of physician hours, and that would also choose to discard (weights = 0) the ICU beds, the SMR, and the total hours of nurses.

Figure 11 shows the cross-efficiency boxplot for the units considered efficient in Model B, with the y-axis limited between 1 and 6 (2 outliers were excluded from the graph). Comparing units 58 and 80, as in Section 5.1 (model A), the results are different. In this case, DMU 80 has a wider range and more outliers, while unit 58 has more consistent results.

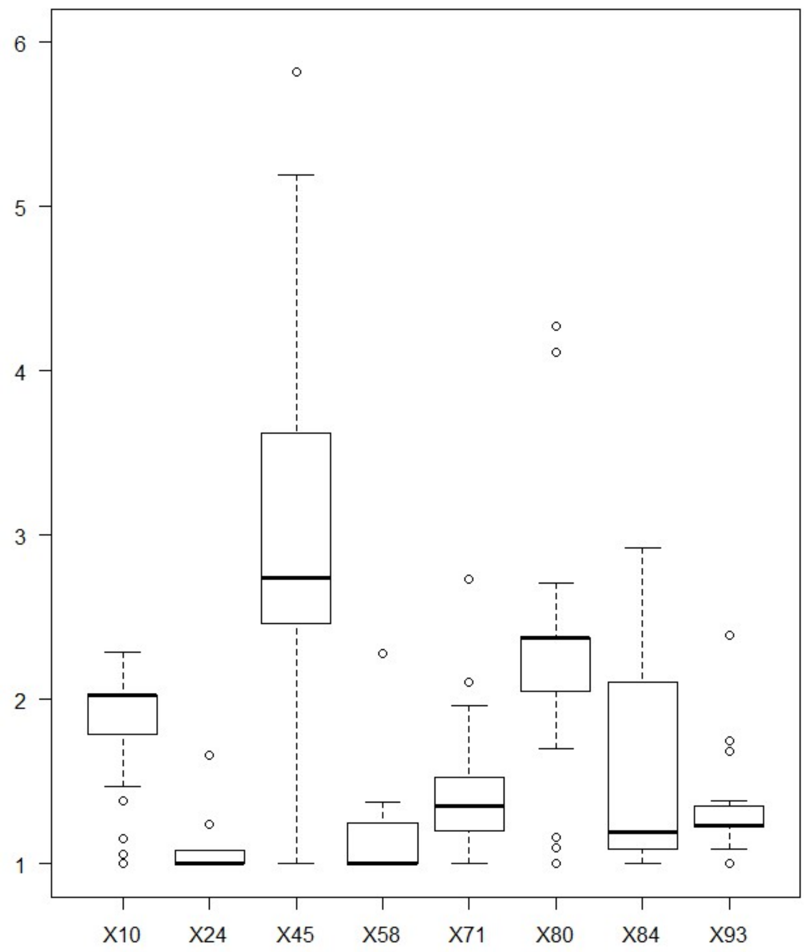

Figure 11 – Cross-efficiency boxplot for the efficient units (Model B)

Source: elaborated by the author

In Figure 11, it is clear that DMU 24 has the most consistent results, that is, that it had efficiency scores close to 1 with most possible weights. The high values of efficiency obtained by DMU 45 are mainly due to units that put high weights on SRU, given that this was an output in which unit 45 had a much higher value than the dataset median. All the weights given by each DMU to each input and output in each model are in Appendices VIII, IX, and X.

DMU 24 showed consistent efficient results in model B when compared to the other units. It was also a reference more often, and it did not have any slacks. DMU 58 also had a great number of results close or equal to one. Unit 45, in its turn, had a great dispersion of the efficiency scores and it was not a reference to any DMUs. This is indicative for the managers that its efficiency score of 1 should not be considered completely adequate and that additional analyses are still necessary.

5.3. Model C

Model C represents how SMR and SRU are related to the capacity of the ICUs. Given the ICU's levels of outputs, it shows how much more occupancy it should have to be considered efficient. Its efficiency distribution is represented in Figure 12.

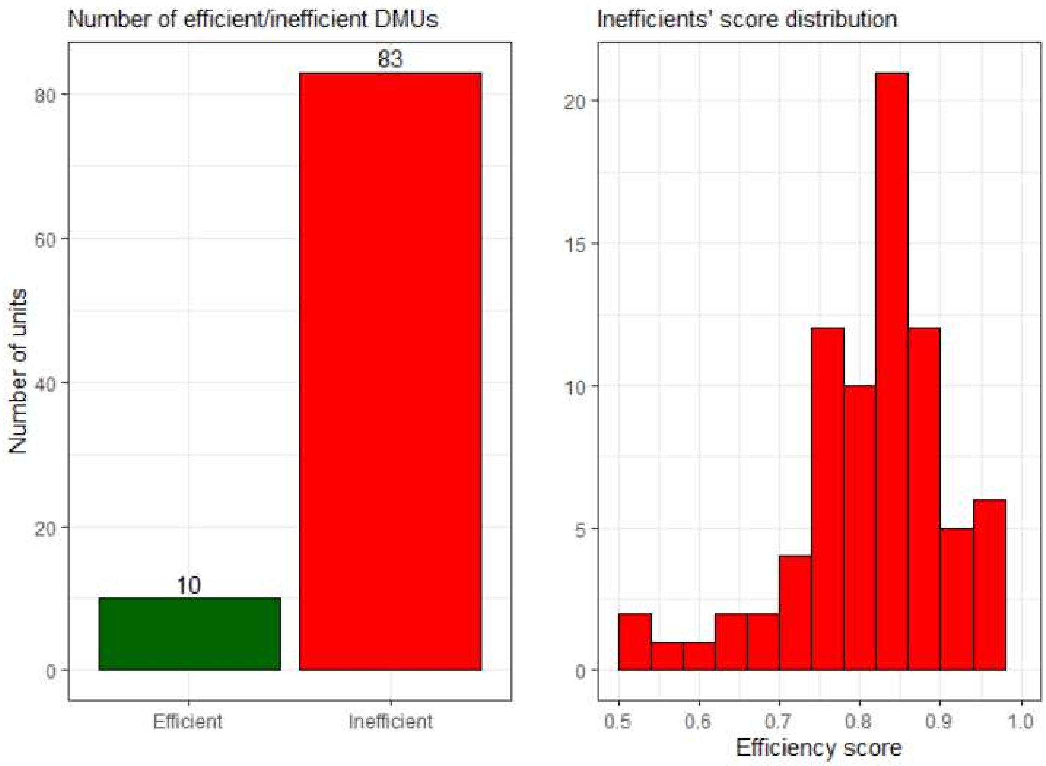

Figure 12 - Number of efficient DMUs and efficiency distribution (Model C)
Source: elaborated by the author

Unit 51, considered inefficient, had as references DMUs 24 (7,57%), 25 (8,29%) and 84 (84,13%). Table 22 shows the actual values of DMUs 51, 24, 25 and 84, and Table 23 shows the calculated targets of inputs and outputs for ICU 51, which are the weighted sum of the variables of its references.

Table 22 - Inputs and outputs of ICUs 24, 25, 51, and 84 in model C

ICU	BOR	SMR	SRU
24	0.74	0.57	0.56
25	0.89	0.64	0.73
51	0.88	0.58	1.31
84	0.96	0.57	1.64

Source: elaborated by the author

Table 23 – Targets of ICU 51 in model C

DMU	BOR	SMR	SRU
51	0.93	0.58	1.31

Source: elaborated by the author

Therefore, in this case, if DMU 51 maintained its level of outputs and raised its occupancy in 5%, it would be considered efficient compared to the same set of DMUs.

One other way to look at cross-efficiencies, besides the representations shown above for the other models, is to rank units according to their score in each round. Then, a graph is set with the lowest and highest ranks achieved by each DMU. This is helpful to interpret scores because they are compared to the other units' scores in the same round (with the same weights). It is also a representation of the DMUs' variation in performance according to the weights.

Figure 13 shows the ranking ranges of each DMU in Model C. There were non-efficient units with high oscillations, such as DMU 50, varying from 3rd to last (93rd) positions; some that did not oscillate as much and were closer to being efficient (DMU 26, from 3rd to 20th); and some that also did not oscillate as much but were closer to being inefficient (DMU 48, from 72th to 89th).

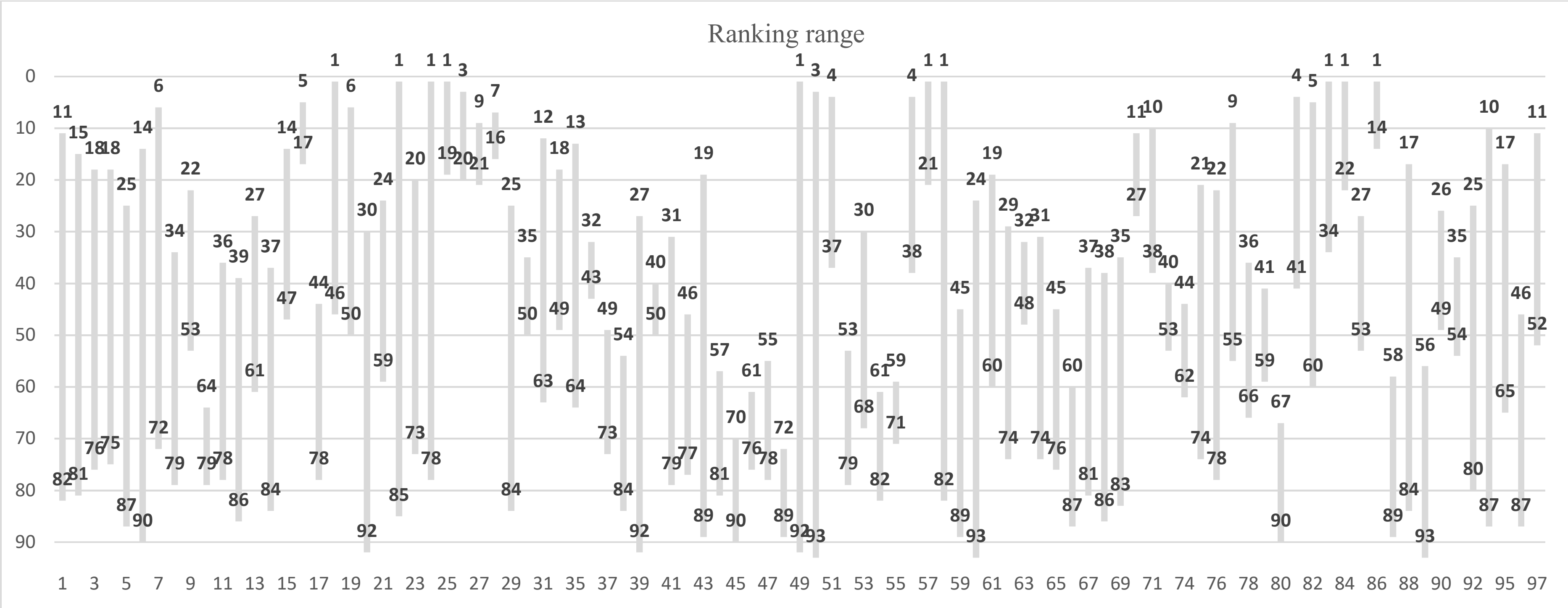

Figure 13 – Cross-efficiency ranking range (Model C)

Source: elaborated by the author

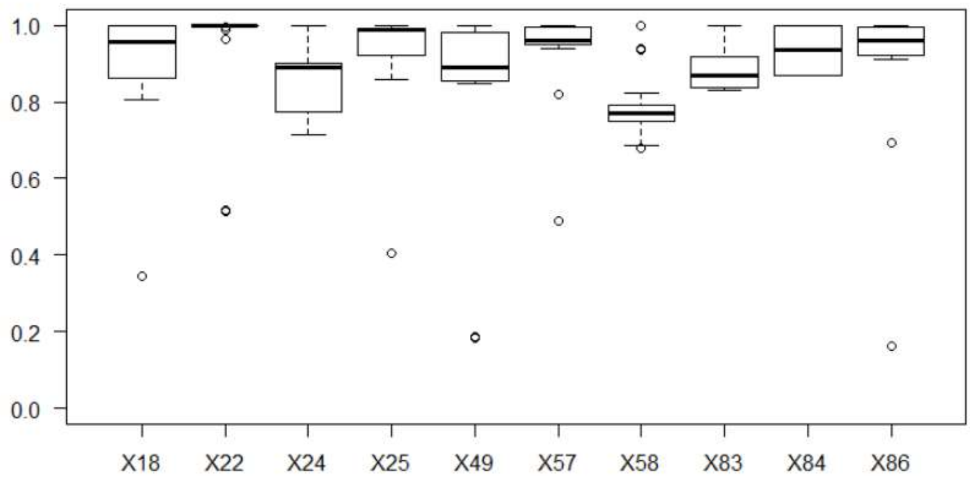

Figure 14 - Cross-efficiency boxplot for the efficient units (Model C)

Source: Elaborated by the author

Figure 14 is the boxplot of cross-efficiencies for the DMUs considered efficient in this model. The y-axis was limited to only show results greater than 0, excluding 5 outliers. It shows that there are cases in which the efficiency of one is actually an outlier (as DMU 58). Unit 22 was efficient in most rounds, with only a few outliers. This is an indication that DMU 22 can be considered the most efficient unit in Model C, while units 58 and 24 have less consistent results.

Considering DMU 22 the most efficient in model C is in line with the results of the reference set, as it was the efficient unit that was a reference more times in this case. Besides, it did not have any slacks.

5.4. Overall results

Units 24, 58, and 84 were considered efficient in all three models. DMU 24 was a reference more times comparing to the other two units both in model A and model B, which had different orientations, showing consistency in input and output results when compared to units 58 and 84. Table 24 shows the inputs and outputs of the three units considered efficient in all models. All units had their outputs lower than the dataset median, except for DMU 84's SRU. This unit was considered efficient in all models mainly because of its low value of SMR, and it was a reference more times in model C because of its high occupancy rate (96%).

Table 24 – Inputs and outputs for the efficient DMUs in all models

ICU	A				B			C	Outputs	
	MD_ Bed10	**Nur_ Bed10**	**NurTec_ Bed10**	**Physio_ Bed10**	**ICU_ Bed**	**MD_ hours**	**Nur_ hours**	**BOR**	**SMR**	**SRU**
24	2.05	2.50	5.00	1.25	8	276	336	0.74	0.57	0.56
58	2.74	3.33	5.00	1.67	6	276	336	0.71	0.52	0.77
84	1.70	0.80	5.00	1.25	8	252	108	0.96	0.57	1.64
Median	**1.67**	**1.71**	**5.00**	**1.00**	**13**	**372**	**396**	**0.84**	**1.00**	**1.15**

Source: Elaborated by the author

Regarding the dispersion of the results, the outcome was similar. In model A, all three units had medium dispersion, with DMU 24 having somewhat more consistent results. In model B, DMU 24 also had better results, with DMU 84 being much less consistent than the others. Finally, in model C, DMU 84 had the most consistent results. Overall, DMU 24 had more steady results and was a reference more times to other units. Unit 84, although being efficient in all three models, had the best results in model C, which was due to its high occupancy rate.

6
Post-DEA analysis

Some categorical non-discretionary variables were selected to understand if and how efficiency varies between the categories. The selected variables were the type and size of the hospital, the type of the ICU, and the proportion between the number of ICU beds and hospital beds. Table 25 shows the mean efficiencies that the DMUs in each category had in each of the three models, the mean values of SMR and SRU, the number of DMUs in each category, and the number of units considered efficient in each category and in each model.

Table 25 – Mean efficiencies in each category

	Model A	**Model B**	**Model C**	**SMR**	**SRU**	**n**	**#Ef A**	**#Ef B**	**#Ef C**
Hospital type									
Public	0.56	2.25	0.84	1.38	2.10	17	1	0	1
Private, philanthropic	0.71	1.72	0.81	1.09	1.30	19	3	1	2
Private, for-profit	**0.77**	**1.48**	**0.86**	**0.90**	**1.15**	57	12	7	7
Hospital size									
Small	0.67	**1.64**	0.78	1.04	1.24	9	2	1	1
Medium	**0.75**	1.70	**0.86**	1.03	**1.23**	33	5	2	2
Large	0.71	1.66	0.85	**1.02**	1.45	51	9	5	7
ICU type									
Mixed	0.71	1.72	0.84	1.03	1.42	75	11	4	7
Surgical	0.73	1.55	0.85	1.05	1.07	8	2	0	0
Medical	0.58	1.81	0.65	1.07	1.02	1	0	0	0
Neurological	**0.92**	**1.10**	**0.96**	**0.64**	**0.95**	5	3	3	3
Others	0.69	1.66	0.79	1.38	1.20	4	0	1	0
Proportion of ICU beds									
Low	0.69	**1.63**	**0.85**	1.05	1.53	31	5	6	5
Medium	0.71	1.68	**0.85**	1.02	1.28	31	4	1	2
High	**0.76**	1.71	0.83	**1.01**	**1.25**	31	7	1	3

bold: best mean values in each variable and in each model

Source: elaborated by the author

The most assertive result between the four variables was the hospital type. In all the models, the for-profit hospitals had the best efficiency scores. It also had the best values of SMR and SRU and the highest proportion of efficient units in all three models. However, in model C, the three categories had similar average scores, which indicates that, even though public hospitals had poor outcomes, they were working with higher occupancy, when compared to the private units.

Hospital size and proportion of ICU beds had ambiguous results. In model B, which considers the structure of the ICU, the results were better for small hospitals and low proportion ICUs. In model C, that evaluates the strained capacity of the ICU, the results were similar between the categories in both variables.

SMR was very similar between the hospital sizes, but SRU was considerably higher in large hospitals. The neurological ICU type had much better results, but the distribution of the number of ICUs is very uneven between the categories, which may have distorted the results. The ICUs with higher proportion of beds also had better results of SMR and SRU.

A deeper look at the variables that compose model A is useful to interpret the efficiency results. Table 26 shows their median per hospital type, which was the categorical variable with the most significant results.

Table 26 – Median values of variables per category (Model A)

	MD_ Bed10	Enf_ Bed10	EnfTec_ Bed10	Fisio_ Bed10	SMR	SRU
Hospital Type						
Public	1.76	1.82	5.00	1.03	1.29	2.13
Private, philanthropic	1.43	1.60	5.26	1.00	1.11	1.14
Private, for-profit	1.70	1.71	5.00	1.00	0.88	1.07

Source: elaborated by the author

The median values per hospital type show that the inputs are relatively similar between the categories. However, the outputs are lower for for-profit hospitals, higher for philanthropic hospitals, and even higher for public hospitals, which explains the difference in the efficiency scores.

7
Conclusion

Efficiency assessment is especially important in the healthcare scenario, as it analyzes the performance of organizations that deal with lives. For ICUs, specifically, it is even more relevant, since it deals with severe and high-cost cases. Besides, efficiency measures are capable of uniting all stakeholders' interests.

This work used Data Envelopment Analysis to evaluate 93 ICUs, using a database that had information on 129,680 patients. DEA is considered useful for performance assessment in the healthcare scenario because it can deal with multiple inputs and outputs at the same time, which is not possible with other tools. This research used SMR and SRU as output measures, and it had three different perspectives: the staffing patterns, the structure of the ICU, and the capacity of the ICU, represented as the bed occupancy rate.

DEA results were represented in different ways to show its use and to demonstrate how efficiency scores should not be seen as final and only results. The efficiency scores themselves might be misleading, as they do not account for slacks (if the unit had input surplus or output shortfall), and reference sets (in how many rounds a DMU was considered efficient).

Also, cross-efficiency results show that variations in efficiency are also a way of differentiating between units, especially the efficient ones, as the flexibility given to the weights by the DEA model allows units to have all but one input (and output) weight equal to zero. Different representations of the cross-efficiency results were presented: the ranges of the efficiency scores, their boxplots, and the range of the DMUs' ranks.

DEA can be a useful tool for hospital managers as the unit's efficiency is evaluated by comparing its data with other units, and not with theoretical performance. The tables and figures presented in this work help the interpretation of the results. Unit 58, for example, was considered efficient in an input-oriented model (Model A), but it was not a reference to others. In model B, however, an output-oriented model, it was a reference 51 times. This result shows that unit 58 was considered efficient because it had very low SMR and SRU when compared to others, but relatively high use of resources, as it was not a reference in the input-oriented model. In all three models, it had low variation in the efficiency scores, which indicates consistency in the results.

The definition of targets is also useful for managers. It compares inefficient units with the efficient ones that have the most achievable results and defines targets based on that data. The targets then can be seen as the basis for the definition of goals for each variable used.

The analysis of the efficiency scores among the categorical variables showed that, on average, private for-profit hospitals had better efficiency results, and that large ICUs had better SMR and SRU. These results are useful to have a better understanding of the system, which can be useful for private institutions as well as for public health management. Investigations could be performed to understand the reasons for the discrepancy of efficiency scores between categories.

The main contribution of this work, besides presenting visualization aids and interpretation of the results, was to use patient-level data (SMR and SRU) as outputs. This is especially important in the healthcare scenario, as results can vary greatly depending on the case-mix. Thereby, the mortality and the use of resources were adjusted by the severity of the patient.

For future works, the use of patient-level metrics in both sides (inputs and outputs) and the incorporation of uncertainty could lead to more accurate results. The choice of other inputs and outputs can also provide other perspectives besides the ones examined in this work. Besides, the use of other databases could improve the analyses.

8
References

ADLER, N.; FRIEDMAN, L.; SINUANY-STERN, Z. Review of ranking methods in the data envelopment analysis context. **European Journal of Operational Research**, v. 140, n. 2, p. 249–265, 2002.

ALAM, T. Evaluating efficiency of hospitals in the Kingdom of Saudi Arabia: DEA - an operational research technique approach. **International Journal of Mechanical Engineering and Technology**, v. 9, n. 10, p. 1400–1405, 2018.

ANDERSEN, P.; PETERSEN, N. C. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. **Management Science**, v. 39, n. 10, p. 1261–1264, 1993.

AZADEH, A. et al. An integrated algorithm for performance optimization of neurosurgical ICUs. **Expert Systems with Applications**, v. 43, n. December 2005, p. 142–153, 2016.

BAHRAMI, M. A. et al. Data envelopment analysis for estimating efficiency of intensive care units: a case study in Iran. **International Journal of Health Care Quality Assurance**, v. 31, n. 4, p. 276–282, 2018.

BAHRAMPOUR, M.; GOODARZI, G.; TOHIDI, M. Determination of technical efficiency of intensive care units in hospitals afilliated to Kerman University of Medical Sciences by stochastic frontier analysis in 2008. **Journal of Kerman University of Medical Sciences**, v. 20, n. 6, p. 596–605, 2013.

BANKER, R.; CHANG, H.; COOPER, W. Simulation studies of efficiency, returns to scale and misspecification with nonlinear functions in DEA. **Annals of Operations Research**, v. 66, p. 233–253, 1996.

BANKER, R. D.; CHARNES, A.; COOPER, W. W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. **Management Science**, v. 30, n. 9, p. 1078–1092, 1984.

BLACK, N. Patient reported outcome measures could help transform healthcare. **BMJ (Online)**, v. 346, n. 7896, p. 1–5, 2013.

BOUSSOFIANE, A., DYSON, R.G., THANASSOULIS, E. Applied data envelopment analysis. **European Journal of Operational Research**, v. 52, n. 1, p. 1–15, 1991.

BRESLOW, M. J.; BADAWI, O. Severity scoring in the critically ill: Part 1 - Interpretation and accuracy of outcome prediction scoring systems. **Chest**, v. 141, n. 1, p. 245–252, 2012.

CHARNES, A. et al. A DEVELOPMENTAL STUDY OF DATA ENVELOPMENT ANALYSIS IN MEASURING THE EFFICIENCY OF MAINTENANCE UNITS IN THE U.S. AIR FORCES. 1985, [S.l: s.n.], 1985. p. 95–112.

CHARNES, A.; COOPER, W. W.; RHODES, E. Measuring the efficiency of decision making units. **European Journal of Operational Research**, v. 2, n. 6, p. 429–444, 1978.

COHEN-KADOSH, S.; SINUANY-STERN, Z. Hip fracture surgery efficiency in Israeli hospitals via a network data envelopment analysis. **Central European Journal of Operations Research**, 2018.

COOPER, W.; SEIFORD, L.; ZHU, J. **Handbook on Data Envelopment Analysis - International Series in Operations Research & Management Science**. [S.l: s.n.], 2004.

DERVAUX, B. et al. Performance of French intensive care units: A directional distance function approach at the patient level. **International Journal of Production Economics**, v. 120, n. 2, p. 585–594, 2009.

DONABEDIAN, A. Evaluating the quality of medical care. **Milbank Memorial Fund Quarterly**, v. 44, p. 166–203, 1966.

DONABEDIAN, Avedis. The quality of medical care. v. 200, n. 1978, p. 856–864, 1978.

DOYLE, J.; GREEN, R. Efficiency and Cross-eficiency in DEA: Derivations, Meanings and Uses. **Journal of the Operational Research Society**, v. 45, n. 5, p. 567–

578, 1994.

DYSON, R. G. et al. Pitfalls and protocols in DEA. **European Journal of Operational Research**, v. 132, n. 2, p. 245–259, 2001.

EL-JARDALI, F. et al. The impact of hospital accreditation on quality of care: Perception of Lebanese nurses. **International Journal for Quality in Health Care**, v. 20, n. 5, p. 363–371, 2008.

FERREIRA, D.; MARQUES, R. C. Identifying congestion levels, sources and determinants on intensive care units: the Portuguese case. **Health Care Management Science**, v. 21, n. 3, p. 348–375, 2018.

GARLAND, A. Improving the ICU. **Chest**, v. 127, n. 6, p. 2151–2164, 2005.

GARRATT, A. et al. of Patient Assessed Health Outcome Measures Assessed Health Outcome Measures. v. 324, n. December 2008, 2002.

GIMÉNEZ, V.; KEITH, J. R.; PRIOR, D. Do healthcare financing systems influence hospital efficiency? A metafrontier approach for the case of Mexico. **Health Care Management Science**, v. 1, 2019.

GOLANY, B.; ROLL, Y. An application procedure for DEA. **Omega**, v. 17, n. 3, p. 237–250, 1989.

GOSHTASEBI, A. et al. Assessing hospital performance by the Pabon Lasso model. **Iranian Journal of Public Health**, v. 38, n. 2, p. 119–124, 2009.

GUTACKER, N. et al. TRULY INEFFICIENT OR PROVIDING BETTER QUALITY OF CARE? ANALYSING THE RELATIONSHIP BETWEEN RISK-ADJUSTED HOSPITAL COSTS AND PATIENTS' HEALTH OUTCOMES. v. 22, p. 931–947, 2013.

GYRD-HANSEN, D.; OLSEN, K. R.; SØRENSEN, T. H. Socio-demographic patient profiles and hospital efficiency: Does patient mix affect a hospital's ability to perform? **Health Policy**, v. 104, n. 2, p. 136–145, 2012.

HALKOS, G.; PETROU, K. N. Treating undesirable outputs in DEA: A critical review. **Economic Analysis and Policy**, v. 62, p. 97–104, 2019.

HOLLINGSWORTH, B.; DAWSON, P. .; MANIADAKIS, N. Efficiency measurement of health care: a review of non-parametric methods and applications. **Health care management science**, v. 2, n. 3, p. 161–172, 1999.

HUANG, S. C.; LIU, D. C.; LU, Z. F. Measuring efficiency of hand surgery departments using Data Envelopment Analysis(DEA). **Proceedings - 2010 IEEE 17th International Conference on Industrial Engineering and Engineering Management, IE and EM2010**, p. 1189–1193, 2010.

KEEGAN, M. T.; SOARES, M. What every intensivist should know about prognostic scoring systems and risk-adjusted mortality. **Revista Brasileira de Terapia Intensiva**, v. 28, n. 3, p. 264–269, 2016.

KOHL, S. et al. The use of Data Envelopment Analysis (DEA) in healthcare with a focus on hospitals. **Health Care Management Science**, p. 1, 2018.

LACKO, R.; HAJDUOVÁ, Z.; HURNÝ, F. Explaining the efficiency of anaesthesiology and intensive care wards in the Slovak Republic. **Problems and Perspectives in Management**, v. 16, n. 1, p. 166–172, 2018.

LAUDICELLA, M.; OLSEN, K. R.; STREET, A. Examining cost variation across hospital departments-a two-stage multi-level approach using patient-level data. **Social Science and Medicine**, v. 71, n. 10, p. 1872–1881, 2010.

LIM, S.; ZHU, J. DEA cross-efficiency evaluation under variable returns to scale. **Journal of the Operational Research Society**, v. 66, n. 3, p. 476–487, 2015.

MANT, J. Process versus outcome indicators in the assessment of quality of health care. **International Journal for Quality in Health Care**, v. 13, n. 6, p. 475–480, 2001.

MEHRTAK, M.; YUSEFZADEH, H.; JAAFARIPOOYAN, E. Pabon Lasso and Data Envelopment Analysis: A Complementary Approach to Hospital Performance Measurement. **Global Journal of Health Science**, v. 6, n. 4, 2014.

MELLO, J. C. et al. Curso de análise de envoltória de dados. 2005, [S.l: s.n.], 2005.

MIGDADI, Y. K.; AL-MOMANI, H. S. The operational determinants of hospitals' inpatients departments efficiency in Jordan. **International Journal of Operational Research**, v. 32, n. 1, p. 1–23, 2018.

MIN, A. et al. Impact of Medicare Advantage penetration and hospital competition on technical efficiency of nursing care in US intensive care units. **International Journal of Health Planning and Management**, v. 33, n. 3, p. 733–745, 2018.

______. Organizational Factors Associated With Technical Efficiency of Nursing

Care in US Intensive Care Units. **Journal of Nursing Care Quality**, v. 34, n. 3, p. 242–249, 2019.

MORENO, R. P. et al. SAPS 3 - From evaluation of the patient to evaluation of the intensive care unit. Part 2: Development of a prognostic model for hospital mortality at ICU admission. **Intensive Care Medicine**, v. 31, n. 10, p. 1345–1355, 2005.

NATHANSON, B. H. et al. An exploratory study using data envelopment analysis to assess neurotrauma patients in the intensive care unit. **Health Care Management Science**, v. 6, n. 1, p. 43–55, 2003.

NUNAMAKER, T. Measuring routine nursing service efficiency: a comparison of cost per patient day and data envelopment analysis model. **Health Services Research**, v. 18, 1983.

OSMAN, I. H. et al. Data envelopment analysis model for the appraisal and relative performance evaluation of nurses at an intensive care unit. **Journal of Medical Systems**, v. 35, n. 5, p. 1039–1062, 2011.

OZCAN, Y. **Health care benchmarking and performance evaluation: an assessment using Data Envelopment Analysis (DEA)**. Berlin: Springer, 2014.

PALMER, S.; TORGERSON, D. J. Economic notes: definitions of efficiency. **BMJ (Clinical research ed.)**, v. 318, n. 7191, p. 1136, 1999.

PORTER, M. E. What is value in health care? **The New England journal of medicine**, v. 363, n. 26, p. 2477–81, 2010.

RAY, B., SAMADDAR, D., TODI, S., RAMAKRISHNAN, N., JOHN, G., RAMASUBBAN, S. Quality indicators for ICU: ISCCM guidelines for ICUs in India. **Indian Journal of Critical Care Medicine**, v. 13, n. 4, p. 173–206, 2009.

RETZLAFF-ROBERTS, D.; CHANG, C. F.; RUBIN, R. M. Technical efficiency in the use of health care resources: A comparison of OECD countries. **Health Policy**, v. 69, n. 1, p. 55–72, 2004.

REWA, O. G. et al. Indicators of intensive care unit capacity strain: A systematic review. **Critical Care**, v. 22, n. 1, p. 1–13, 2018.

RHODES, G. et al. Comparing EU hospital efficiency using diagnosis-related groups. **European Journal of Public Health**, v. 7, n. 3 SUPPL., p. 42–50, 1997.

ROTHEN, H. et al. Variability in outcome and resource use in intensive care units. **Intensive Care Medicine**, v. 33, n. 8, p. 1329–1336, 2007.

ROTHEN, H. U.; TAKALA, J. Can outcome prediction data change patient outcomes and organizational outcomes? **Current Opinion in Critical Care**, v. 14, n. 5, p. 513–519, 2008.

SALLUH, J. I. F.; SOARES, M.; KEEGAN, M. T. Understanding intensive care unit benchmarking. **Intensive Care Medicine**, v. 43, n. 11, p. 1703–1707, 2017.

SEXTON, T. R.; SILKMAN, R. H.; HOGAN, A. J. Data envelopment analysis: Critique and extensions. **New Directions for Program Evaluation**, v. 1986, n. 32, p. 73–105, 1986.

SHERMAN, H. Hospital Efficiency Measurement and Evaluation: Empirical Test of a New Technique. **Medical Care**, v. 22, n. 10, p. 922–938, 1984.

SIEGEL, T. et al. Prospective assessment of the standardized mortality ratio (SMR) as a measure of quality of care in an intensive care unit — a single-centre study. **Anaesthesiology Intensive Therapy**, v. 47, n. 4, p. 328–332, 2015.

SOARES, M. et al. Effects of organizational characteristics on outcomes and resource use in patients with cancer admitted to intensive care units. **Journal of Clinical Oncology**, v. 34, n. 27, p. 3315–3324, 2016.

TONE, K. Slacks-Based measure of efficiency. **International Series in Operations Research and Management Science**, v. 164, p. 195–209, 2011.

TSEKOURAS, K. et al. Does the adoption of new technology boost productive efficiency in the public sector? the case of ICUs system. **International Journal of Production Economics**, v. 128, n. 1, p. 427–433, 2010.

WALKER, D. M. Does participation in health information exchange improve hospital efficiency? **Health Care Management Science**, v. 21, n. 3, p. 426–438, 2018.

XENOS, P. et al. Efficiency and productivity assessment of public hospitals in Greece during the crisis period 2009-2012. **Cost Effectiveness and Resource Allocation**, v. 15, n. 1, p. 1–12, 2017.

ZAMPIERI, F. G. et al. ICU staffing feature phenotypes and their relationship with patients' outcomes: an unsupervised machine learning analysis. **Intensive Care Medicine**,

v. 45, n. 11, p. 1599–1607, 2019.

APPENDIX I – Efficiency results of all the DMUs in all models

DMU	A			B			C		
	Slacks?	# ref	Score	Slacks?	# ref	Score	Slacks?	#ref	Score
1	Yes	-	0.576	Yes	-	2.376	Yes	-	0.911
2	Yes	-	0.539	Yes	-	2.252	Yes	-	0.879
3	Yes	-	0.628	Yes	-	1.402	Yes	-	0.880
4	No	4	1.000	Yes	-	1.059	No	-	0.788
5	Yes	-	0.536	Yes	-	2.712	Yes	-	0.842
6	Yes	-	0.404	No	-	2.436	Yes	-	0.881
7	Yes	-	0.425	Yes	-	2.082	Yes	-	0.945
8	Yes	-	0.652	Yes	-	1.591	No	-	0.764
9	Yes	-	0.719	Yes	-	1.455	No	-	0.857
10	Yes	-	0.704	No	10	1.000	Yes	-	0.753
11	Yes	-	0.597	Yes	-	1.375	No	-	0.773
12	Yes	-	0.829	Yes	-	1.389	Yes	-	0.737
13	Yes	-	0.676	Yes	-	1.408	Yes	-	0.855
14	No	2	1.000	Yes	-	1.087	Yes	-	0.818
15	No	8	1.000	Yes	-	1.428	Yes	-	0.902
16	Yes	-	0.847	Yes	-	1.335	No	-	0.981
17	Yes	-	0.929	Yes	-	1.395	Yes	-	0.816
18	No	2	1.000	Yes	-	1.043	Yes	27	1.000
19	No	3	1.000	Yes	-	1.065	Yes	-	0.986
20	Yes	-	0.512	Yes	-	2.868	Yes	-	0.833
21	Yes	-	0.814	Yes	-	1.355	Yes	-	0.865
22	Yes	-	0.588	Yes	-	2.142	No	75	1.000
23	No	19	1.000	Yes	-	1.100	Yes	-	0.880
24	No	18	1.000	No	63	1.000	No	2	1.000
25	Yes	-	0.835	Yes	-	1.162	No	19	1.000
26	Yes	-	0.796	Yes	-	1.276	No	-	0.997
27	Yes	-	0.963	Yes	-	1.241	No	-	0.966
28	Yes	-	0.759	Yes	-	1.272	No	-	0.977
29	Yes	-	0.826	Yes	-	1.267	Yes	-	0.771
30	Yes	-	0.591	Yes	-	1.672	No	-	0.834
31	Yes	-	0.888	Yes	-	1.256	No	-	0.836
34	Yes	-	0.726	Yes	-	1.520	Yes	-	0.880
35	Yes	-	0.574	Yes	-	2.022	Yes	-	0.893
36	Yes	-	0.742	Yes	-	1.671	No	-	0.850
37	Yes	-	0.626	Yes	-	1.856	No	-	0.759
38	Yes	-	0.602	Yes	-	2.029	Yes	-	0.712
39	No	45	1.000	Yes	-	1.616	No	-	0.544
40	Yes	-	0.537	No	-	1.271	No	-	0.832
41	Yes	-	0.474	Yes	-	1.458	Yes	-	0.833
42	Yes	-	0.474	Yes	-	1.479	Yes	-	0.808
43	Yes	-	0.495	Yes	-	2.405	Yes	-	0.861
44	Yes	-	0.671	Yes	-	2.062	Yes	-	0.759
45	Yes	-	0.760	No	-	1.000	Yes	-	0.699
46	Yes	-	0.686	Yes	-	2.041	Yes	-	0.756
47	Yes	-	0.699	Yes	-	1.482	No	-	0.741
48	Yes	-	0.885	Yes	-	3.188	Yes	-	0.725

49	Yes	-	0.577	Yes	-	3.470	No	18	1.000
50	Yes	-	0.499	Yes	-	3.797	Yes	-	0.968
51	No	57	1.000	Yes	-	1.103	No	-	0.940
52	Yes	-	0.764	Yes	-	2.001	Yes	-	0.781
53	Yes	-	0.791	Yes	-	1.691	Yes	-	0.849
54	Yes	-	0.744	Yes	-	2.379	Yes	-	0.757
55	Yes	-	0.611	Yes	-	1.999	No	-	0.761
56	Yes	-	0.671	Yes	-	1.662	No	-	0.981
57	Yes	-	0.721	Yes	-	1.445	No	9	1.000
58	No	0	1.000	No	51	1.000	Yes	0	1.000
59	Yes	-	0.577	Yes	-	1.812	Yes	-	0.651
60	Yes	-	0.751	Yes	-	1.589	No	-	0.527
61	Yes	-	0.935	Yes	-	1.367	No	-	0.815
62	Yes	-	0.586	Yes	-	2.080	Yes	-	0.843
63	Yes	-	0.555	Yes	-	1.681	Yes	-	0.845
64	Yes	-	0.645	Yes	-	1.596	No	-	0.760
65	Yes	-	0.384	Yes	-	2.270	Yes	-	0.810
66	Yes	-	0.566	Yes	-	1.919	Yes	-	0.769
67	Yes	-	0.573	No	-	1.836	Yes	-	0.820
68	Yes	-	0.559	No	-	1.896	Yes	-	0.815
69	Yes	-	0.517	Yes	-	2.014	Yes	-	0.821
70	Yes	-	0.923	Yes	-	1.068	No	-	0.925
71	No	7	1.000	No	7	1.000	Yes	-	0.961
72	Yes	-	0.819	Yes	-	1.375	No	-	0.829
74	Yes	-	0.440	Yes	-	2.029	Yes	-	0.820
75	Yes	-	0.517	Yes	-	1.919	Yes	-	0.871
76	Yes	-	0.376	Yes	-	2.292	Yes	-	0.847
77	Yes	-	0.875	Yes	-	1.251	No	-	0.870
78	Yes	-	0.795	Yes	-	1.770	Yes	-	0.831
79	Yes	-	0.976	Yes	-	1.957	Yes	-	0.825
80	No	74	1.000	No	11	1.000	Yes	-	0.603
81	Yes	-	0.797	No	-	1.094	No	-	0.992
82	No	1	1.000	Yes	-	1.096	No	-	0.941
83	No	3	1.000	Yes	-	1.050	No	0	1.000
84	No	11	1.000	No	11	1.000	No	30	1.000
85	Yes	-	0.943	Yes	-	1.525	No	-	0.848
86	Yes	-	0.768	Yes	-	1.299	No	13	1.000
87	Yes	-	0.864	Yes	-	1.945	Yes	-	0.643
88	Yes	-	0.397	Yes	-	2.513	Yes	-	0.865
89	Yes	-	0.397	Yes	-	2.646	Yes	-	0.524
90	Yes	-	0.595	Yes	-	1.592	Yes	-	0.859
91	Yes	-	0.565	Yes	-	1.814	Yes	-	0.838
92	Yes	-	0.581	Yes	-	1.523	Yes	-	0.787
93	Yes	-	0.703	No	7	1.000	No	-	0.703
95	No	5	1.000	Yes	-	1.216	Yes	-	0.882
96	Yes	-	0.527	Yes	-	1.305	Yes	-	0.667
97	Yes	-	0.593	Yes	-	1.862	Yes	-	0.928

APPENDIX II – Slacks (model A)

DMU	MD_Bed10	Nur_Bed10	NurTec_Bed10	Physio_Bed10	SMR_inverse	SRU_inverse
1	0.253	0.000	0.000	0.603	0.000	0.283
2	0.237	0.000	0.000	0.703	0.000	0.084
3	0.102	0.000	0.000	0.437	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000
5	0.157	0.000	0.000	0.631	0.098	0.460
6	0.192	0.000	0.000	0.485	0.107	0.321
7	0.087	0.000	0.000	0.324	0.000	0.351
8	0.000	0.285	0.000	0.034	0.000	0.000
9	0.532	0.000	0.000	0.078	0.000	0.000
10	0.870	0.000	0.000	1.085	0.038	0.000
11	0.291	0.000	0.000	0.221	0.000	0.000
12	0.312	0.000	0.000	0.160	0.055	0.000
13	0.045	0.000	0.000	0.117	0.000	0.000
14	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.000	0.000
16	0.000	0.673	0.000	0.000	0.000	0.059
17	0.130	0.000	0.000	0.175	0.156	0.000
18	0.000	0.000	0.000	0.000	0.000	0.000
19	0.000	0.000	0.000	0.000	0.000	0.000
20	0.000	0.436	0.000	0.618	0.264	0.402
21	0.000	0.569	0.000	0.376	0.000	0.000
22	0.135	0.000	0.000	0.481	0.000	0.027
23	0.000	0.000	0.000	0.000	0.000	0.000
24	0.000	0.000	0.000	0.000	0.000	0.000
25	0.000	0.000	0.000	0.020	0.000	0.000
26	0.000	0.000	0.000	0.130	0.000	0.000
27	0.316	0.000	0.000	0.020	0.000	0.000
28	0.000	0.000	0.000	0.056	0.000	0.000
29	0.000	0.122	0.000	0.000	0.000	0.000
30	0.000	0.000	0.000	0.376	0.000	0.000
31	0.487	0.000	0.000	0.000	0.000	0.000
34	0.375	0.000	0.000	0.535	0.000	0.000
35	0.000	0.184	0.000	0.475	0.000	0.220
36	0.067	0.000	0.000	0.312	0.000	0.000
37	0.235	0.000	0.000	0.000	0.000	0.000
38	0.202	0.000	0.000	0.336	0.000	0.094
39	0.000	0.000	0.000	0.000	0.000	0.000
40	0.203	0.000	0.000	0.407	0.000	0.004
41	0.085	0.000	0.000	0.460	0.000	0.065
42	0.085	0.000	0.000	0.462	0.000	0.077
43	0.000	0.017	0.000	0.432	0.089	0.541
44	0.000	0.016	0.354	0.488	0.000	0.209
45	0.485	0.000	0.000	1.073	0.025	0.637
46	0.000	0.000	0.544	0.534	0.000	0.079
47	0.000	0.191	0.297	0.309	0.000	0.000
48	0.483	0.000	0.000	0.433	0.235	0.343
49	0.506	0.000	0.000	0.205	0.218	0.584

50	0.193	0.000	0.000	0.098	0.311	0.649
51	0.000	0.000	0.000	0.000	0.000	0.000
52	0.647	0.000	0.000	0.236	0.000	0.254
53	0.526	0.000	0.000	0.306	0.000	0.000
54	0.673	0.000	0.000	0.374	0.000	0.302
55	0.000	0.005	0.378	0.392	0.000	0.020
56	0.467	0.000	0.000	0.059	0.000	0.000
57	0.275	0.000	0.000	0.143	0.000	0.000
58	0.000	0.000	0.000	0.000	0.000	0.000
59	0.000	0.163	0.000	0.453	0.000	0.000
60	0.280	0.000	0.000	0.222	0.000	0.000
61	0.000	0.000	1.166	0.126	0.000	0.000
62	0.288	0.000	0.000	0.429	0.000	0.381
63	0.320	0.000	0.000	0.356	0.000	0.074
64	0.207	0.000	0.000	0.306	0.000	0.000
65	0.135	0.000	0.000	0.460	0.000	0.363
66	0.000	0.051	0.000	0.215	0.145	0.000
67	0.149	0.000	1.132	0.296	0.000	0.437
68	0.223	0.000	1.223	0.397	0.001	0.421
69	0.000	0.138	0.186	0.243	0.000	0.445
70	0.546	0.000	0.000	0.000	0.000	0.000
71	0.000	0.000	0.000	0.000	0.000	0.000
72	0.437	0.000	0.082	0.134	0.000	0.000
74	0.060	0.000	0.000	0.129	0.000	0.179
75	0.000	0.000	0.000	0.284	0.000	0.000
76	0.034	0.000	0.000	0.257	0.000	0.191
77	0.000	0.000	0.000	0.020	0.000	0.000
78	0.439	0.000	0.000	0.538	0.000	0.000
79	0.130	0.000	1.315	0.000	0.000	0.171
80	0.000	0.000	0.000	0.000	0.000	0.000
81	0.000	0.000	0.000	0.234	0.000	0.000
82	0.000	0.000	0.000	0.000	0.000	0.000
83	0.000	0.000	0.000	0.000	0.000	0.000
84	0.000	0.000	0.000	0.000	0.000	0.000
85	0.000	0.000	0.605	0.436	0.000	0.031
86	0.000	0.000	0.000	0.389	0.000	0.000
87	0.000	0.556	1.493	0.568	0.000	0.000
88	0.383	0.000	0.000	0.324	0.000	0.435
89	0.161	0.000	0.000	0.360	0.007	0.443
90	0.033	0.000	0.000	0.207	0.000	0.107
91	0.100	0.000	0.000	0.288	0.000	0.157
92	0.168	0.000	0.000	0.091	0.000	0.190
93	0.034	0.000	0.000	0.052	0.000	0.000
95	0.000	0.000	0.000	0.000	0.000	0.000
96	0.092	0.000	0.000	0.142	0.000	0.000
97	0.261	0.000	0.000	0.531	0.000	0.169

APPENDIX III – Slacks (model B)

DMU	ICU_Bed	MD_hours	Nur_hours	SMR_inv	SRU_inv
1	17.693	384	288	0.000	0.000
2	5.132	108	60	0.000	0.000
3	0.000	0	0	0.130	0.000
4	1.087	0	124	0.000	0.000
5	11.000	228	348	0.000	0.216
6	0.000	0	0	0.000	0.000
7	4.000	60	120	0.000	0.267
8	4.309	60	228	0.000	0.000
9	2.165	108	60	0.000	0.000
10	0.000	0	0	0.000	0.000
11	0.000	60	60	0.359	0.000
12	2.000	120	60	0.360	0.000
13	0.000	60	60	0.151	0.000
14	3.000	60	120	0.695	0.000
15	11.430	91	0	0.000	0.000
16	27.000	408	1368	0.000	0.247
17	12.000	348	180	0.561	0.000
18	30.000	540	1716	0.144	0.000
19	29.000	648	1200	0.203	0.000
20	0.000	0	137	0.000	0.000
21	22.000	468	1032	0.180	0.000
22	12.038	180	60	0.000	0.000
23	2.000	108	60	0.386	0.000
24	0.000	0	0	0.000	0.000
25	0.780	0	0	0.000	0.000
26	0.070	0	0	0.000	0.000
27	3.127	60	0	0.000	0.000
28	0.989	0	0	0.000	0.000
29	4.000	120	168	0.201	0.000
30	27.398	480	588	0.000	0.000
31	13.927	396	456	0.000	0.000
34	22.000	780	516	0.128	0.000
35	14.000	120	240	0.000	0.035
36	10.916	180	336	0.000	0.000
37	8.201	168	60	0.000	0.000
38	9.062	120	0	0.000	0.000
39	7.929	60	564	0.000	0.000
40	0.000	0	0	0.000	0.000
41	0.000	0	59	0.000	0.000
42	0.000	0	57	0.000	0.000
43	2.000	0	12	0.000	0.235
44	13.929	84	60	0.000	0.000
45	0.000	0	0	0.000	0.000
46	11.951	60	0	0.000	0.000
47	3.390	0	71	0.000	0.000

48	20.570	396	336	0.000	0.000
49	5.000	120	0	0.000	0.331
50	4.000	60	120	0.000	0.505
51	29.000	228	480	0.000	0.460
52	8.000	168	60	0.000	0.121
53	5.000	168	0	0.290	0.000
54	7.879	168	0	0.000	0.000
55	32.512	456	504	0.000	0.000
56	9.692	276	336	0.000	0.000
57	2.978	0	0	0.000	0.000
58	0.000	0	0	0.000	0.000
59	2.000	0	120	0.076	0.000
60	3.606	0	0	0.000	0.000
61	24.000	228	228	0.000	0.131
62	3.026	11	0	0.000	0.000
63	0.900	0	0	0.000	0.000
64	9.206	228	60	0.000	0.000
65	6.000	204	216	0.000	0.182
66	11.000	120	120	0.624	0.000
67	0.000	0	0	0.000	0.000
68	0.000	0	0	0.000	0.000
69	3.000	0	12	0.000	0.177
70	0.715	81	0	0.000	0.000
71	0.000	0	0	0.000	0.000
72	3.353	40	0	0.000	0.000
74	3.788	84	192	0.000	0.000
75	6.000	84	0	0.128	0.000
76	4.043	84	0	0.000	0.000
77	24.000	336	396	0.000	0.055
78	27.000	708	336	0.204	0.000
79	9.217	0	0	0.000	0.000
80	0.000	0	0	0.000	0.000
81	0.000	0	0	0.000	0.000
82	27.724	612	648	0.000	0.000
83	58.000	792	1176	0.000	0.419
84	0.000	0	0	0.000	0.000
85	15.895	145	0	0.000	0.142
86	8.891	84	120	0.000	0.000
87	26.000	168	576	0.167	0.000
88	29.000	1308	960	0.000	0.220
89	23.000	732	624	0.000	0.175
90	19.000	276	384	0.000	0.167
91	19.000	360	384	0.000	0.072
92	4.000	0	0	0.000	0.352
93	0.000	0	0	0.000	0.000
95	12.000	120	60	0.597	0.000
96	0.000	0	84	0.128	0.000
97	10.000	228	0	0.000	0.110

APPENDIX IV – Slacks (model C)

DMU	BOR_inv	SMR_inv	SRU_inv
1	0.000	0.000	0.192
2	0.000	0.012	0.000
3	0.000	0.154	0.000
4	0.000	0.000	0.000
5	0.000	0.000	0.189
6	0.000	0.077	0.000
7	0.000	0.000	0.310
8	0.000	0.000	0.000
9	0.000	0.000	0.000
10	0.000	0.127	0.000
11	0.000	0.000	0.000
12	0.000	0.191	0.000
13	0.000	0.041	0.000
14	0.000	0.513	0.000
15	0.000	0.005	0.000
16	0.000	0.000	0.000
17	0.000	0.334	0.000
18	0.000	0.000	0.000
19	0.000	0.058	0.000
20	0.000	0.197	0.000
21	0.000	0.059	0.000
22	0.000	0.000	0.000
23	0.000	0.227	0.000
24	0.000	0.000	0.000
25	0.000	0.000	0.000
26	0.000	0.000	0.000
27	0.000	0.000	0.000
28	0.000	0.000	0.000
29	0.000	0.070	0.000
30	0.000	0.000	0.000
31	0.000	0.000	0.000
34	0.000	0.034	0.000
35	0.000	0.000	0.174
36	0.000	0.000	0.000
37	0.000	0.000	0.000
38	0.000	0.000	0.056
39	0.000	0.000	0.000
40	0.000	0.000	0.000
41	0.000	0.026	0.000
42	0.000	0.023	0.000
43	0.000	0.000	0.148
44	0.000	0.000	0.166
45	0.000	0.000	0.509
46	0.000	0.000	0.050
47	0.000	0.000	0.000

48	0.000	0.103	0.000
49	0.000	0.000	0.000
50	0.000	0.048	0.070
51	0.000	0.000	0.000
52	0.000	0.000	0.208
53	0.000	0.140	0.000
54	0.000	0.000	0.221
55	0.000	0.000	0.000
56	0.000	0.000	0.000
57	0.000	0.000	0.000
58	0.000	0.000	0.000
59	0.000	0.022	0.000
60	0.000	0.000	0.000
61	0.000	0.000	0.000
62	0.000	0.000	0.344
63	0.000	0.000	0.020
64	0.000	0.000	0.000
65	0.000	0.000	0.332
66	0.000	0.314	0.000
67	0.000	0.000	0.365
68	0.000	0.000	0.139
69	0.000	0.000	0.309
70	0.000	0.000	0.000
71	0.000	0.109	0.000
72	0.000	0.000	0.000
74	0.000	0.000	0.136
75	0.000	0.056	0.000
76	0.000	0.000	0.118
77	0.000	0.000	0.000
78	0.000	0.091	0.000
79	0.000	0.000	0.038
80	0.000	0.154	0.000
81	0.000	0.000	0.000
82	0.000	0.000	0.000
83	0.000	0.000	0.000
84	0.000	0.000	0.000
85	0.000	0.000	0.000
86	0.000	0.000	0.000
87	0.000	0.077	0.000
88	0.000	0.000	0.272
89	0.000	0.000	0.200
90	0.000	0.000	0.028
91	0.000	0.000	0.097
92	0.000	0.000	0.104
93	0.000	0.000	0.000
95	0.000	0.392	0.000
96	0.000	0.017	0.000
97	0.000	0.000	0.141

APPENDIX V – Values of targets (model A)

DMU	MD_Bed10	Nur_Bed10	NurTec_Bed10	Physio_Bed10	SMR_inv	SRU_inv
1	0.69	0.89	2.76	0.12	0.80	0.86
2	0.71	0.98	2.70	0.13	0.79	0.86
3	0.93	0.85	3.14	0.19	0.81	1.00
4	1.36	2.36	5.00	0.00	1.41	1.05
5	0.79	1.28	2.53	0.20	0.80	0.86
6	0.64	0.69	2.78	0.02	0.72	0.87
7	0.76	1.15	2.76	0.25	0.92	0.85
8	1.09	1.54	3.26	0.51	1.12	1.07
9	1.29	1.88	3.19	0.72	1.27	1.03
10	1.04	1.41	2.82	0.32	0.87	1.00
11	1.42	2.01	2.99	0.63	1.08	1.12
12	1.65	1.96	3.32	0.67	1.07	1.28
13	1.65	2.00	3.38	0.73	1.15	1.27
14	1.82	2.47	4.55	0.91	0.99	1.64
15	1.18	0.68	4.50	0.68	1.03	1.09
16	1.04	1.93	3.46	0.58	1.44	0.85
17	1.60	1.43	3.72	0.59	1.02	1.28
18	1.24	3.18	14.21	1.13	1.56	1.71
19	1.45	2.43	5.95	1.60	1.47	1.68
20	0.63	0.66	2.79	0.01	0.71	0.87
21	1.16	1.60	4.34	0.80	1.17	1.32
22	0.66	0.69	2.94	0.11	0.83	0.86
23	2.29	2.36	4.00	1.00	1.25	1.62
24	2.05	2.50	5.00	1.25	1.77	1.79
25	1.71	2.09	4.17	1.02	1.57	1.37
26	1.63	1.99	3.98	0.86	1.39	1.39
27	1.61	1.93	3.85	0.94	1.49	1.22
28	1.56	1.90	3.80	0.89	1.45	1.21
29	1.62	1.94	4.13	0.69	1.23	1.41
30	0.76	0.93	3.30	0.38	1.12	0.87
31	1.29	2.10	4.44	0.44	1.52	1.05
34	1.15	1.23	3.63	0.45	1.08	1.17
35	0.68	0.80	3.02	0.20	0.95	0.85
36	1.05	1.65	2.89	0.51	1.10	0.94
37	0.80	0.92	3.13	0.25	0.96	0.94
38	0.68	0.75	3.01	0.18	0.91	0.85
39	1.43	3.83	1.43	0.97	1.18	0.82
40	0.71	0.91	3.02	0.26	1.00	0.84
41	0.72	1.01	2.66	0.13	0.78	0.86
42	0.72	1.01	2.66	0.13	0.78	0.86
43	0.67	0.83	2.72	0.06	0.74	0.87
44	0.67	0.78	3.00	0.18	0.93	0.85
45	0.78	1.27	2.53	0.20	0.80	0.86
46	0.72	0.72	3.06	0.19	0.90	0.84
47	0.68	0.81	3.20	0.19	0.92	0.87

48	0.78	1.27	2.53	0.20	0.80	0.86
49	0.73	1.05	2.63	0.13	0.77	0.86
50	0.80	1.35	2.50	0.22	0.82	0.86
51	0.86	1.35	3.71	0.86	1.74	0.76
52	0.80	1.28	2.73	0.31	0.96	0.84
53	1.08	1.22	3.04	0.30	0.87	1.06
54	0.73	1.06	2.66	0.15	0.80	0.86
55	0.67	0.76	2.98	0.16	0.90	0.85
56	0.91	1.68	2.72	0.51	1.14	0.83
57	1.04	1.60	3.20	0.66	1.32	0.90
58	2.74	3.33	5.00	1.67	1.92	1.30
59	0.95	1.40	2.89	0.33	0.93	0.98
60	0.95	1.50	3.00	0.53	1.19	0.88
61	0.94	1.05	3.82	0.70	1.40	0.86
62	0.67	0.80	2.93	0.16	0.88	0.85
63	0.69	0.84	3.08	0.26	1.02	0.84
64	1.00	0.95	3.62	0.50	1.16	0.94
65	0.73	1.05	2.72	0.18	0.84	0.86
66	0.70	0.76	2.97	0.09	0.74	0.93
67	0.72	0.64	3.00	0.11	0.80	0.85
68	0.62	0.62	2.81	0.00	0.71	0.87
69	0.64	0.67	2.87	0.06	0.78	0.86
70	1.72	1.02	5.13	1.02	1.51	1.01
71	2.46	1.11	5.56	1.11	1.26	1.48
72	1.08	0.68	4.01	0.55	1.04	0.93
74	0.82	1.38	2.64	0.31	0.94	0.85
75	0.74	0.74	3.33	0.22	0.85	0.93
76	0.65	0.68	2.91	0.09	0.80	0.86
77	1.06	1.27	4.66	0.85	1.53	1.00
78	0.86	0.91	3.18	0.21	0.88	1.01
79	0.88	1.22	3.57	0.00	0.95	0.93
80	0.62	0.62	2.81	0.00	0.71	0.87
81	1.08	1.08	3.99	0.56	1.10	1.13
82	1.55	1.68	5.88	0.78	1.73	1.25
83	0.99	1.41	4.61	0.84	1.82	0.84
84	1.70	0.80	5.00	1.25	1.75	0.61
85	1.01	0.83	3.69	0.57	1.25	0.77
86	1.02	1.39	4.09	0.82	1.47	1.02
87	0.67	0.83	3.59	0.12	0.82	0.92
88	0.69	0.87	2.72	0.09	0.76	0.87
89	0.66	0.78	2.74	0.05	0.73	0.87
90	0.75	1.02	3.21	0.42	1.20	0.82
91	0.73	0.97	3.05	0.31	1.06	0.83
92	0.79	1.16	3.20	0.49	1.26	0.81
93	1.16	1.44	3.95	0.83	1.56	1.02
95	1.18	1.18	6.00	1.00	0.96	1.47
96	1.10	1.75	2.63	0.42	0.93	0.97
97	0.85	0.74	3.33	0.34	1.03	0.81

APPENDIX VI – Values of targets (model B)

DMU	ICU_Bed	Total_MD	Total_Nur	SMR_inv	SRU_inv
1	6.31	12.69	10.31	1.89	1.38
2	13.00	14.00	9.00	1.43	1.41
3	10.00	9.00	7.00	1.08	1.02
4	6.43	12.57	10.43	1.88	1.40
5	6.00	13.00	10.00	1.92	1.30
6	8.00	11.00	6.00	0.99	0.89
7	7.96	10.00	10.00	1.74	0.94
8	7.69	11.31	11.69	1.79	1.71
9	9.00	13.82	10.00	1.75	1.42
10	5.00	14.00	6.00	0.84	1.00
11	7.00	12.00	11.00	1.84	1.54
12	8.00	11.00	12.00	1.77	1.79
13	8.00	11.63	11.00	1.55	1.67
14	11.00	13.00	10.00	0.99	1.64
15	8.00	11.00	12.00	1.77	1.79
16	6.00	13.00	10.00	1.92	1.30
17	8.00	11.00	12.00	1.77	1.79
18	8.00	11.00	12.00	1.77	1.79
19	8.00	11.00	12.00	1.77	1.79
20	8.00	11.00	12.00	1.77	1.79
21	8.00	11.00	12.00	1.77	1.79
22	17.42	17.90	9.00	1.46	1.47
23	8.00	11.00	12.00	1.77	1.79
24	8.00	11.00	12.00	1.77	1.79
25	7.22	11.78	11.22	1.82	1.60
26	8.00	8.00	12.00	1.39	1.39
27	8.07	9.00	12.00	1.57	1.28
28	7.01	11.99	11.01	1.84	1.55
29	8.00	11.00	12.00	1.77	1.79
30	6.60	12.40	10.60	1.87	1.45
31	6.07	12.93	10.07	1.91	1.32
34	8.00	11.00	12.00	1.77	1.79
35	6.00	13.00	10.00	1.92	1.30
36	7.08	11.92	11.08	1.83	1.56
37	13.62	15.39	10.00	1.59	1.55
38	13.00	15.00	9.00	1.62	1.34
39	6.07	12.93	10.07	1.91	1.32
40	8.00	12.00	9.00	1.55	1.29
41	8.00	11.00	9.00	1.33	1.36
42	8.00	12.00	9.00	1.36	1.37
43	6.50	12.25	9.00	1.87	1.13
44	6.07	12.93	10.07	1.91	1.32
45	6.00	6.00	7.00	0.78	0.22
46	7.05	11.95	11.05	1.84	1.56
47	8.07	8.00	12.00	1.40	1.31

48	7.43	11.57	11.43	1.81	1.65
49	6.00	13.00	10.00	1.92	1.30
50	6.00	13.00	10.00	1.92	1.30
51	6.00	13.00	10.00	1.92	1.30
52	6.00	13.00	10.00	1.92	1.30
53	13.00	16.17	8.00	1.11	1.34
54	13.51	16.88	8.00	1.64	1.14
55	7.49	11.51	11.49	1.80	1.66
56	6.31	12.69	10.31	1.89	1.38
57	6.02	12.98	10.02	1.91	1.31
58	6.00	13.00	10.00	1.92	1.30
59	8.00	11.00	12.00	1.77	1.79
60	9.97	12.00	9.00	1.70	1.26
61	6.00	13.00	10.00	1.92	1.30
62	10.00	10.00	6.00	1.42	0.76
63	9.00	7.00	6.00	1.02	0.76
64	6.79	12.21	10.79	1.86	1.49
65	6.00	13.00	10.00	1.92	1.30
66	11.41	13.30	10.00	1.05	1.64
67	9.00	8.00	4.00	0.80	0.41
68	9.00	8.00	4.00	0.71	0.45
69	8.29	9.00	7.00	1.50	0.81
70	9.00	6.00	30.00	1.51	1.01
71	9.00	6.00	30.00	1.26	1.48
72	9.00	6.00	30.00	1.39	1.24
74	10.00	14.58	6.00	1.24	0.88
75	14.00	15.26	10.00	1.46	1.60
76	10.26	14.34	10.00	1.74	1.44
77	6.00	13.00	10.00	1.92	1.30
78	35.00	30.00	4.00	0.88	1.01
79	16.00	18.68	8.00	1.53	1.23
80	16.00	9.00	5.00	0.71	0.87
81	10.00	11.00	9.00	1.35	1.38
82	6.28	12.72	10.28	1.90	1.37
83	6.00	13.00	10.00	1.92	1.30
84	8.00	10.00	6.00	1.75	0.61
85	6.00	13.00	10.00	1.92	1.30
86	6.51	13.16	10.00	1.89	1.32
87	8.00	11.00	12.00	1.77	1.79
88	6.00	13.00	10.00	1.92	1.30
89	6.00	13.00	10.00	1.92	1.30
90	6.00	13.00	10.00	1.92	1.30
91	6.00	13.00	10.00	1.92	1.30
92	6.00	13.00	10.00	1.92	1.30
93	8.00	13.63	9.00	1.81	1.18
95	8.00	11.00	12.00	1.77	1.79
96	6.00	10.00	9.00	0.93	0.97
97	6.00	13.00	10.00	1.92	1.30

APPENDIX VII – Values of targets (model C)

DMU	BOR_inv	SMR_inv	SRU_inv
1	0.965	0.797	0.771
2	0.965	0.800	0.778
3	1.010	0.967	1.000
4	1.054	1.409	1.050
5	0.964	0.706	0.589
6	0.963	0.686	0.549
7	0.973	0.920	0.807
8	1.033	1.124	1.075
9	1.039	1.273	1.033
10	1.009	0.964	0.996
11	1.042	1.077	1.122
12	1.084	1.202	1.285
13	1.079	1.188	1.268
14	1.177	1.498	1.643
15	1.032	1.038	1.086
16	1.027	1.435	0.790
17	1.082	1.198	1.280
18	1.195	1.555	1.712
19	1.186	1.526	1.677
20	0.963	0.646	0.469
21	1.092	1.229	1.318
22	0.965	0.826	0.829
23	1.172	1.482	1.623
24	1.350	1.766	1.785
25	1.119	1.571	1.374
26	1.114	1.388	1.386
27	1.088	1.492	1.219
28	1.083	1.446	1.215
29	1.116	1.304	1.408
30	0.999	1.119	0.865
31	1.068	1.522	1.050
34	1.055	1.111	1.175
35	0.976	0.948	0.800
36	1.007	1.098	0.936
37	0.995	0.959	0.935
38	0.972	0.909	0.809
39	1.002	1.182	0.816
40	0.985	1.003	0.836
41	0.965	0.810	0.798
42	0.965	0.804	0.786
43	0.963	0.649	0.474
44	0.974	0.927	0.805
45	0.965	0.778	0.733
46	0.972	0.900	0.811
47	0.980	0.922	0.866

48	0.963	0.670	0.517
49	0.962	0.552	0.280
50	0.962	0.552	0.280
51	1.074	1.738	0.763
52	0.977	0.958	0.798
53	1.024	1.013	1.056
54	0.965	0.801	0.781
55	0.974	0.903	0.831
56	0.998	1.139	0.827
57	1.025	1.325	0.904
58	1.414	1.916	1.301
59	1.006	0.954	0.985
60	1.008	1.187	0.879
61	1.029	1.401	0.855
62	0.970	0.883	0.815
63	0.982	1.017	0.784
64	1.014	1.163	0.936
65	0.967	0.844	0.825
66	0.992	0.909	0.930
67	0.965	0.799	0.776
68	0.964	0.706	0.588
69	0.965	0.775	0.727
70	1.061	1.511	1.012
71	1.135	1.367	1.484
72	1.002	1.043	0.934
74	0.975	0.937	0.803
75	0.992	0.909	0.930
76	0.965	0.805	0.787
77	1.062	1.532	0.996
78	1.012	0.974	1.009
79	0.976	0.949	0.800
80	0.976	0.861	0.871
81	1.043	1.100	1.125
82	1.191	1.730	1.248
83	1.159	1.824	0.839
84	1.045	1.751	0.610
85	1.002	1.251	0.736
86	1.056	1.469	1.022
87	0.988	0.899	0.918
88	0.964	0.762	0.702
89	0.964	0.724	0.625
90	0.998	1.203	0.740
91	0.985	1.056	0.775
92	1.002	1.258	0.727
93	1.070	1.561	1.020
95	1.131	1.353	1.468
96	1.003	0.945	0.973
97	0.983	1.029	0.781

APPENDIX VIII – Weights (model A)

DMU	MD_Bed10	Nur_Bed10	NurTec_Bed10	Physio_Bed10	Free Weight	SMR_inv	SRU_inv
1		0.108	0.174		0.394	0.228	
2		0.102	0.163		0.370	0.215	
3		0.244	0.134		-0.157	0.106	0.699
4	0.735			0.723	-0.092	0.775	
5		0.075	0.174		0.536		
6		0.056	0.131		0.404		
7		0.076	0.122		0.277	0.161	
8	0.274		0.108		-0.063	0.206	0.450
9		0.102	0.165		0.075	0.250	0.316
10		0.081	0.209		0.187		0.519
11		0.088	0.141		0.064	0.214	0.270
12		0.079	0.204		0.181		0.504
13		0.091	0.146		0.067	0.222	0.280
14				1.099	-1.771		1.687
15	0.428	0.729			-0.032	0.650	0.332
16	0.032		0.158	0.456	0.092	0.526	
[illegible]		0.276	0.144		-0.179		0.866
[illegible]	0.806				-14.307		8.940
[illegible]	0.548		0.035		-0.173		0.699
[illegible]	0.226		0.133		0.512		
[illegible]	0.350		0.094		-0.127	0.218	0.520
[illegible]		0.297	0.130		0.320	0.324	
[illegible]			0.191	0.236	-0.001		0.617
[illegible]			0.200		-0.873	0.808	0.250
[illegible]	0.000	0.095	0.153		0.069	0.231	0.293
[illegible]	0.000	0.095	0.153		0.069	0.231	0.293
[illegible]		0.118	0.191		0.086	0.290	0.366
[illegible]	0.000	0.095	0.153		0.069	0.231	0.293
[illegible]	0.056		0.094	0.506	-0.535	0.137	0.846
[illegible]	0.232	0.243	0.057		-0.314	0.340	0.606
31		0.030	0.153	0.329	-0.175	0.465	0.339
34		0.256	0.114		-0.120	0.325	0.422
35	0.310		0.121		0.406	0.178	
36		0.118	0.190		0.086	0.288	0.364
37		0.105	0.169	0.001	0.076	0.257	0.324
38		0.291	0.127		0.314	0.317	
39			0.699		1.000		
40		0.094	0.150		0.339	0.197	
41		0.090	0.144		0.326	0.189	
42		0.090	0.144		0.326	0.189	
43	0.218		0.128		0.495		
44	1.000				0.455	0.233	
45		0.106	0.247		0.760		
46	0.382	0.571			0.242	0.493	
47	1.031				0.027	0.289	0.468
48		0.124	0.288		0.885		

49		0.081	0.188		0.577		
50		0.070	0.162		0.499		
51	0.434		0.169		0.568	0.249	
52		0.135	0.216		0.491	0.285	
53		0.129	0.208		0.095	0.315	0.399
54		0.140	0.224		0.508	0.295	
55	0.917				0.418	0.214	
56		0.111	0.178		0.081	0.270	0.341
57		0.107	0.172		0.078	0.260	0.329
58			0.200		-1.770	1.446	
59	0.277		0.109		-0.064	0.208	0.454
60		0.118	0.191		0.087	0.289	0.366
61	0.344	0.586			-0.026	0.523	0.267
62		0.107	0.171		0.388	0.225	
63		0.253	0.111		0.274	0.276	
64		0.282	0.104		-0.111	0.332	0.394
65		0.071	0.114		0.258	0.150	
66	0.343		0.109		-0.159		0.779
67		0.901			0.449	0.155	
68		0.901			0.559		
[illegible]	0.813				0.370	0.189	
[illegible]		0.478	0.029	0.277	-0.601	0.662	0.518
[illegible]		0.901			-0.443		0.972
[illegible]		1.205			0.584	0.211	0.016
[illegible]		0.078	0.126		0.285	0.165	
[illegible]	0.356	0.317	0.006		-0.267	0.366	0.507
[illegible]		0.192	0.084		0.207	0.209	
[illegible]	0.241	0.319	0.046		-0.506	0.456	0.685
[illegible]		0.343	0.152		-0.160	0.436	0.566
[illegible]		0.800		1.884	-0.905	1.982	
[illegible]	1.613				1.000		
[illegible]	0.249	0.261	0.061		-0.337	0.365	0.651
[illegible]		0.280		0.678	-1.003	0.442	0.992
[illegible]	1.010				-1.771	1.519	
84		1.250			0.623	0.215	
85	0.419	0.627			0.266	0.541	
86	0.325	0.155	0.054		-0.294	0.297	0.612
87	1.282				0.033	0.360	0.582
88		0.076	0.121		0.275	0.160	
89		0.055	0.129		0.397		
90		0.097	0.155		0.351	0.203	
91		0.097	0.155		0.351	0.203	
92		0.093	0.148		0.336	0.195	
93		0.220	0.098		-0.103	0.279	0.363
95	0.239	0.608			-0.168		0.796
96		0.088	0.141		0.064	0.214	0.271
97		0.269	0.118		0.291	0.294	

APPENDIX IX – Weights (model B)

DMU	ICU_Bed	MD_hours	Nur_hours	Free Weight	SMR_inv	SRU_inv
1				2.376	1.025	0.318
2				2.252	0.971	0.301
3	0.006	0.003	0.004	-0.384		1.000
4		0.007		-0.617	0.457	0.338
5				2.712	1.416	
6	0.010	0.006	0.007	-0.761	0.339	1.445
7				2.082	1.087	
8				1.591	0.686	0.213
9				1.455	0.628	0.194
10	0.006	0.003	0.004	-0.385		1.004
11	0.216			-0.136		0.891
12				1.389		0.778
13				1.408		0.789
14				1.087		0.609
15			0.002	0.901	0.503	0.443
16				1.335	0.697	
17				1.395		0.781
18				1.043		0.584
19				1.065		0.596
20	0.127	0.028		-4.851	0.165	1.976
21				1.355		0.759
22				2.142	0.924	0.286
23				1.100		0.616
24				1.000		0.560
25				1.162	0.501	0.155
26				1.276	0.550	0.170
27				1.241	0.535	0.166
28				1.272	0.549	0.170
29				1.267		0.710
30				1.672	0.721	0.223
31				1.256	0.541	0.168
34				1.520		0.851
35				2.022	1.055	
36				1.671	0.720	0.223
37				1.856	0.801	0.248
38				2.029	0.875	0.271
39				1.616	0.697	0.216
40	0.037	0.009	0.002	-1.634	0.475	0.626
41	0.074	0.016		-2.844	0.097	1.158
42	0.075	0.016		-2.884	0.098	1.175
43		0.020		-2.180	1.541	
44				2.062	0.889	0.276
45		0.017		-1.819	1.286	
46				2.041	0.880	0.273
47		0.010		-0.863	0.640	0.474
48				3.188	1.375	0.426

49				3.470	1.811	
50				3.797	1.982	
51				1.103	0.576	
52				2.001	1.044	
53				1.691		0.947
54				2.379	1.026	0.318
55				1.999	0.862	0.267
56				1.662	0.717	0.222
57				1.445	0.623	0.193
58				1.000	0.522	
59				1.812		1.015
60				1.589	0.685	0.212
61				1.367	0.714	
62			0.002	1.712	0.972	0.301
63			0.003	1.060	0.592	0.521
64				1.596	0.688	0.213
65				2.270	1.185	
66				1.919		1.075
67	0.058	0.014	0.004	-2.566	0.746	0.982
68	0.060	0.015	0.004	-2.648	0.770	1.014
69		0.017		-1.825	1.290	
70			0.002	0.746	0.416	0.367
71			0.006			0.674
72			0.002	0.961	0.536	0.472
74				2.029	0.875	0.271
75				1.919		1.075
76				2.292	0.988	0.306
77				1.251	0.653	
78				1.770		0.991
79				1.957	0.844	0.262
80		0.010		-0.632		1.148
81	0.005	0.003	0.003	-0.381	0.170	0.723
82				1.096	0.472	0.146
83				1.050	0.548	
84		0.002	0.004		0.308	0.755
85			0.001	1.338	0.799	
86				1.299	0.560	0.174
87				1.945		1.089
88				2.513	1.312	
89				2.646	1.381	
90				1.592	0.831	
91				1.814	0.947	
92				1.523	0.795	
93		0.008		-0.907	0.641	
95				1.216		0.681
96	0.249	0.001		-0.524		1.028
97				1.862	0.972	

APPENDIX X – Weights (model C)

DMU	BOR_inv	Free Weight	SMR_inv	SRU_inv
1	0.943	0.887	0.034	
2	0.909	0.868		0.017
3	0.870	0.664		0.217
4	0.746	0.527	0.106	0.103
5	0.877	0.824	0.032	
6	0.917	0.876		0.017
7	0.971	0.881	0.073	
8	0.741	0.561	0.036	0.155
9	0.826	0.632	0.061	0.144
10	0.746	0.570		0.186
11	0.741	0.561	0.036	0.155
12	0.680	0.519		0.169
13	0.794	0.606		0.198
14	0.694	0.530		0.173
15	0.877	0.670		0.219
16	0.952	0.802	0.086	0.060
17	0.752	0.574		0.187
18	0.840	0.642		0.209
19	0.833	0.636		0.208
20	0.862	0.823		0.016
21	0.794	0.606		0.198
22	1.031	0.787		0.257
23	0.752	0.574		0.187
24	0.741	-0.216	0.497	0.189
25	0.893	0.631	0.127	0.124
26	0.893	0.676	0.043	0.187
27	0.885	0.625	0.126	0.122
28	0.901	0.689	0.067	0.157
29	0.690	0.527		0.172
30	0.833	0.702	0.076	0.053
31	0.781	0.552	0.111	0.108
34	0.833	0.636		0.208
35	0.917	0.833	0.069	
36	0.847	0.648	0.063	0.147
37	0.763	0.578	0.037	0.160
38	0.730	0.662	0.055	
39	0.543	0.458	0.049	0.035
40	0.847	0.714	0.077	0.054
41	0.862	0.823		0.016
42	0.840	0.802		0.015
43	0.893	0.839	0.033	
44	0.781	0.709	0.059	
45	0.725	0.681	0.026	
46	0.775	0.704	0.059	
47	0.758	0.579	0.056	0.132
48	0.752	0.718		0.014

49	1.042	1.000		
50	1.010	0.970		
51	0.877	-0.256	0.589	0.224
52	0.800	0.726	0.060	
53	0.826	0.631		0.206
54	0.787	0.740	0.029	
55	0.781	0.658	0.071	0.050
56	0.980	0.826	0.089	0.062
57	0.980	0.826	0.089	0.062
58	0.709	-1.035	0.927	0.199
59	0.645	0.493		0.161
60	0.524	0.441	0.047	0.033
61	0.794	0.561	0.113	0.110
62	0.870	0.789	0.066	
63	0.862	0.782	0.065	
64	0.752	0.575	0.056	0.131
65	0.840	0.763	0.064	
66	0.775	0.592		0.193
67	0.847	0.796	0.031	
68	0.847	0.796	0.031	
69	0.847	0.796	0.031	
70	0.870	0.614	0.124	0.120
71	0.847	0.647		0.211
72	0.826	0.632	0.061	0.144
74	0.840	0.763	0.064	
75	0.877	0.670		0.219
76	0.877	0.824	0.032	
77	0.820	0.579	0.117	0.113
78	0.820	0.626		0.204
79	0.847	0.769	0.064	
80	0.617	0.471		0.154
81	0.952	0.721	0.046	0.199
82	0.787	-0.229	0.528	0.201
83	0.862	-3.273	2.343	
84	0.962	0.873	0.073	
85	0.847	0.714	0.077	0.054
86	0.943	0.667	0.134	0.131
87	0.649	0.496		0.162
88	0.901	0.847	0.033	
89	0.543	0.511	0.020	
90	0.862	0.782	0.065	
91	0.847	0.769	0.064	
92	0.787	0.715	0.060	
93	0.658	0.465	0.094	0.091
95	0.781	0.596		0.195
96	0.667	0.509		0.166
97	0.943	0.856	0.071	