UNIVERSIDADE DO ALGARVE

FACULDADE DE ECONOMIA

USING DATA ENVELOPMENT ANALYSIS TO ASSESS THE EFFICIENCY OF RETAIL STORES IN PORTUGAL

Ion Buraga

Dissertação para obtenção do grau de Mestre em Gestão Empresarial

Mestrado em Gestão Empresarial

Trabalho efetuado sob orientação de:

Professor Doutor Sérgio Pereira dos Santos

Professora Doutora Carla Alexandra E. Filipe Amado

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DECLARAÇÃO DE AUTORIA DE TRABALHO

Declaro ser o autor deste trabalho, que é original e inédito. Autores e trabalhos consultados estão devidamente citados no texto e constam na listagem de referências incluídas.

Ion Buraga

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I thank all those who have been with me, supporting and motivating me during this journey.

In particular, I thank Prof. Sérgio Santos and Prof. Carla Amado, my advisors, for the orientation and availability throughout the execution of this dissertation.

Resumo

O mercado de retalho está cheio de concorrência feroz e clientes cada vez mais exigentes. Esses são alguns dos fatores que levaram a uma crescente preocupação com a eficiência no setor do retalho. Esta dissertação aplica a metodologia Data Envelopment Analysis (DEA), seguindo uma orientação de *output*, para 34 lojas de uma empresa mundial do setor de retalho não-alimentar que opera em Portugal, a fim de avaliar a eficiência relativa das mesmas. Os resultados mostram que a maioria das lojas são tecnicamente ineficientes e devem aprender com as poucas consideradas eficientes. Também apresentam que muitas lojas não são eficientes do ponto de vista da escala, sendo que a maioria delas são demasiado grandes. O estudo ilustra a utilidade do DEA para avaliar a eficiência relativa das lojas de retalho dado o contexto do estudo.

Palavras-chave: Eficiência; *Data Envelopment Analysis* (DEA); *Benchmarking*; lojas de retalho.

Abstract

The retail marketplace is packed with fearful competition and more and more demanding customers. These are some of the factors that lead to an ever-increasing preoccupation with efficiency in the retail sector. This dissertation applies the Data Envelopment Analysis (DEA) methodology, following an output orientation, to 34 stores of a non-food worldwide retail company operating in Portugal in order to assess their relative efficiency. The results show that most of the stores are technically inefficient and should learn from the few efficient ones. It also identifies that many stores are not scale efficient, being most of them too big. The study illustrates the usefulness of DEA to evaluate the relative efficiency of the retail stores given the context of the study.

Keywords: Efficiency; Data Envelopment Analysis (DEA); Benchmarking; retail stores.

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1. Introduction

Portugal has a long and successful history of trading and retailing. In times when maritime trade was the most important trading form, Portugal served as Europe's gate to the Atlantic Ocean and thereby to international retail (Wagner *et al.*, 2014) .

Nowadays the retail sector is still a very important sector for the Portuguese economy. According to the Statistical Yearbook of Portugal for 2018, the turnover generated by trade enterprises, in 2017, amounted to 137,5 billion euros, corresponding to 37.0% of the turnover considered in the Integrated Business Account System. The retail sector represents 35.9% of the turnover made by the trade sector, demonstrating the importance of this sector in the Portuguese economy.

The Portuguese retail sector is dominated by four commercial groups, two Portuguese (Sonae, Jeronimo Martins) and two French (Les Mousquetaires, Auchan), all being huge players in the retail sector. These four commercial groups generated, in 2017, according to data from Retail-Index (2019), a total turnover of 12,431 billion euros.

Overall, the retail marketplace is at its mature stage, meaning that the growth slowed down while the competition intensified. As the companies are fighting for market share, consumers became more and more accustomed with an omnipresent and unlimited range of products (Preuss, 2014).

Cost reduction is essential to the survival of organizations, demonstrating the importance of being as efficient as possible. Efficiency usually refers to the ability to make the most of the resources one has available, that is, the capacity to obtain the highest amount of outputs using the minimum amount of inputs. Even though high profitability is not necessarily directly related to high efficiency, an increase of efficiency can have some positive impact on the profits obtained (Camanho & Dyson, 1999).

Data Envelopment Analysis (DEA), developed by Charnes, Cooper and Rhodes in 1978, is a non-parametric linear programming technique used to measure the relative efficiency of Decision Making Units (DMU). It also allows the identification of the best performing units within a set of comparable DMUs. These best performing units will serve as a reference for the inefficient ones.

This dissertation aims to explore the utility of the DEA technique to evaluate the relative efficiency of a group of non-food retail stores. Therefore, the DEA technique is going to be used in order to evaluate the performance of 34 retail stores of a non-food worldwide retail company operating in Portugal. The study will use the annual data from year 2018.

With this purpose in mind, the dissertation starts with a review of the literature on performance assessment in retailing using DEA as their main method, based on the key published studies. After that, the DEA methodology is described, focusing on its origins, key concepts and the orientations of the classic models. It follows the presentation and discussion of the results obtained by applying the technique to the data from 34 retail stores. The dissertation finishes by presenting the main conclusions of the study, discussing its limitations and outlining suggestions for future research.

2. Review of literature on performance assessment in retailing

When someone usually talks about efficiency of an organization, they usually refer to its success in producing the highest possible amount of outputs given a set of inputs. Measuring the productive efficiency of an industry is important to the economic theorist as well as the economic policy maker (Farrell, 1957).

Farrell's (1957) work extended the works of Pareto (1906), Koopmans (1951) and Debreu (1951), being the first author to suggest a form of evaluating the efficiency without the usage of production functions defined theoretically. Koopmans (1951) was the first to introduce "technical efficiency as a feasible input/output vector where it is impossible to increase any output (and/or reduce any input) without simultaneously reducing other output (and/or increasing any other input)" (Ruggiero, 2000: 138).

Based on the work of Farrell (1957) and Farrell & Fieldhouse (1962), Charnes, Cooper, & Rhodes (1978) introduced DEA as an evaluation tool for assessing the efficiency of DMUs in order to improve the planning and control of these activities. The first model proposed by these authors assumed constant returns to scale.

> "The value of data envelopment analysis (DEA) lies in its capability to relatively evaluate the individual efficiency or performance of a decision making unit (DMU) within a target group of interest that operates in a certain

> application domain such as the banking industry, health care industry, agriculture industry, transportation industry, etc." (Liu *et al.*, 2013: 893).

Initially the first published applications of DEA were on the public sector, not for profit and mainly in education (Seiford, 1996). One of these first applications is Bessent & Bessent (1980) work, that applied the methodology to compare elementary schools in an urban school district.

Banker *et al.*, (1984) introduced a variable returns to scale model for measuring scale efficiency. The models introduced by Charnes, Cooper, & Rhodes (1978) and Banker *et al.*, (1984) are commonly called as the CCR model and BCC model, respectively, and represent the conventional DEA models. The conventional DEA models can have either an input orientation (when the goal is to reduce the inputs while maintaining the output level) or an output orientation (when the goal is to maximize the outputs maintaining the input level). Charnes *et al.*, (1985) introduced the non-oriented additive model that combines both input and output orientations, unlike the two previous models. The works by Charnes *et al.* (1978), Banker *et al.* (1984) and Charnes *et al.* (1985) were unanimously considered some of the most influential papers in the DEA literature (Seiford, 1996).

DEA application areas have evolved a lot since the first years, and the technique has been applied to several different industries. Banking, health care, agriculture and farming, transportation and education represent the areas where DEA has been most commonly applied (Liu *et al.* ,2013).

Even though retail is not the area where DEA has been used the most, there are still some studies that applied the technique to this sector.

Most of the existing studies in retail applied DEA to food retail stores, like the study of Donthu & Yoo (1998), which evaluated 24 stores of a fast food restaurant chain, Vaz *et al.*, (2010) which analysed 14 hypermarkets and 56 supermarkets of a Portuguese retail chain, Vyt & Cliquet (2017) which measured the efficiency of 38 stores from a French supermarket retail chain, Goic *et al.*, (2015) that used the technique to evaluate relative category performance of a supermarket in South America and Keh & Chu (2003) that studied the relative efficiency of 13 grocery stores from United States of America (USA).

There have also been some studies focused on the non-food retail stores where DEA has been applied: Alves & Portela (2015) evaluated 63 Parfois stores, Xavier *et al.*, (2015b) analysed 26 stores of a women retail service brand and Xavier *et al.*, (2015a) estimated the efficiency of the 40 retail stores of a clothing company. All these studies focused on the Portuguese context. There are other studies, however, which focused on other countries, as it is the case of the work of Ko *et al.,* (2017), who evaluated 32 stores of a household goods retailer in Korea, Zervopoulos *et al.*, (2016) who studied 36 firms that operate in the USA, both from the food and non-food retail sector, and Balios *et al.*, (2015) who investigated 320 companies from Greece covering all sectors of retail business activity.

Even though DEA has been the base methodology for all the above studies, the modelling choices were different. Some of them used more complex models. Vaz *et al.*, (2010), for example, used the network DEA model, allowing the re-allocation of resources between stores and the identification of the purpose of each section. Others used more standard DEA models such as the CCR and BCC models. Lau (2013) used the CCR model as well as the BCC model, Ko *et al.*, (2017) used the BCC model in order to find out the factors affecting the efficiency of chain stores and Banker *et al.*, (2010) used the BCC model to compute the relative productivity of retail outlets.

In order to apply the DEA methodology successfully, the choice of input and output variables is an extremely critical aspect.

The input variables considered in most of the existing studies are similar. Typically, there is an input related to the workforce, which can be, the number of employees, as in Ko *et al.,* (2017) and Zervopoulos *et al.*, (2016), the number of full-time equivalent employees, used by Vyt & Cliquet (2017), Vaz & Camanho (2012) and Alves & Portela (2015), or the salaries, as in Xavier *et al.,* (2015b) and Thomas *et al.* (1998); another input commonly used relates to the area of the store (e.g. Vaz *et al.,* 2010; Vaz & Camanho, 2012; Ko *et al.,* 2017; Vyt & Cliquet, 2017). The average stock available in store has also been used in several studies as is the case of Vaz & Camanho (2012), Banker *et al.,* (2010) and Alves & Portela (2015). The less common input variables relate to the liabilities of the company, used in Balios *et al.*, (2015), or the spoiled products of the store, that indicate the number of products lost, spoiled or whose validity expired, used by Vaz *et al.* (2010).

When choosing the inputs to include in the DEA models to determine retail stores efficiency, it is common to include a set of non-discretionary factors that also affect the efficiency, like the population, market size, purchasing power per capita index and age of the store. Some authors used these factors as additional inputs in the DEA model (e.g. Alves & Portela, 2015), while others have considered them in a second stage analysis (e.g. Banker *et al.*,2010).

In the classic DEA models, the analyst is required to choose the orientation of the model which can be input-oriented or output-oriented.

While some studies use an input-oriented model, as in Balios *et al.*, (2015) and Lau (2013), most of them use an output-oriented model, seeking output expansion instead of input contraction. In general, outputs are related to sales, where it can be aggregated into only one variable or disaggregated into several. For example, Alves & Portela (2015) chose to disaggregate the sales variable by product category in order to better understand the importance of product diversity in the performance of the stores: sales of textiles, sales of non-textile, sales of shoes, among others. In turn, Goic *et al.,* (2015), Keh & Chu (2003), Xavier *et al.*, (2015a), Balios *et al.*, (2015) and Thomas *et al.* (1998) used the sales volume as a single output.

Most DEA applications found out that the majority of the stores assessed had efficiency issues: Ko *et al.,* (2017) found out that about 70% of the stores studied were inefficient, concluding that there was room for improving performance without increasing the resources; Vaz *et al.,* (2010) concluded that only 7 of the 70 stores studied were considered efficient and that the total sales of the store chain could increase by 6% without extra resources and Balios *et al.,* (2015) found out that most of the firms studied show a great inefficiency and should reduce substantially their input consumption. Yet not all conclusions were so pessimistic. Vaz & Camanho (2012) concluded, for example, that the opportunity for efficiency improvement is not very large since the performance is uniform across the different stores.

As the analysis of the literature shows, there have been many studies on efficiency of chain stores using DEA. However, the retail sector still does not have many studies when compared to the other sectors, such as banking, education, health care or transportation, so more studies are needed. Especially it is important to examine different types of inefficiency in order to better understand the causes behind the results. In specific, it is useful to measure resource efficiency and cost efficiency. It is also necessary to gain a better understanding regarding the determinants of each type of inefficiency. In particular, it is important for research to be carried in order to answer the following question: which factors explain the relative efficiency identified in retail stores of different sectors?

3. Methodology for performance assessment

3.1. DEA

Charnes *et al.* (1978) introduced a powerful non-parametric linear programming methodology that measures the relative efficiency of any decision making unit (DMU), each using multiple resources (inputs) in order to obtain multiple results (outputs).

> "To allow for applications to a wide variety of activities, we use the term Decision Making Unit (=DMU) to refer to any entity that is to be evaluated in terms of its abilities to convert inputs into outputs. These evaluations can involve governmental agencies and non-profits organizations. The evaluation can also be directed to educational institutions and hospitals as well as police forces (or subdivision thereof) or army units for which comparative evaluations of their performance are to be made"(Cooper *et al.*, 2004: 8).

The original idea behind DEA was to provide a methodology that was able to identify, from a set of comparable DMUs, the ones that exhibited the best practices and therefore would form an efficient frontier.

The CCR model introduced by Charnes et al. (1978), comprehends both technical and scale efficiencies using the optimal value of the ratio form, being obtained directly from the data without requiring any specification of weights and being able to calculate the relative efficiency of DMUs (Gökşen *et al.*, 2015). The model introduced by Charnes et al. (1978), uses "the optimization method of mathematical programming to generalize the Farrell (1957) single-output/input technical efficiency measure to the multiple output/multiple-input case…" (Førsund & Sarafoglou, 2002: 32). Note that DEA allows to identify the relative efficiency of the given DMUs and not the absolute efficiency, which means that it will determine the efficient DMUs when compared to the remaining DMUs of the sample that is being studied.

The CCR model is applicable only to organizations that are described by constant returns to scale globally, which means that a proportional increase (or decrease) in the inputs is assumed to cause a proportional increase (or decrease) in the outputs. This model can take two orientations, the input oriented CCR model and the output oriented CCR model.

Consider a set of n DMUs, with each DMU j, (j=1, . . ., n), where every one of them uses m inputs, x_{ij}, i (i = 1,. . . ,m) generating s outputs, y_{rj}, r (r = 1,. . . ,s). For each DMU j_0 evaluated it is possible to obtain the relative efficiency measure defined by the ratio between the weighted sum of all the outputs (y_{rj_0}) and the weighted sum of all the inputs (x_{ij_0})(Cook & Seiford, 2009). This way, the numerous inputs and outputs are reduced respectively to a single virtual value of input and a single virtual value of output by allocating the weight of each input i ,v_i, (i = 1,. . . ,m) and the weight of each output r ,μ_r, (r = 1,. . . ,s) (Fernandes *et al.*, 2007).

The input-oriented model to evaluate the efficiency of a given DMU j_0, admitting the existence of constant returns to scale (CRS), is defined by the model (2.1) (Charnes et al., 1978).

$$max\{e_{j_0} = \frac{\sum_{r=1}^{s} \mu_r \, y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$$

Subject to:

$$\frac{\sum_{r=1}^{s} \mu_r \, y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad j = 1, \ldots, n,$$

$$v_i \geq \varepsilon, \qquad i = 1, \ldots, m,$$

$$\mu_r \geq \varepsilon, \qquad r = 1, \ldots, s\} \qquad (2.1)$$

Where ε is a non-archimedian value used to enforce strict positivity on the variables. It is observed that in the original paper Charnes *et al.* (1978) restricted the variables just to be non-negative (allowing $\varepsilon = 0$), introducing the imposition of a strictly positive limit ($\varepsilon > 0$) in a follow-up paper, Charnes et al. (1981), (Cook & Seiford, 2009).

The model (2.1) aims to maximize the efficiency value of DMU j_0, being subjected to a restriction that ensures that the weights used lead to an efficiency value that is less or equal to 100% for all units in the sample. The efficiency of each member of the reference set of j=1, . . ., n DMUs is rated relative to the others.

In the original DEA models, CCR and BCC, each DMU can freely choose the weight assigned to each input and output in order to maximize its efficiency (Cooper et al., 2004). So, the weight value that may maximize the value of a DMU for the model (2.1), may not be the same as the weight value that maximizes the model for the remaining DMUs. This flexibility in the choice of the weighting grants that a DMU will only be considered inefficient when there is no other weight profile that allows a more favourable alternative, which suggests that its activity can in fact be improved (Cooper et al., 2004).

The efficiency value obtained in model (2.1) results by comparing the current performance of each unit with the best performance observed in the other DMUs, considering the amount of inputs utilized and the results obtained (Fernandes *et al.*, 2007). The DEA model allows to distinguish between the efficient DMUs, and the inefficient ones of a given sample of DMUs. In the input-oriented model "a DMU is not efficient if it is possible to decrease any input without increasing any other input and without decreasing any output"(Charnes *et al.*, 1981).

The efficiency value can also be obtained through an output-oriented model, that also admits the existence of constant returns to scale and it is defined by the model (2.2) (Charnes et al., 1978) .

$$min\{h_{j_0} = \frac{\sum_{i=1}^{m} v_i x_{ij_0}}{\sum_{r=1}^{s} \mu_r y_{rj_0}}$$

Subject to:

$$\frac{\sum_{i=1}^{m} v_i x_{ij}}{\sum_{r=1}^{s} \mu_r y_{rj}} \geq 1, \quad j = 1, \ldots, n,$$

$$v_i \geq \varepsilon, \qquad i = 1, \ldots, m,$$

$$\mu_r \geq \varepsilon, \qquad r = 1, \ldots, s\} \qquad (2.2)$$

The relative efficiency of a given DMU j_0 is obtained by $1/h^*_{j_0}$ in the model (2.2)(Charnes et al., 1978). The output-oriented model defines efficiency as the inverse of the maximum factor with which every output can be equally augmented without increasing the amount of utilized inputs. In the output-oriented perspective a DMU cannot be classified as efficient "if it is possible to increase any output without increasing any input and without decreasing any other output" (Charnes *et al.*, 1981).

Assuming the existence of CRS, according to the theorem (1.1) the efficiency value of the input-oriented model and the output-oriented model are equivalent, being verified that $e^*{}_{j_0} = 1/h^*{}_{j_0}$.

> **"Theorem 1.1**: Let (μ^*, v^*) be an optimal solution for the input-oriented model. Then $(1/\mu^*, \mu^*/v^*) = (\mu^{**}, v^{**})$ is optimal for the corresponding output-oriented model. Similarly, if (μ^{**}, v^{**}) is optimal for the output oriented model then $(1/\mu^{**}, \mu^{**}/v^*) = (\mu^*, v^*)$ is optimal for the input oriented model " (Cooper et al., 2004: 17).

The models (2.1) and (2.2) are in the fractional form and according to Charnes *et al.* (1978), can be converted to the respective linear programming (LP) models, (2.3) and (2.4).

$$max\{e_{j_0} = \sum_{r=1}^{s} \mu_r y_{rj_0}$$

Subject to:

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1,$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1, \ldots, n,$$

$$v_i \geq \varepsilon, \qquad i = 1, \ldots, m,$$

$$\mu_r \geq \varepsilon, \qquad r = 1, \ldots, s\} \qquad (2.3)$$

$$max\{h_{j_0} = \sum_{i=1}^{m} v_i x_{ij_0}$$

Subject to:

$$\sum_{i=1}^{s} u_r y_{rj_0} = 1,$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1, \ldots, n,$$

$$v_i \geq \varepsilon, \qquad i = 1, \ldots, m,$$

$$\mu_r \geq \varepsilon, \qquad r = 1, \ldots, s\} \qquad (2.4)$$

Via the duality theorem of mathematical programming, the models (2.3) and model (2.4) can be converted to their envelopment form, obtaining the models (2.5) and (2.6), respectively (Cook & Seiford, 2009). The model (2.5) is input oriented and the model (2.6) is output oriented.

$min\{e_{j_0} = \theta_0 - \varepsilon\,(\sum_{r-1}^{s} s_i + \sum_{i-1}^{m} s_r)$

Subject to:

$\theta_0 x_{ij_0} - \sum_{j-1}^{n} x_{ij}\,\lambda_j - s_i = 0, \quad i = 1, \ldots, m,$

$\sum_{j-1}^{n} y_{rj}\,\lambda_j - s_r = y_{rj_0}, \quad r = 1, \ldots, s,$

$\lambda_j, s_i, s_r \geq 0, \forall_{j,i,r}\}$ (2.5)

$max\{h_{j_0} = \delta_0 + \varepsilon\,(\sum_{i=1}^{m} s_i + \sum_{r=1}^{s} s_r)$

Subject to:

$\delta_0 y_{rj_0} - \sum_{j=1}^{n} y_{rj}\,\lambda_j + s_r = 0, r = 1, \ldots, s,$

$\sum_{j=1}^{n} x_{ij}\,\lambda_j + s_i = x_{ij_0}, \quad i = 1, \ldots, m,$

$\lambda_j, s_i, s_r \geq 0, \forall_{j,i,r}\}$ (2.6)

The efficient DMUs are considered benchmarks (the organizational units that are examples of good performance) and define the efficiency frontier. The inefficient units are projected to the efficiency frontier, and one or more efficient DMUs are being designated as benchmarks for each inefficient DMU (Vaz et al., 2010). Having an efficient DMU assigned as a benchmark for a unit said inefficient, permits to identify the good practices that should be implemented in the inefficient unit for it to attain efficiency (Donthu & Yoo, 1998). An illustration of the projection to the efficiency frontier of the input-oriented CCR model and output-oriented CCR model can be seen, respectively, in figure 1.1 and figure 1.2.

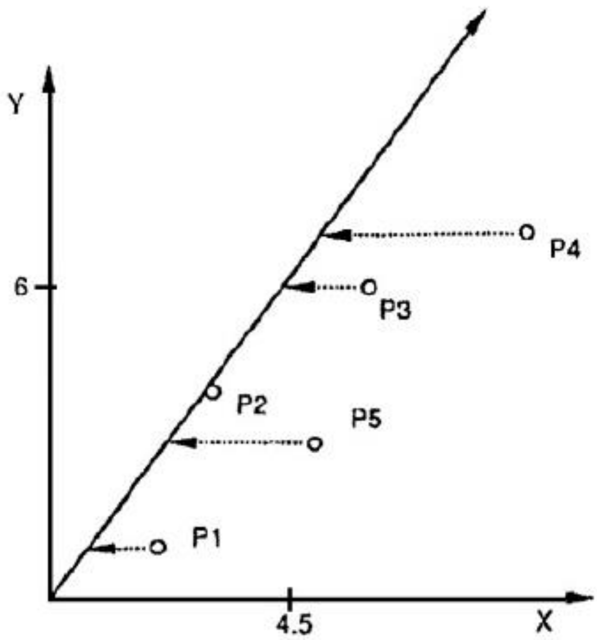

Figure 1.1 - Projection to the frontier for the input oriented CCR model (Cooper et al., 2004)

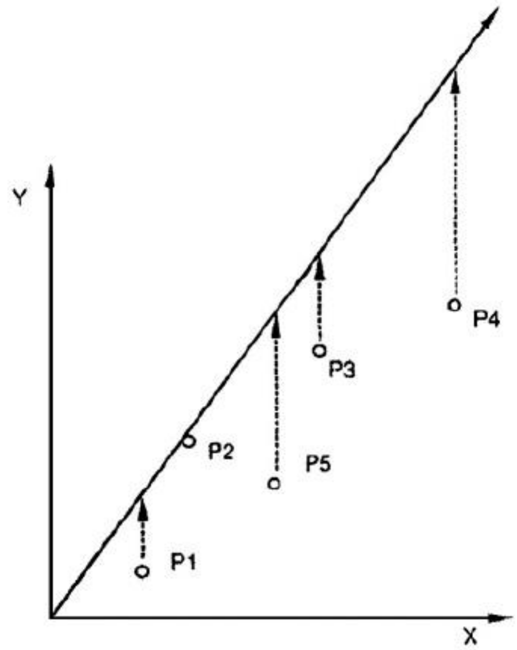

Figure 1.2 - Projection to the frontier for the output oriented CCR model (Cooper et al., 2004).

The model presented by Banker, Charnes and Cooper (1984) known as the BCC model, extended the CCR model to accommodate technologies that exhibit variable returns to scale (VRS) (Ray, 2004). The only difference between the BCC and CCR model is that the BCC model includes the convexity condition $\sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0, \forall_j$ in its constrains (Cooper et al., 2006). So as expected, these models share properties in common and present some differences.

The input-oriented BCC model and the output-oriented BCC model that evaluated the efficiency of DMU_0 is given respectively by the model (2.7) and (2.8).

$min\{e_{j_0} = \theta - \varepsilon (\sum_{r-1}^{s} s_i + \sum_{i=1}^{m} s_r)$

Subject to:

$\theta x_{ij_0} - \sum_{j-1}^{n} x_{ij} \lambda_j - s_i = 0,\ i = 1, \ldots, m,$

$\sum_{j-1}^{n} y_{rj} \lambda_j - s_r = y_{rj_0},\ r = 1, \ldots, s,$

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

$\lambda_j, s_i, s_r \geq 0, \forall_{j,i,r}\}$ (2.7)

$max\{h_{j_0} = \Phi + \varepsilon (\sum_{i=1}^{m} s_i + \sum_{r=1}^{s} s_r)$

Subject to:

$\Phi y_{rj_0} - \sum_{j=1}^{n} y_{rj} \lambda_j + s_r = 0,\ r = 1, \ldots, s,$

$\sum_{j=1}^{n} x_{ij} \lambda_j + s_i = x_{ij_0},\ i = 1, \ldots, m,$

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

$\lambda_j, s_i, s_r \geq 0, \forall_{j,i,r}\}$ (2.8)

The efficiency obtained using the CCR models is called *global technical efficiency* (TE) since it takes no scale effect in consideration, while the efficiency using the BCC models is called *local pure technical efficiency* (PTE). If a DMU is called efficient (100% score) in both CCR and BCC models, it is operating in the *most productive scale size*. If a DMU has a 100% efficiency score in the BCC model but a low efficiency score in the CCR model, then the DMU in question is operating efficiently locally, but not globally (Cooper *et al*., 2006). An illustration of the efficiency frontier given the CCR model and the BCC model can be seen, respectively, in figure 1.3 and figure 1.4.

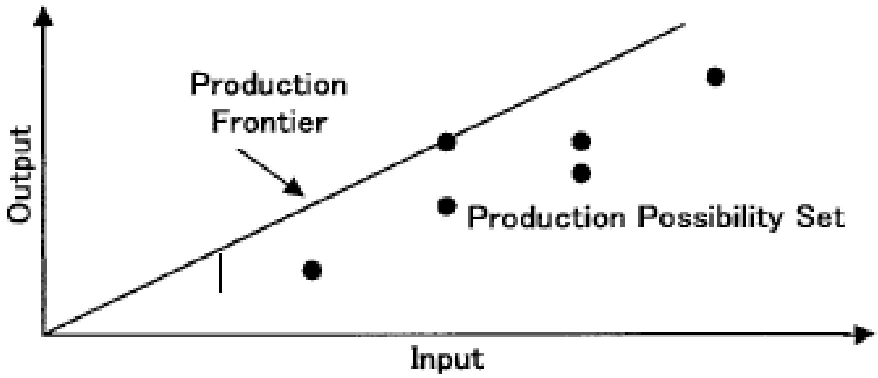

Figure 1.3 – Production Frontier of the CCR Model (Cooper *et al.*, 2006).

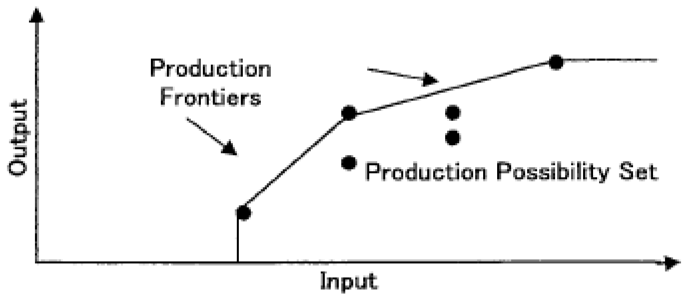

Figure 1.4 – Production Frontier of the BCC Model *(Cooper* et al., *2006)*

Let the CCR and BCC scores of a DMU be θ^*CCR and θ^*BCC respectively. The *scale efficiency* is defined by the following equation (Cooper et al., 2006):

$$SE = \frac{\theta^*CCR}{\theta^*BCC} \quad (2.9)$$

The scale efficiency value cannot be in any case greater than 1. From the above equation we can obtain the following equations (Cooper et al., 2006):

$\theta^*CCR = \theta^*BCC \times SE$ or,

$[TechnicalEff.(TE)] = [PureTechnicalEff.(PTE)] \times [ScaleEff.(SE)].$ (2.10)

In this respect, a given DMU can be pure technical efficient yet not scale efficient, or vice versa. The goal is to obtain the highest score (100%) in both pure technical and scale efficiency, and therefore be considered technically efficient.

The number of DMUs (*n*) to be studied cannot be a random number. Usually in DEA, *n*, the number of the DMUs, is considerably larger than the combination of the number of inputs and the number of outputs (Cooper et al., 2006). The reason being that if the number of DMUs (*n*) is less than the combined number of inputs and outputs, there will be many DMUs that will be identified as efficient and the efficiency discrimination among DMUs will become questionable given the inadequate number of degrees of freedom (Cooper et al., 2006). In the DEA model the number of degrees of freedom will increase with the number of DMUs and decrease with the number of inputs and outputs. In this respect, a general rule that is used as guidance is the following (Cooper *et al.*, 2006).

$$n \geq \max\{m \times s, 3(m+s)\}$$

Where: *n* = number of DMUs

m = number of inputs

s = number of outputs.

4. Empirical application

This chapter discusses the application of the DEA technique to assess the efficiency of 34 stores of a non-food worldwide retail organization operating in Portugal. The data used was provided directly by the company, not being available to the public. The names of the stores cannot be disclaimed for confidentiality reasons and all the data was multiplied by an unknown coefficient in order to protect the identity of the company. This transformation of data is not a problem considering that DEA allows to determine the relative efficiency, as long as all the data, across all the stores, have been transformed using the same coefficient. In fact, this procedure ensures that the relative efficiency scores are maintained because, as discussed by Ali and Seiford (1990), both CCR and BCC models are units invariant. In this respect, the multiplication of all data by a scalar does not affect the reliability of the study.

4.1. DEA models specification

In order to determine the efficiency of each store, two different DEA models were applied: a Technical Efficiency DEA Model (Model 1), aimed at assessing the efficiency of the stores in terms of the quantity of resources used and the quantity of outputs produced ; and a Cost Efficiency DEA Model (Model 2) , intended to determine the cost efficiency of the given DMUs by comparing the costs that the stores had to incur to obtain their monetary outputs.

These two DEA models are all output oriented. This choice was made because the organization is currently more focused in maximizing their outputs in order to continuously grow their market share, than to minimize the inputs. Also, the DEA models were applied assuming the existence of both CRS and VRS. This decision is based on the importance given to the measurement of the Technical Efficiency (TE) and Pure Technical Efficiency (PTE) of each store, obtained using their CRS and VRS scores. As previously discussed, the Scale Efficiency (SE) is given by the ratio between the CRS and VRS scores.

4.2. Inputs and outputs

The input and output variables used in the DEA models are presented in Table 1. These inputs and outputs are all supported by the literature, since there are many articles that use them or a variation of them. The set of variables used accurately describes the production process that takes place in the stores as these variables capture the results obtained, as well as the main resources necessary to achieve these results.

The input variables included in the technical efficiency model, DEA Model 1, are: the area of the store, used as an input in various other studies (e.g. Vaz et al., 2010; Vaz & Camanho, 2012; Ko et al., 2017; Vyt & Cliquet, 2017), and the number of paid hours, which relates to the workforce of the store. For this specific model the output variables related to the quantity of outputs produced by the stores. In particular, the following outputs were considered: the quantity of articles sold in store, the quantity of articles sold by PLUS, the number of transactions made in store and the number of transactions made by PLUS. PLUS is an application that allows a customer to buy an article that is not available in the store using a screen available in the store (online purchase). Every time someone buys an item through this system they need to pay it in the store, consequently, the store gets a percentage of the revenue generated by this sale. The PLUS data was considered important for this study since all the items sold through the PLUS app represent minimum costs to the store (related only with the time of the employees that support the sale, since the product does not need shelf space and is directly delivered to the customer, yet it still brings revenue to the store. The number of transactions relates to the number of times someone bought anything and it is different from the quantity of items sold. Buying 1 or 20 items at once only counts as one transaction. The decision to use simultaneously the quantity of items sold and the number of transactions was made since these two variables together allow for a perception of the sales made but also gives indirectly an indication of the number of clients that a store has, a variable that we could not obtain, despite being considered relevant for the study.

Table 1 - Inputs and outputs used in the two DEA models

Indicators	DEA Model 1 - Technical Efficiency	DEA Model 2 - Cost Efficiency
Inputs	X_1 : Area of the store (AREA)	X_3 : Total operating costs (COSTS)
	X_2 : Number of paid hours (HOURS)	X_4 :Average stock value (STOCK)
		X_5 :Total value of the products spoiled of the store (TOTSPOIL)
Outputs	Y_1 :Number of articles sold in store (QTSTORE)	Y_5 :Total sales value made in store (SALSTORE)
	Y_2 :Number of articles sold by PLUS (QTPLUS)	Y_6 :Total sales value made by PLUS (SALPLUS)
	Y_3 :Number of transactions made in store (TRSTORE)	Y_7 :Total annual profit (PROFIT)
	Y_4 :Number of transactions made by PLUS (TRPLUS)	

The input variables used in the cost efficiency model, DEA Model 2, were: the total operating costs, a variable which was used by Balios *et al.*, (2015) in their study; the value of the average stock available in the store also used by Alves & Portela (2015) and the total value of the products spoiled in the store, also used by Vaz *et al.*, (2010). The amount of stock a store has as well as its value fluctuates constantly, therefore, the average stock value was considered for this model. The value of the spoiled products represents the articles that were returned by customers and that do not have the conditions to be sold again or the items that were used internally by the store.

In terms of outputs for this model, we used: the total sales value made in store; the total sales value made using the PLUS and the total profit obtained by the store. These output variables or a variation of them were commonly used across various studies (e.g. Goic *et al.*, 2015; Keh & Chu , 2003 ; Xavier *et al.*, 2015a ; Balios *et al.*, 2015 ;Thomas *et al.* ,1998) supporting the decision made.

It is important to emphasize that the data values of the profit variable, one of the output indicators of the cost DEA model, suffered an addition of a scalar (translation). It was added the absolute value of the minimum profit value recorded, plus one unit, to the original profit value of every store. This translation was required since there were some stores that were exhibiting negative profit values. The CCR model requires all the input and output values to be strictly positive (Charnes *et. al.*, 1978) and the BCC model requires that all the input and output values are non-negative (Banker et al., 1984), hence the importance of the translation employed. The need to transform the output value, by adding a scalar, limits the effectiveness of the scores obtained from the cost efficiency model. As discussed by Ali & Seiford (1990), in the BCC model, the translation of the data values does not alter the efficient frontier and the classification of DMUs as efficient or inefficient. However, the inefficiency scores obtained for the inefficient DMUs will be different when a scalar is added.

Table 2 lists the input and output indicators discussed previously, along with the summary of their key descriptive statistics.

Table 2 – Summary statistics of the input and output variables in the two DEA models.

Indicators	DEA model	Average	Std Dev	Min	Max
Inputs					
X_1 : **AREA** (m^2)	1	6802,58	3787,14	1876,55	19591,50
X_2 : **HOURS**	1	97082,82	73311,70	18588,97	428360,08
X_3 : **COSTS (€)**	2	2681729,46	1684837,86	462537,67	9038421,44
X_4 : **STOCK (€)**	2	2256958,31	1073237,04	790061,13	5374376,86
X_5 : **TOTSPOIL (€)**	2	72696,52	66642,59	6314,96	360695,95
Outputs					
Y_1 : **QTSTORE**	1	1681402,58	1093090,12	189565,24	6245041,61
Y_2 : **QTPLUS**	1	103906,95	50354,42	9376,49	259191,33
Y_3 : **TRSTORE**	1	584101,85	320654,39	65213,22	1862302,33
Y_4 : **TRPLUS**	1	36448,99	15011,29	3225,65	77292,14
Y_5 : **SALSTORE (€)**	2	15481518,27	13676323,59	1941758,06	60158818,45
Y_6 : **SALPLUS (€)**	2	946810,44	512187,62	96045,48	2496803,93
Y_7 : **PROFIT (€)**	2	883303,62	626942,53	1,00	3681571,87

5. Results presentation and discussion

The results of the analysis made, regarding the technical efficiency of the retail stores being studied under the CRS assumption are summarized in Table 3. These results suggest that the stores have a considerable scope for efficiency improvement. They indicate that the efficiency varies considerably throughout the various stores, demonstrating the importance of sharing the best practices of the efficient stores with the inefficient ones. In order to compute the DEA results, the Efficiency Measurement System (EMS) (Scheel, 2000) was used.

5.1.Technical efficiency

The DEA results show that when comparing all the stores to each other, there are only 9 stores that are efficient according to their use of resources (Store 1 , Store 2, Store 3, Store 4, Store 5, Store 6, Store 14, Store 21 and Store 34) representing 26,47% of the total number of stores studied. The results indicate that the average resource efficiency score of the stores is about 80%, with a standard deviation of 18,45% and that 52,94% of the stores (18 stores) present a resource efficiency score below average. Given that the orientation chosen for the resource efficiency model was the output orientation, this means that, taking in consideration the resources of the inefficient DMUs, there is a possibility for them to increase the number of transactions and quantity of items sold in about 25 %. The store that shows the lowest technical efficiency score is Store 21, with a very low score of 14,08%. The very low efficiency score associated with Store 21 can be justified by the fact that it is a very recent store (it has been operating for only one year) and is a considerably large store.

Table 3 - DMU technical efficiency scores, benchmarks and sum of the respective CRS scale multipliers. Source: Own elaboration, based on the results obtained from Efficiency Measurement System (EMS) software, version 1.3, developed by Scheel (2000)

	DEA Model 1 - Technical Efficiency		
DMU	**TE Score (%)**	**Benchmarks**	$\sum\lambda$
Store 1	100,00%	0	
Store 2	100,00%	1	
Store 3	100,00%	7	
Store 4	100,00%	7	
Store 5	100,00%	14	
Store 6	100,00%	16	
Store 7	75,84%	3 (0,21) 5 (1,55)	1,76
Store 8	66,84%	3 (0,24) 5 (1,71)	1,95
Store 9	62,29%	3 (0,58) 5 (2,12)	2,7
Store 10	87,89%	4 (1,34) 14 (0,23)	1,57
Store 11	75,85%	4 (0,99) 6 (1,06) 14 (0,15)	2,2
Store 12	61,23%	5 (0,35) 6 (2,39)	2,74
Store 13	71,71%	6 (1,31) 21 (0,54)	1,85
Store 14	100,00%	7	
Store 15	88,51%	4 (0,62) 6 (1,25) 14 (0,19)	2,06
Store 16	85,48%	6 (1,24) 21 (0,52)	1,76
Store 17	90,11%	2 (0,06) 6 (0,71) 14 (0,69)	1,46
Store 18	73,22%	3 (2,34) 5 (1,69)	4,03
Store 19	65,98%	4 (0,31) 5 (0,73) 6 (2,15)	3,19
Store 20	69,79%	3 (0,07) 5 (3,06)	3,13
Store 21	100,00%	3	
Store 22	98,83%	4 (1,76) 14 (0,58)	2,34
Store 23	96,58%	4 (0,53) 6 (0,81) 14 (0,56)	1,9
Store 24	62,18%	5 (3,03) 6 (1,35)	4,38
Store 25	68,38%	3 (1,00) 5 (3,29)	4,29
Store 26	77,69%	6 (1,93) 21 (0,39) 34 (0,04)	2,36
Store 27	14,08%	3 (2,78)	2,78
Store 28	70,54%	5 (3,24) 6 (1,16)	4,4
Store 29	82,79%	4 (1,22) 6 (1,16) 14 (0,53)	2,91
Store 30	70,83%	5 (0,11) 6 (3,94)	4,05
Store 31	68,88%	5 (2,42) 6 (2,03)	4,45
Store 32	69,19%	5 (1,02) 6 (3,74)	4,76
Store 33	65,24%	5 (4,15) 6 (3,99)	8,14
Store 34	100,00%	1	
Number of efficient branches	9		
% of efficient branches	26,47%		
% of bellow average scores branche	52,94%		
Scores average(%)	80,00%		
Scores Std. Dev.(%)	18,45%		
Scores Max (%)	100,00%		
Scores Min. (%)	14,08%		

These results indicate a considerable scope for improvement and the need for the inefficient stores to learn the best practices from the best performers of the company. In particular, there are two efficient stores that are worth emphasizing, the Store 5 that serves as benchmark for 14 stores and Store 6 that serves as benchmark for 16 stores, serving as a benchmark for most of the inefficient stores.

5.1.1 Pure technical efficiency

Considering that the inefficiency of the stores can have different sources, we decided to explore the extent to which the scale of operation impacts on the performance of the stores and if the stores that are scale inefficient should increase or decrease their size in order to operate closer to the most efficient scale size. In order to do so, we additionally run Model 1 under the VRS assumption. The results are summarized in table 4.

Regarding the resource efficiency of the stores, with the assumption that there are variable returns to scale, the results show that there are 12 stores that reach a pure technical efficiency score of 100%. The stores considered pure technically efficient are Store 1, Store 2, Store 3, Store 4, Store 5, Store 6, Store 15, Store 21, Store 22, Store 30, Store 33 and Store 34. The average pure technical score is 91,73%, much higher than the average technical resource efficiency score (80,00%), highlighting the negative effect that the incorrect scale of the stores presents to the company. The analysis of the results allows us to conclude that there are 3 stores (Store 22, Store 30 and Store 33) that are technical inefficient yet become efficient when compared with stores of similar size, indicating that their scale of operation is influencing their performance negatively. This is more evident in the cases of Store 30 and Store 33, that despite being managed efficiently locally (PTE = 100%), are not scale efficient (SE < 100%) indicating potential to improve their resource efficiency globally.

The results presented in Table 4 also indicate the benchmarks that is, the stores that serve as an example of good performance, for every inefficient store. The DMUs that serve as a benchmark correspond to the efficient DMUs that are similar to the projection of the inefficient DMU to the efficient frontier. For example, Store 10 has as benchmarks 3 efficient stores (Store 4, Store 5 and Store 22) while Store 27 has as benchmarks Store 6 and Store 21. The benchmarks allow to identify the targets for the input and output variables that would make the inefficient stores efficient.

Table 4 - DMUs pure technical efficiency scores, benchmarks and scale efficiency of DEA Model 1. Source: Own elaboration, based on the results obtained from Efficiency Measurement System (EMS) software, version 1.3, developed by Scheel (2000)

	DEA MODEL 1 - Technical Efficiency		
DMU	PTE (%)	Benchmarks	SE (%)
Store 1	100,00%	0	100,00%
Store 2	100,00%	0	100,00%
Store 3	100,00%	0	100,00%
Store 4	100,00%	2	100,00%
Store 5	100,00%	4	100,00%
Store 6	100,00%	8	100,00%
Store 7	88,69%	5 (0,75) 21 (0,08) 22 (0,17)	85,51%
Store 8	77,94%	6 (0,78) 21 (0,09) 30 (0,13)	85,76%
Store 9	76,10%	4 (0,36) 21 (0,55) 22 (0,08)	81,85%
Store 10	89,21%	4 (0,27) 5 (0,33) 22 (0,40)	98,51%
Store 11	86,03%	5 (0,32) 21 (0,31) 22 (0,37)	88,17%
Store 12	73,09%	6 (0,03) 21 (0,97)	83,77%
Store 13	79,02%	21 (0,95) 22 (0,03) 30 (0,01) 33 (0,00)	90,74%
Store 14	100,00%	2	100,00%
Store 15	97,82%	5 (0,29) 21 (0,40) 22 (0,31)	90,49%
Store 16	96,19%	6 (0,18) 21 (0,64) 30 (0,19)	88,87%
Store 17	96,32%	14 (0,30) 21 (0,68) 34 (0,02)	93,55%
Store 18	96,94%	6 (0,34) 21 (0,23) 30 (0,44)	75,53%
Store 19	94,69%	6 (0,35) 30 (0,65)	69,68%
Store 20	91,11%	6 (0,44) 21 (0,13) 30 (0,44)	76,61%
Store 21	100,00%	19	100,00%
Store 22	100,00%	9	98,83%
Store 23	99,08%	6 (0,01) 14 (0,16) 21 (0,38) 22 (0,46)	97,48%
Store 24	83,86%	21 (0,63) 30 (0,19) 33 (0,18)	74,15%
Store 25	89,73%	21 (0,64) 30 (0,34) 33 (0,02)	76,21%
Store 26	96,78%	21 (0,58) 30 (0,40) 34 (0,02)	80,28%
Store 27	16,14%	6 (0,66) 21 (0,34)	87,25%
Store 28	98,21%	21 (0,18) 30 (0,82) 33 (0,00)	71,82%
Store 29	96,62%	22 (0,92) 33 (0,05) 34 (0,04)	85,69%
Store 30	100,00%	12	70,83%
Store 31	95,96%	21 (0,26) 30 (0,64) 33 (0,10)	71,78%
Store 32	99,32%	21 (0,17) 22 (0,37) 30 (0,14) 33 (0,31)	69,66%
Store 33	100,00%	7	65,24%
Store 34	100,00%	3	100,00%
Number of efficient branches	12		9
% of efficient branches	35,29%		26,47%
% of bellow average scores branche	29,41%		47,06%
Scores average(%)	91,73%		87,01%
Scores Std. Dev.(%)	15,50%		11,53%
Scores Max (%)	100,00%		100,00%
Scores Min. (%)	16,14%		65,24%

The target for the variables is calculated given the efficiency score presented by the inefficient stores, the original value of the variables and the slack that the given variables present. All the inefficient stores present slacks, being that only the efficient stores have a slack value of zero. Table 5 and 6 contain the targets for the input and output variables for Store 10 and Store 27, respectively.

Table 5 – Target for the input and output variables of Store 10 (BCC)

Outputs and Inputs	Original Value	Slack	Projected Value
AREA(m^2)	4024,20	0	4024,20
HOURS	58403,79	0	58403,79
QTSTORE	974545,05	11486,3	1103941,56
QTPLUS	100577,16	0	112736,94
TRSTORE	351832,01	13958,58	408327,08
TRPLUS	36310,55	1023,48	41723,97

Table 6 – Target for the input and output variables of Store 27 (BCC)

Outputs and Inputs	Original Value	Slack	Projected Value
AREA(m^2)	7836,60	4763,98	3072,62
HOURS	51618,94	0	51618,94
QTSTORE	180188,74	0	1116683,69
QTPLUS	9376,49	26942,25	85051,20
TRSTORE	61987,57	15632,38	399787,94
TRPLUS	3225,65	10567,61	30557,94

For Store 10, the target for the output variable, quantity of items sold by PLUS (QTPLUS), was calculated as such:

Projected value = $original\ value\ \times\ (1 \div\ efficiency\ score\ of\ the\ DMU)\ +\ slack$

$$= 100577{,}16\ \times\ (1 \div\ 0{,}8921)\ +\ 0\ \cong 112736{,}94$$

Each input and output variable have a weight value associated that indicates the importance that was given to that variable. The sum of all the weights allocated to the input variables should be 1, as well as the sum of all the weights assigned to the output variables. For example, for Store 10 the weights were distributed as such, 0,06 for the area of the store, 0,94 for the number of paid hours. In which regards the output variables all the weight was given to the quantity of items sold by PLUS. The weight assignment for Store 27 was considerably different, as a weight of 1 was given to the input "number of paid hours" and a weight of 1 was also given to the output "number of items sold in store". The weight values reflect the importance that was given to each variable while the model run. So, using Store 10 as an illustrative example, for the input variables most of the weight was allocated to the number of paid hours and for the output variables, all the importance was given to the number of articles sold by PLUS. This distribution of the weight may or may not reflect what the company values. Therefore, in a future study a weight restriction set that reflects the preferences of the managers of the company should be taken into consideration.

5.1.2 Scale efficiency

The results, presented in table 4, show that there are only nine stores (Store 1, Store 2, Store 3, Store 4, Store 5, Store 6, Store 14, Store 21 and Store 34) that are considered scale efficient (SE = 100%). This indicates that the efficiency of many stores is affected negatively by their inappropriate size. Store 33 presents the lowest scale efficiency score (65,24%), while it is pure technical efficient, it is being hugely harmed by its inappropriate size.

Following the method of Sherman & Zhu (2006) for evaluating scale efficiency given the scale multipliers of the benchmarks of the inefficient DMUs ($\sum \lambda_j$), the results in Table 4 suggest that all the stores that present scale inefficiency are too big , indicating Decreasing Returns to Scale (DRS).

The results show that there are 22 stores that are neither pure technical efficient nor scale efficient. Therefore, improving their resource efficiency is probably going to require an increase of their technical efficiency as well as their scale efficiency. Although, they are all considered inefficient they do not all require the same improvement intervention, as some of them present a high scale efficiency score, yet a way lower pure technical efficiency score (Store 13 and Store 27), suggesting that the inefficiency may be caused mainly by a managerial problem and not because of the operation scale.

5.2.Cost efficiency

In order to identify the cost efficiency of each store, Model 2 was run under the VRS assumption. Considering that the variable “profit” had to be transformed, some trials were performed with the addition of different constants. These trials allowed us to conclude that the scores obtained by each store did not change significantly, showcasing that the results are robust to different constants.

The results of this research, summarized in table 7, show that there are only 11 stores (Store 3, Store 4, Store 5, Store 6, Store 10, Store 15, Store 21, Store 22, Store 27, Store 33 and Store 34) considered cost efficient. The average cost efficiency score is 90,17% with a standard deviation of 9,27 % and with 50% of the stores presenting a cost efficiency score below average. The results suggest that, on average, the inefficient units should increase their monetary outputs in about 10,9 %. Store 1, Store 9 and Store 25 present the lowest cost efficiency score with 71,63%, 73,81% and 74,68%, respectively. These results highlight the high scope for improvement that some stores present and the necessity for the inefficient stores to learn from the best performers of the company. In especial, Store 6 that serves as benchmark for 16 stores, Store 22 that serves as benchmark for 15 stores and Store 34 that serves as benchmark for 17 stores. These three stores serve as benchmark for most of inefficient stores and should be studied thoroughly, since they can help most of the inefficient stores to become efficient.

Table 7 - DMUs cost efficiency scores and benchmarks of DEA Model 2. Source: Own elaboration, based on the results obtained from Efficiency Measurement System (EMS) software, version 1.3, developed by Scheel (2000)

	DEA MODEL 2 - Cost Efficiency	
DMU	Cost-efficiency (%)	Benchmarks
Store 1	71,63%	5 (0,97) 22 (0,03) 34 (0,00)
Store 2	89,09%	3 (0,19) 4 (0,24) 5 (0,56)
Store 3	100,00%	1
Store 4	100,00%	1
Store 5	100,00%	6
Store 6	100,00%	16
Store 7	81,98%	5 (0,44) 6 (0,32) 22 (0,23)
Store 8	84,97%	5 (0,67) 10 (0,25) 33 (0,08)
Store 9	73,81%	6 (0,56) 15 (0,20) 22 (0,20) 33 (0,05)
Store 10	100,00%	3
Store 11	85,86%	6 (0,51) 22 (0,47) 34 (0,02)
Store 12	78,80%	10 (0,78) 21 (0,05) 33 (0,17)
Store 13	85,59%	6 (0,57) 22 (0,32) 33 (0,02) 34 (0,09)
Store 14	93,48%	5 (0,40) 22 (0,55) 34 (0,04)
Store 15	100,00%	1
Store 16	83,91%	6 (0,81) 22 (0,01) 34 (0,18)
Store 17	80,55%	6 (0,71) 22 (0,13) 34 (0,16)
Store 18	91,86%	6 (0,71) 33 (0,28) 34 (0,00)
Store 19	76,44%	6 (0,79) 34 (0,21)
Store 20	81,01%	6 (0,74) 33 (0,21) 34 (0,05)
Store 21	100,00%	3
Store 22	100,00%	15
Store 23	99,47%	6 (0,27) 22 (0,68) 34 (0,05)
Store 24	83,07%	6 (0,51) 22 (0,24) 34 (0,25)
Store 25	74,68%	6 (0,39) 22 (0,25) 33 (0,32) 34 (0,03)
Store 26	87,24%	5 (0,22) 10 (0,00) 21 (0,51) 33 (0,27)
Store 27	100,00%	0
Store 28	89,57%	6 (0,47) 21 (0,12) 33 (0,40) 34 (0,01)
Store 29	98,90%	22 (0,93) 34 (0,07)
Store 30	88,61%	6 (0,47) 22 (0,14) 33 (0,28) 34 (0,11)
Store 31	92,63%	6 (0,52) 22 (0,19) 34 (0,30)
Store 32	92,66%	6 (0,25) 22 (0,48) 34 (0,27)
Store 33	100,00%	10
Store 34	100,00%	17
Number of efficient branches	11	
% of efficient branches	32,35%	
% of bellow average scores branche	50,00%	
Scores average(%)	90,17%	
Scores Std. Dev.(%)	9,27%	
Scores Max (%)	100,00%	
Scores Min. (%)	71,63%	

5.3. Technical efficiency versus cost efficiency

Figure 2 displays the pure technical efficiency and the cost efficiency simultaneously, permitting to compare the overall efficiency of the stores in the two DEA models. The red lines represent the average efficiency score given the pure technical efficiency and the cost efficiency, allowing the clustering of the stores into four different groups. The first quadrant represents the group of stores that overall present the best performances in both criteria, outperforming the remaining stores, not only in terms of pure technical efficiency but also in terms of cost efficiency.

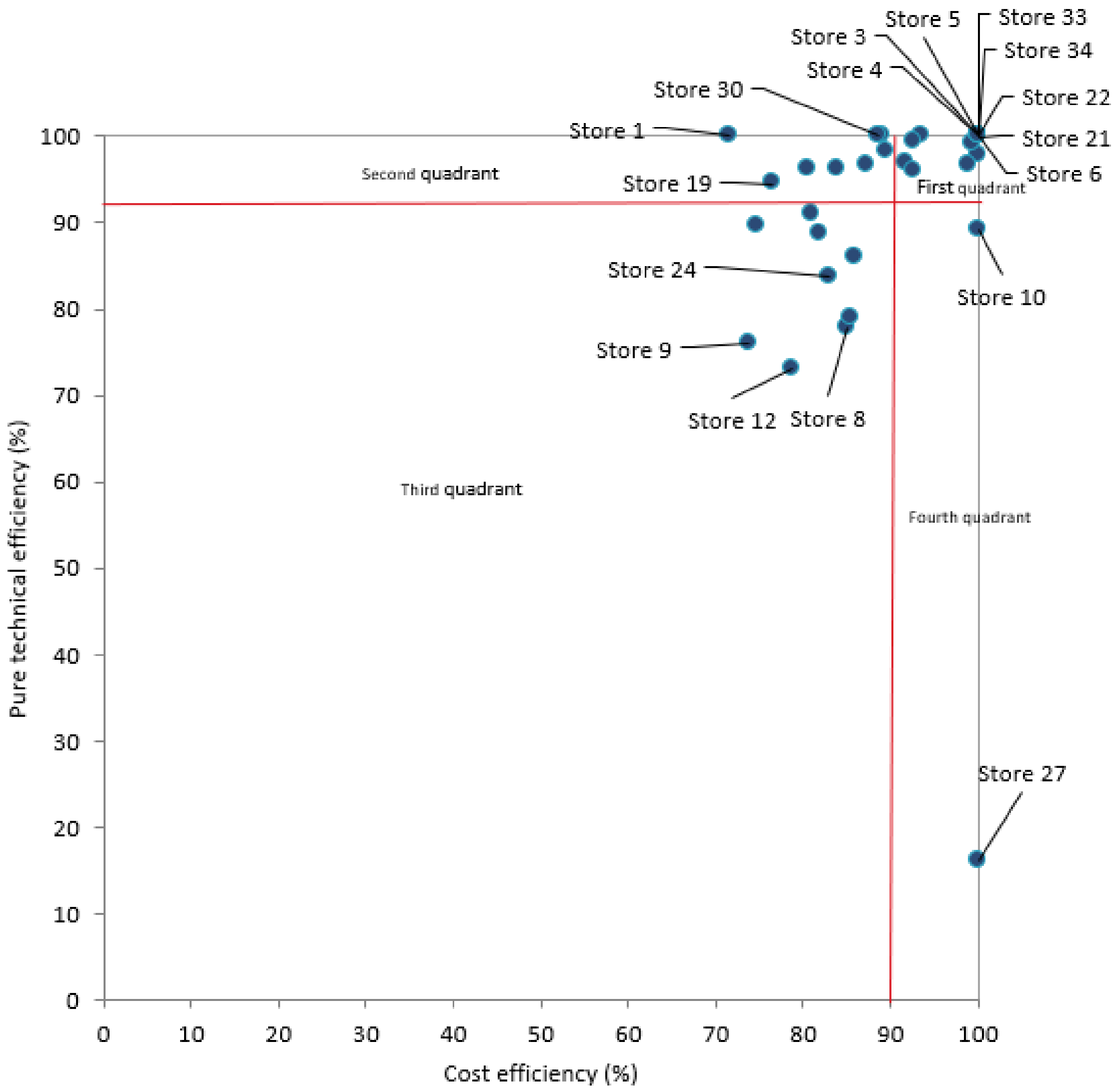

Figure 2- Projection of the pure technical efficiency and the cost efficiency given the VRS assumption.

The main goal of the company should be to bring all the stores to the first quadrant. The second quadrant is composed by the stores that present an above average performance in terms of pure technical efficiency, yet their cost efficiency score is below average. The fourth quadrant contains the stores that have an above average cost efficiency score, however, have a low pure technical efficiency score. Finally, the third quadrant contains the worst performing stores in both models. By analysing figure 2, it can be observed that there are eight stores that are considered efficient in both models. These are stores 3, 4, 5, 6, 21, 22, 33 and 34. The results show that even though store 1 and 30 are pure technical efficient, they are performing below average given the cost efficiency DEA model, so the focus of the company should be to improve the monetary outputs of these companies. The stores 10 and 27, situated in the fourth quadrant, present a cost efficiency score of 100% while their pure technical efficiency score is below average, so their focus should be to improve their technical efficiency. The stores 24, 9, 12 and 8 are some of the worst performing stores, showing efficiency scores below average in both models, and therefore, are those that can improve the most. In which regard these scores, the main focus of the company should be to increase their technical and cost efficiency, since they are the ones that present most potential for improvement.

It is important to highlight that the output variable profit , used in the cost efficiency model (Model 2) suffered a transformation by a scalar. Although, according to Ali & Seiford (1990) the translation of the data values does not alter the efficient frontier and the classification of DMUs as efficient or inefficient, it will modify the inefficiency scores obtained for the inefficient stores. So, this aspect should be considered while interpreting the results presented.

5.4. Cost efficiency and some of its determinants

The existence of any kind of correlations between the cost efficiency and other variables considered as possible determinants of the cost efficiency (e.g. percentage of satisfied customers, percentage of satisfied workers, percentage of sales made by PLUS, percentage of publicity costs and percentage of personnel costs) could provide very useful information to the company since it would tell what its main focus area should be. In order to determine the existence of a relationship between the cost efficiency and some of its possible determinants, the Spearman rank correlation coefficient was calculated. “The Spearman rank correlation coefficient is a nonparametric measurement correlation used to verify the relation that existing between two sets of data" (Dodge, 2008:502). The results obtained are summarized in table 8.

Table 8 – Correlation between cost efficiency and some of its determinants (Spearman correlation)

	Cost-efficiency (%)	%Satisfied Costumers	% Satisfied workers	% Plus sales	% Publicity costs	% Personnel costs
Cost-efficiency (%)	1,00					
%Satisfied Costumers	0,28	1,00				
% Satisfied workers	0,24	0,84	1,00			
% Plus sales	0,38	0,23	0,40	1,00		
% Publicity costs	0,43	0,70	0,76	0,36	1,00	
% Personnel costs	0,37	0,44	0,43	0,11	0,68	1

The results indicate that there is a positive correlation between the cost efficiency and the determinants studied indicating that an improvement in any determinant will likely improve the efficiency value in some degree. The percentage of costs with publicity is the determinant that presents the highest correlation coefficient registered (0,43), so we can affirm that there is a moderate positive correlation between this determinant and the cost efficiency. The remaining determinants present a weaker correlation between them and the cost efficiency. Although, no strong correlation between the determinants studied and the cost efficiency was registered, this result was anticipated, as an increase in the cost efficiency will likely require the improvement of several factors simultaneously and not just one.

Is important to highlight the strong correlation between the percentage of satisfied workers and the percentage of satisfied customers (0,84) meaning that if the company wants to improve the satisfaction of its customers, should focus on improving the satisfaction of its workers as well.

6. Conclusion

The retail sector is very competitive and most of the times companies need to work with small margins in order to keep a competitive price appealing to the customers and have a leverage against their competition. Therefore, the importance of assessing and increasing the efficiency of the companies that operate in this sector. Inefficiency usually leads to a substantial loss in terms of outputs, harming the companies results.

The main purpose of this study was to undertake a benchmarking analysis of the stores of a non-food worldwide retail company operating in Portugal, using, for the purpose, a non-parametric technique, called Data Envelopment Analysis. This technique was used to determine the relative efficiency of each store, given the amount of inputs consumed and the amount of outputs produced.

The DEA technique presents many advantages when compared to other techniques. For instance, it is a non-parametric technique, so, it does not require the definition of a production function, as an initial condition. Also, it is a very powerful linear programming methodology that allows the usage of multiple inputs and outputs, identifies the Decision Making Units that are considered inefficient, and provides information that can help identifying the causes of the inefficiency (by decomposing global efficiency into several types). The results obtained are very important to the company analysed, as they not only identify which stores are efficient and which are inefficient, but also provide suggestions regarding the next step to follow in order to transform an inefficient store into an efficient one. Based on the benchmarks identified and on the targets estimated for the inputs and outputs, it is possible to implement an improvement programme for each inefficient store.

In this study, 34 stores of a non-food retail company operating in Portugal were analysed. In order to better analyse the stores, we used two different models, both output oriented, one that focused on technical efficiency (including inputs and outputs related only with volumes), and one that focused on the cost efficiency (including inputs and outputs expressed in monetary values). The technical efficiency DEA model used as inputs, the area of the store and the number of paid hours. As outputs it used the number of articles sold in store, the number of articles sold by PLUS, the number of transactions made in store and the number of transactions made by PLUS. The cost efficiency DEA model used as inputs, the total operating costs, the average stock value and the total value of the spoiled products by the store, as outputs it used the total sales value made in store , the total sales value made by PLUS and the total annual profit. The information used was provided by the company and is not of public use.

The application of the CRS and VRS models allowed us to conclude that there is a major difference between the different stores, most of them being considered inefficient. Given the technical efficiency model it can be concluded that there is an average potential for improvement of the technical efficiency of 25%, of which about 16% corresponds to scale progress. Consequently, it can be affirmed that if the best practices were to be adopted, the stores should sell 25% more products given the amount of resources they are currently using. Most of the improvements are scale related, given that the results suggest that if the stores were run at an optimal scale, they would produce, on average, 16% more outputs.

By running the cost efficiency DEA model, it was determined that there is an average potential for improvement of the cost efficiency of about 10,9%. Therefore, the stores could improve their monetary outputs by 10,9%, if they were to become efficient.

By running the technical efficiency model as well as the cost efficiency model, it was possible to identify the stores that present the best overall performance, being efficient in both models. These stores should be used as a reference for the inefficient stores.

Although, the company could benefit from the results obtained from this study, there are some restrictions related with the data available and related with the need to transform one of the outputs. For these reasons, the results of this research should be interpreted with caution. The methodological concern relates with the fact that the DEA model does not allow negative values, therefore, the output value, total annual profit, was transformed adding the absolute value of the minimum profit registered between all the stores, plus one unit, to the original value of each DMU. Even though this transformation of the data does not affect the efficiency frontier, it may affect the efficiency scores of the inefficient units. The apprehensions regarding the data limitation, come mostly from the possible existence of other factors, such as, location of the store and purchasing power of the local population that have not been taken in consideration in this study and may also help understand the relative efficiency of the stores, as well as the fact that the data used in the present research was restricted to a one year period (year 2018).

As a recommendation for the future studies, it is considered important to include the data of several years and determine if the results obtained are consistent year after year, or if significant fluctuations occur. Future studies should also include data regarding characteristics of the population covered by the stores as well as regarding the level of competition faced by the stores, as these variables, although non-discretionary, may have an influence on the efficiency of the stores. An in-depth study of some benchmark stores should also be undertaken in order to identify the factors associated with their performance.

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