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Measuring the Performance of a Dehydration Plant of Apples

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ABSTRACT

Given the importance of the Chilean dried-fruit market and the characteristics of the industrial process of dehydration, it becomes imperative for companies to measure the efficiency of their production processes in order to identify critical areas and take the necessary actions to improve them. Hence, the present work performs an efficiency analysis for the production of dried apples in a plant of the Maule region, Chile. The methodology used is Data Envelopment Analysis, considering both discretionary and non-discretionary variables. The results indicate that the application of the model without non-discretionary variables shows higher efficiency indices than the model with non-discretionary variables. Additionally, the efficiency analysis results, segregated by variety, origin, and fruit type, indicate that the selection of these segregations could be used to increase the production or generate higher efficiencies. Finally, the technological change in the same plant is analysed through the Malmquist index. The findings of this research could help improve the decision-making process of managers concerned with the efficient use of resources within the company.

Keywords: Performance; Productivity; Efficiency Analysis; Processed Food Industry; Dried Apples; Data Envelopment Analysis.

1. Introduction

Over the past few decades, the consumer demand for both fresh and processed food has increased substantially. It is interesting to note that what was once thought to be a choice of an elite who have the intellectual ability to grasp the importance of consuming healthy fresh products, today is becoming the choice of a larger category of the population.

Chile is well recognized internationally as one of the top fresh fruit suppliers. Considering the Southern Hemisphere alone, Chile is the leading shipper of fresh fruits, representing 59.3% of all fresh fruit exports from the region. Among exported fresh fruits we can find apples and fresh grapes which alone account for more than 50% of the total fresh

Chilean fruit exports (ProChile, 2012). According to the Food and Agriculture Organization of the United Nations, Chile's food exports have grown at an average annual rate of 10% over the past decade (USDA, 2013).

The generally accepted definition of *fresh food* describes these products as holding the same state as where they were harvested. We say generally accepted because the meaning of the term *fresh* is somehow always changing. Take, for example, the case of food that travels for weeks or even months all over the world in refrigerated containers: though months´ old, the food is sold in supermarkets under the label of *fresh*. In this context, it becomes imperative that we define three main aspects of *fresh*: (a) space: *Where* does the fresh food come from?, (b) time: *How long* has it been since the fresh food was harvested?, and (c) composition/material: *What* is there in the fresh food (chemical substances, special gases, wax, bacteria, dirt)?

Processed food, on the other hand, according to The United States Federal Food, Drug, and Cosmetic Act, Section 201, Chapter II, can be defined as "any food other than a raw agricultural commodity and includes any raw agricultural commodity that has been subject to processing, such as canning, cooking, freezing, dehydration, or milling". The parameters contained in this definition are used by the concerned authorities (*i.e.*, *Food and Drug Administration*) to regulate the quality and safety in the food processing industry in a market in which consumers of dried food are demanding not only products with a high nutritional value, but also with enhanced textural properties (Szczesniak, 1971). However, the optimization of the relevant parameters to achieve appropriate equilibrium between quality and safety continues to present major challenges in food processing. It is essential to point out that dried fruit is an important category of processed foods on the market with a worldwide annual production of 9.5 million metric tons in 2012, which represents a 13% increase with respect to the production in 2011 (International Nut and Dried Fruit Council, 2013).

In this context, it becomes relevant to discuss the issue of the food supply chains, especially given the fact that these are considered to be an important part of the global economy (Baldwin, 2012; Ghosh, 2010). A supply chain represents a sequence of activities established with the purpose of satisfying customers´ demands (Christopher, 2005) by delivering fresh products with the best quality possible (Tijskens, Koster, & Jonker, 2001).

The fresh food supply chain is a complex process due to the high volume, but also due to various attributes of the food products (Bourlakis and Weightman, 2004); as such, food has a perishable nature and there are high requirements for traceability and cost pressure (Opara, 2003). Moreover, concerns related to fragility and food security are constantly present on the international agenda (Cohen and Garrett, 2010). In fact, within food supply chains, there is a continuous quality change from the moment the raw material leaves the producer until the product is bought by the final consumer. Any activity established in the chain has a potential impact on the product, due to the interaction between the surrounding environment and the product itself (Apaiah, Hendrix, Meerdink, & Linnemann, 2005; Broekmeulen, 2001). This phase contributes considerably to the determination of the product's final cost as well as to the quality perceived by the consumer. Hence, this is a very important matter for the design and management of the distribution of the supply chain, for aiming to deliver a product at the precise moment, for ensuring the desired quality level, and for maintaining the product management costs (storage, refrigeration, etc.) as low as possible. Along with the above, the presence of the inevitable biological variability of products and the uncertainty, both of which affect some aspects of the management of the delivery process, make this phase even more complex (Dabbene, Gay, & Sacco, 2008).

The term Agri-Food Supply Chains (ASC) was generated to describe exactly the activities from production to distribution of agricultural or horticultural products (Aramyan, Ondersteijn, van Kooten, & Lansink, 2006). The ASC are formed by the companies responsible for the production (farmers), distribution, processing, and marketing of products to the final consumers (Ahumada and Villalobos, 2009). With the purpose of developing a mathematical model for this supply chain, each product can be considered as an "object" described by a dynamic model, which takes into account the physiological processes that occur in the same product. These processes are generally affected by the surrounding environmental conditions (e.g., temperature, humidity, etc.) that affect the product. At the same time, the products, by themselves, may affect the intermediate environment (Dabbene, Gay, & Sacco, 2008).

Given the importance of the Chilean dried-fruit market and the characteristics of the industrial process of dehydration, it becomes imperative for companies to measure the efficiency of their production processes in order to identify critical areas and take the necessary actions to improve them.

The subsequent sections of the paper are organized as follows. The next section contextualizes the supply chain of dried apples. Thereafter, the theoretical background is presented by means of introducing the Data Envelopment Analysis (DEA) models used for the efficiency and productivity change analysis. The succeeding section discusses the factors considered for the analysis, followed by the main results. The final section concludes the paper and provides managerial implications.

2. Contextualizing the supply chain of dried apples

In relation to the types of products and supply chains previously mentioned, the dehydration of food has certain particularities and high relevance for the Chilean market. In 2009, the exports of processed fruits and vegetables amounted to US$1,244 million, which includes preserved fruits (US$335 million), dried fruits and vegetables (US$452 million), frozen fruits and vegetables (US$275 million) and juices (US$182 million). Within the dried ones, apple exports reached 6.5% of the total, with an estimated amount of US$30 million approximately. In addition, the company in which the study was conducted covers around 43.0% of the total national exports (Chilealimentos, 2010); hence, the effect of any improvement implemented as a consequence of this work, would be notoriously amplified. In this context, Fig. 1 shows the major components of the supply chain of dried fruits and vegetables.

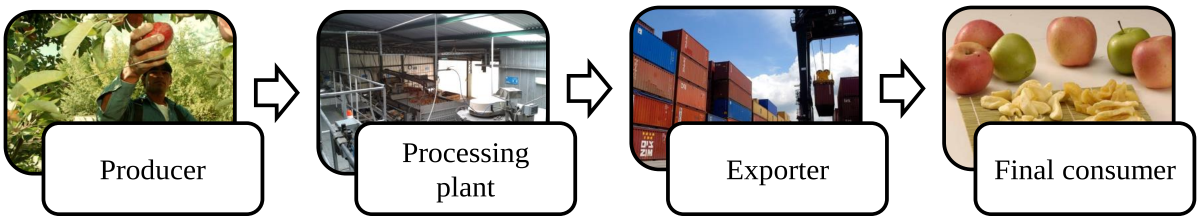

Fig. 1. Supply chain of dried apples.

The producer (farmer) is responsible for producing and providing fruits and vegetables that will be subsequently treated in the processing plant, in which the fruits will be received, selected, dried, packaged, and stored; so then, the final products, which are considered as ingredients for other companies, will be delivered to the exporter, who will be in charge of delivering these final products to consumers around the world, as shown in Fig. 2.

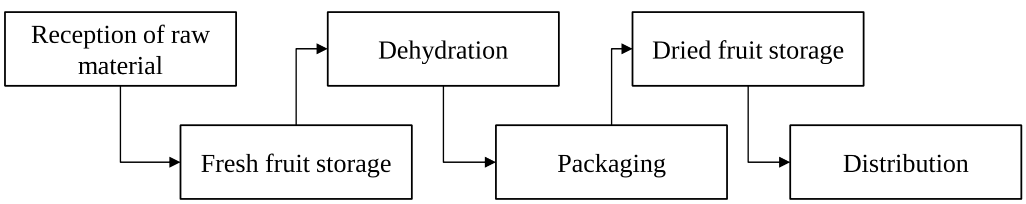

Fig. 2. Dehydration production process.

The technique of dehydration is probably the oldest food preservation method used by mankind. The removal of moisture prevents the growth and reproduction of microorganisms that cause putrefaction and diminishes many deteriorative reactions caused by the same. Also, there is a substantial reduction in weight and volume, which minimizes the packaging, storage, and transportation costs, allowing the storage of the product at a normal environmental temperature.

With regards to the mentioned process of dehydration, Fig. 3 shows the stages required for the production of apple cubes, which is the product most traded abroad by the national industry.

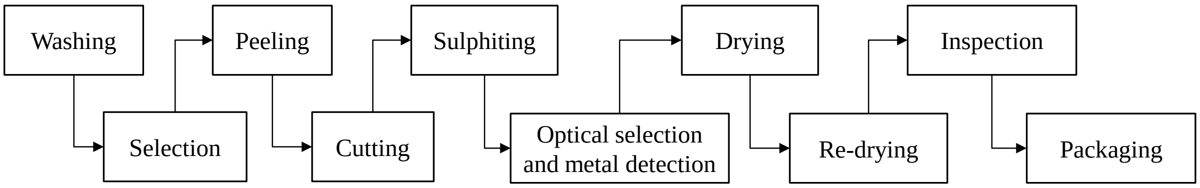

Fig. 3. Diagram of the production stages of apple cubes.

In the above figure, we can observe that the dehydration begins with washing. The apples considered for the process are washed with water and a solvent that allows the reduction of the bacterial load; then these apples are selected, in order to detect deteriorated fruits or fruits that do not meet the standard quality of the process. Subsequently, these apples are transported to the peeling operation, which is performed by two Atlas machines that are pre-configured for the type and size of the apples. These machines extract the skin and core of the apples, so their settings are crucial for the productive yield, because if one machine is set for smaller apples, this machine will extract more flesh than necessary, which could negatively affect the performance. After the apples are peeled, they must be cut to obtain the cubes, whose size is predetermined by the client; in this stage, it is desirable to have fruits with high pressure, so that the cut will be more accurate. Once the fresh fruits are cut and ready to go into the dryers, a bisulfite compound is spread over these fruits, which aims at stopping the oxidation of the fruits. This is called the Sulphiting process. Later, there is an optical selection, mainly by colour, and a metal detection; so then, they can go for drying, in which a series of continuous hot air ovens powered by steam are used. In this process, it is very important to control the fruit moisture before the entry and the time of the process, as these factors will affect the costs and quality of the final product. Then, if necessary, the apples go to a re-drying, which aims at reducing the fruit moisture between 3% and 5% approximately. Finally, the dried apple cubes are inspected and packaged.

Along with a strong increase in energy costs, the interest in drying techniques increases, too. Innovation techniques and the development of new methods have been made for a wide range of products, especially for instant reconstitutable ingredients, from fruits and vegetables with properties that might not have been seen before.

Despite the importance of the food sector, the management of the ASC has received little attention in the literature. The reason could be that this particular type of management is complicated given the specificity of the product or of the process characteristics. These characteristics often limit the possibilities to integrate the Supply Chain[1] in the ASCs (Van Donk, Akkerman, & Van der Vaart, 2008). Regarding the modeling approaches, the inclusion of specific characteristics of the food is necessary for the correct development of this area. One of the essential characteristics is to consider the quality of the products

[1] According to Van Donk et al. (2008, p. 218), the integration of the supply chain can be described "as the seamless flow of products and information from supplier on to customer".

through the supply chain (Aiying, Akkerman, & Grunow, 2011). Maintaining the high quality of the food, which is degraded depending on the storage and transport conditions (Labuza, 1982), is of vital importance to the performance of the supply chain. Besides being a performance measure by itself, the quality is directly related to other food attributes such as integrity, safety, and shelf life (Aiying et al., 2011). In this regard, Trienekens and Zuurbier (2008) argued that the quality assurance will dominate the production and distribution processes in future food chains. This also means that the flow of products with different quality attributes could be directed through different logistic channels of distribution (with different environmental conditions) and/or different consumers (with different demands for quality) in the supply chain. Indeed, one of the key aspects of the ASC is the integrated view of logistics and quality, which is called by Van der Vorst, van Kooten, Marcelis, Luning, and Beulens (2007) as "quality-controlled logistics". In this context, according to Trienekens and Zuurbier (2008), food products and production processes have a specific number of characteristics that influence the quality and quality assurance through the production process. For example, the production yields are often uncertain due to, among others, the surrounding environmental conditions and the variation of quality of the raw materials inside and among the production lots (Trienekens and Zuurbier, 2008). Hence, it becomes relevant to keep a track of the performance and productivity of the chain, either from a purely industrial standpoint or from a quality standpoint.

Most fruits and vegetables contain over 80% water and, therefore, have a high perishability. Water loss and the moderating account of their losses, which are estimated at more than 30-40% in developing countries, are due to improper handling, transportation, and storage of these fruits and vegetables. Besides physical and economic losses, there are serious losses which occur in the availability of essential nutrients, especially vitamins and minerals.

The necessity to reduce post-harvest losses of perishable horticultural products is very important for developing countries in order to increase their availability, especially in the current context, when the limitations on food production (land, water, and energy) do not stop from expanding. It is increasingly evident that the production of more and better food alone is not enough and should go hand in hand with appropriate post-harvest conservation techniques to minimize losses, thereby increasing the supply and availability of nutrients and giving an economic incentive to produce more. One of the main objectives of food processing is the conversion of perishable foods like fruits and vegetables into stabilized products that can be stored for long periods of time in order to reduce their post-harvest losses and, thereby, generate added value for the retailer. In turn, many process technologies have been used on an industrial scale to preserve fruits and vegetables; thus, the most important technologies are preservation, freezing, and dehydration. Among these, dehydration is especially suitable for developing countries with poor establishment of low temperature and thermal processing facilities. This provides a very effective and practical means of conservation in order to reduce post-harvest losses and compensate for the shortage of supply. The present study focuses on evaluating the efficiency of the dehydration process of apples.

Given the importance of the aforementioned market and the characteristics of the industrial process of dehydration, which is highly sensitive to the cost of energy, it is necessary to maintain a constant monitoring of the performance of the operations in order to maintain a stable evolution of the production to ensure that the production cost stays within the established ranges. Hence, a company needs to have information about the efficiency of the production process of its plant in order to identify critical areas and take the necessary actions to improve them. Thus, it is imperative for a company to know its benchmark processes, which can be used as a reference when its practices become inefficient.

To this end, the present paper performs an efficiency analysis considering the seasons between 2004 and 2010 for the production of dried apples in a plant of the Maule region. The method used to perform this efficiency analysis is DEA. The analysed situation involves performing two approaches for the analysis, in which, on the one hand, purely production factors are studied and, on the other hand, the incidence of the quality factors of fresh fruit on the dehydration process yields is studied. The analysis makes use of two types of models, the model without non-discretionary variables (Discretionary Model - DVM) and the model with non-discretionary variables (Non-discretionary Model - NDM). The main purpose is to find the best way to show two different strategic management situations. One situation assumes that the plant manager has control over some variables that impact fruit quality and the other situation assumes that he/she does not. These variables are “Caliber B”, “Turgor”, “Sugar Content”, and “Strong Bruise”. The comparison between both situations is done aiming to show the effect of the decision-making process on the production process performance, regarding the consumption of fresh fruit and the storage time.

3. Theoretical background

The different approaches to efficiency measurement can be divided broadly into two groups, namely frontier and non-frontier approaches. Each one can further be subdivided into parametric and non-parametric methods (Kumar and Charles, 2009, p. 75). The traditional non-frontier approaches to efficiency measurement are based on the assumption that the observed production in each period is equivalent to the efficient production, that is, the boundary of the technology is assumed to pass through the observed points. Thus, it ignores the distinction between two main sources of productivity growth, that is, technological change and technical efficiency change. Among the frontier approaches, the parametric (econometric) approach assumes an explicit functional form for the underlying production technology and is, thus, subject to specification errors. In addition, here the single optimized regression equation is assumed to apply to each decision-making unit (DMU). In contrast, DEA, originally pioneered by Charnes, Cooper, and Rhodes (1978), does not require any underlying functional form specification, but it enables one to obtain a maximal performance with the sole requirement that each DMU lies on or below the external frontier.

Hence, DEA is handy to use. This fact is reflected in the large amount of literature on theoretical developments and practical applications using DEA, which emerged after the publication of the first model (see, for example, Gattoufi, Oral, & Reisman, 2004; Tavares, 2002).

Nevertheless, the literature regarding the specific use of DEA to perform an efficiency analysis for the production of dried apples is very scarce. The few cases available include the study by Gul (2006), who estimated the technical efficiencies of apple production in Turkey, the study by Mousavi-Avval, Rafiee, and Mohammadi (2011), who analysed the efficiency of farmers, with an emphasis on the optimization of energy consumption and input costs for apple production in Iran, and the study by Wang, Huo, and Kabir (2013), who conducted a two-stage DEA to calculate the technical and cost efficiency of rural household apple production in China. A more general application, to the case of agriculture (which includes apple crops), can be found in the study by Atici and Podinovski (2015), who employed DEA to assess the technical efficiency of units with different specializations.

3.1. DEA models used in efficiency analysis

One of the assumptions in the efficiency analysis was that the dehydration process of a processing plant of fruits and vegetables may exhibit variable returns to scale (VRS), be it increasing, decreasing, or constant, depending on whether an increase of scale, up or down, of an observed maximum value for any input or output can be assumed possible or not. In part, this was due to the fact that at various stages of the process there is human intervention, such as the calibration of the peeling and cutting equipment, whose capacity varies depending on the fruit type and the settings predefined by the plant operating staff. Hence, any variation of the installed capacity of production or of the productivity does not always involve a proportional increase or decrease of the used resources. Thus, the suitable DEA model for this situation corresponds to the one developed by Banker, Charnes, and Cooper (1984), better known as the BCC model or VRS model. It is worth mentioning that the returns to scale reflect the degree to which a proportional increase in all inputs will increase the outputs.

In this efficiency analysis, an input-oriented DEA model was applied, as the quality of the raw materials is the main issue that can be controlled by the company and it could be very difficult to increase the dried kilograms if the wet kilograms have low quality. Thus, if the wet kilograms of the company have a better quality, it will use a lower quantity of raw materials to obtain dried kilograms. According to this, input-oriented DEA models aim at minimizing the input level while the output level is kept constant. The mathematical formulations of these models are presented below.

3.1.1. Input-oriented BCC-DEA model

For all DEA models, the relative efficiency of a given DMU (DMU_0) is calculated in relation to the performance of the *n* observed DMUs (including the analysed DMU), assuming that each DMU consumes m inputs $x_{i0},\ i \in M = 1,2,...,m$, to produce *s* outputs $y_{r0},\ r \in S = 1,2,...,s$. In the case of the input-oriented BCC-DEA model, the objective is to minimize the input level of the DMU_0 (DMU of interest), keeping constant its level of observed outputs and assuming VRS. Given these assumptions, the mathematical formulation for the epsilon form of the input-oriented BCC model in line with Banker, Charnes, and Cooper (1984) is as follows:

$$
\begin{aligned}
&(BCC_I)\ \text{Min}\ \theta - \varepsilon\left(\sum_{r\in S} s_r^+ + \sum_{i\in M} s_i^-\right) \\
&\text{Subject to: } \sum_{j\in N}\lambda_j x_{ij} + s_i^- = \theta x_{i0};\ i \in M\ ; \\
&\qquad \sum_{j\in N}\lambda_j y_{rj} - s_r^+ = y_{r0};\ r \in S\ ; \\
&\qquad \sum_{j\in N}\lambda_j = 1\ ; \\
&\qquad s_i^-,\ s_r^+,\ \lambda_j \geq 0;\ i \in M,\ r \in S,\ j \in N = 1,2,...,n\ ; \\
&\qquad \theta \text{ is unconstrained;} \qquad (1)
\end{aligned}
$$

where:

j – subindex of the set of observed DMUs,
i – subindex of the inputs,
r – subindex of the outputs,
θ – proportion by which all inputs can be reduced,
λ_j – intensity of the participation of the DMU_j in the construction of the "compound" DMU or benchmark,
x_{ij} – quantity of the input *i* consumed by the DMU_j,
y_{rj} – quantity of the output *r* produced by the DMU_j,
x_{i0} – quantity of the input *i* consumed by the DMU of interest (DMU_0),
y_{r0} – quantity of the output *r* produced by the DMU of interest (DMU_0),
s_i^- – input slacks,
s_r^+ – output slacks.

$y_{rj},\ x_{ij} \geq 0$ represent the observed values of the *s* outputs and *m* inputs, respectively, for every DMU of the total set.

In the BCC_I model, shown in system (1), the objective function minimizes the proportion of the input level of the DMU_0, represented by the variable θ, which can be used to produce at least the same output level. The constraint of the system (1) $\sum_{j\in N}\lambda_j x_{ij} + s_i^- = \theta x_{i0}$ guarantees the proportional reduction of inputs until it reaches the efficient frontier. The constraint of the same system $\sum_{j\in N}\lambda_j y_{rj} - s_r^{+} = y_{r0}$ prevents the compound DMU from producing fewer outputs than DMU_0. Finally, the constraint $\sum_{j\in N}\lambda_j = 1$ is known as the convexity restriction, which ensures that inefficient DMUs could only be compared with DMUs that produce a similar output level to them. Hence, the compound DMU is obtained through a convex linear combination of the observed DMUs.

The selection of the non-Archimedean epsilon values plays vital roles in System (1) due to the known fact that some difficulties arise when selecting the infinitesimal because of finite tolerances in computer calculations. Mehrabian, Jahanshahloo, Alirezaee, and Amin (2000) and Amin and Toloo (2004) presented procedures to choose the non-Archimedean epsilon values; recent packages started incorporating this fact into their codes.

According to Coelli, Prasada Rao, and Battese (1998), for the majority of DEA applications, the model used in the efficiency evaluation is the BCC-DEA model. The reason behind is that the majority of production processes operate with VRS.

Given the characteristics of the studied process, there are variables that cannot be changed or controlled by the decision maker, such as those related to the quality or the effect of fruit variety on industrial performance. Hence, the need for incorporating models that evaluate the efficiency, considering non-discretionary variables (NDVs), arises. Below, the input-oriented BCC-DEA model with non-discretionary variables (NDM) is presented.

3.1.2. Input-oriented BCC-DEA model with non-discretionary variables

According to the aforementioned DEA models, these use inputs and outputs that can be modified by the decision maker. However, what happens in a study situation when there are variables, either inputs or outputs, which cannot be modified or are exogenously handled from the reach of the decision maker but that to some extent are relevant for measuring the efficiency? Formally, in the case of the models which were mentioned in the previous subsection, these use discretionary variables (DVs). On the other hand, NDVs refer to variables, inputs or outputs, which cannot be discretionally modified by the decision maker. The authors, Banker and Morey (1986), wrote an article in which they used input- and output-oriented DEA models considering exogenously determined variables or NDVs. In this subsection, we present the mathematical formulation of the NDM.

In line with the input-oriented model presented in the previous subsection, the mathematical formulation with input orientation and NDVs is as follows:

$$\text{Min } \theta - \varepsilon\left(\sum_{r\in S} s_r^{+} + \sum_{i\in M} s_i^{-}\right)$$

Subject to: $$\sum_{j\in N}\lambda_j x_{ij} + s_i^{-} = \theta x_{i0};\ i \in D\ ;$$

$$
\begin{aligned}
&\sum_{j\in N}\lambda_j x_{ij} + s_i^- = x_{i0};\, i \in ND\ ;\\
&\sum_{j\in N}\lambda_j y_{rj} - s_r^+ = y_{r0};\, r \in S\ ;\\
&\sum_{j\in N}\lambda_j = 1\ ;\\
&\lambda_j \geq 0;\ j \in N\ ;\\
&s_i^-,\ s_r^+ \geq 0;\ i \in M,\ r \in S\ ;\\
&\theta\ \text{ is unconstrained.} \qquad (2)
\end{aligned}
$$

where the set *M* is the union of *D* and *ND*.

Productivity and efficiency are related but different concepts (Pérez-Reyes and Tovar, 2009, p. 2252). According to Coelli, Prasada Rao, O'Donnell, and Battese (2005) productivity is essentially a level concept and its measurement can be used to compare the performance of companies or certain units, from a point of view. By contrast, the change in productivity refers to shifts in the productivity performance of the same unit or company through time.

However, the proposed measurement of efficiency in this paper considers homogeneous situations between two or more units of measurement. Leaving aside situations in which a technological change occurs.

In recent years, the measurement of productivity change has generated a great deal of interest among researchers who study the performance and behaviour of firms. In this framework, the Malmquist index was first introduced to the productivity literature by Caves, Christensen, and Diewert (1982). Färe, Grosskopf, Lindgren, and Roos (1994) decomposed the productivity change into technical efficiency change and technical change, and used non-parametric mathematical programming models for its calculation. Thus, with the decomposition of the Malmquist index, we can easily deduce that technical efficiency is only one of the factors that determine productivity (Pérez-Reyes and Tovar, 2009, p. 2252).

It is possible to calculate the envelopment, *i.e.*, the measure of relative efficiency, provided that the optimal production function does not change; this implies that there is not a significant change that alters the nominal capacity of a production system. However, if the company purchases a new machine, or a conveyor belt, etc. (*i.e.*, improves its capabilities), the framework conditions for the measurement of productivity vary, implying that the measurements of efficiency will be significantly different. In this case, it is most likely that the measurement of efficiency presented above lacks of objectivity, because different technologies are involved. This lack of objectivity of DEA is also because DEA results "are highly sensitive to the presence of outliers, since the frontier is constructed from existing observations within the sample used" (Latruffe, Fogarasi, & Desjeux, 2012, p. 3), and because these outliers could be caused by a technology change, which could change the frontier production function estimated by means of DEA. Hence, productivity change requires to be measured, as we know that a technological change occurred in 2007 (*i.e.*, a machinery renovation in the plant) and because the efficiency analysis with DEA models cannot measure, by separate, the effect of a technological change.

3.2. Malmquist productivity change index

The Malmquist productivity change index was introduced by Caves, Christensen, and Diewert (1982), inspired by the work of Malmquist (1953), and its objective is to measure the productivity change between two time periods.

By examining the changes between two time periods, we can have two production technologies for setting the comparison: from the initial time period and from the final time period. Hence, it is possible to obtain two productivity indexes according to the assumed technology. Färe, Grosskopf, Lindgren, and Roos (1992) constructed a DEA-based Malmquist index, which corresponds to the geometric mean of these two productivity indexes.

Unlike other approaches for measuring productivity, Malmquist index also provides information on the origin of the productivity change through the decomposition of this index into two components: one of technical change and another of efficiency change. The first one includes the variation due to the shift of the efficient frontier, so it expresses the degree to which the analysed unit has experienced a technical change. The second expresses the variation attributable to the improvement of the relative performance of the unit with respect to the improvements in each time period, that is, the analysed unit has experienced an efficiency change.

3.2.1. DEA-based Malmquist productivity change index

Let us assume that there is a production function at time t and another one at time t + 1. For a given DMU_0, the calculation of its respective Malmquist index requires: two measurements obtained from the observations made separately in each time period and two measurements obtained from the mixture of the observations made in each time period. Thus, the input-based Malmquist productivity index proposed by Färe, Grosskopf, Lindgren, and Roos (1992), which measures the productivity change for a given DMU_0 between time period t and t + 1, is given by:

$$M_0 = \left[\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^t, y_0^t)} \right]^{1/2} \tag{3}$$

where:

$D_0^t\ x_0^t, y_0^t$ corresponds to the measure of technical efficiency of the DMU_0 in time period t, which is obtained by using the observations of all DMUs in time period t, that is, $D_0^t\left(x_0^t, y_0^t\right) = \theta_0^t$;

$D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)$ corresponds to the measure of technical efficiency of the DMU$_0$ in time period t + 1, which is obtained by using the observations of all DMUs in time period t + 1, that is, $D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right) = \theta_0^{t+1}$;

$D_0^{t}\left(x_0^{t+1}, y_0^{t+1}\right)$ corresponds to the measure of technical efficiency of the DMU$_0$ obtained by replacing the data of DMU$_0$ in time period t with the same data in time period t + 1, while the observations of the rest of DMUs have been made in time period t;

$D_0^{t+1}\left(x_0^{t}, y_0^{t}\right)$ corresponds to the measure of technical efficiency of the DMU$_0$ obtained by replacing the data of DMU$_0$ in time period t + 1 with the same data in time period t, while the observations of the rest of DMUs have been made in time period t + 1.

In the case that $M_0 > 1$, it is assumed that the DMU$_0$ is more productive in relation to the initial period. This increase in the relative productivity of DMU$_0$ could be due to different causes. On one hand, it is possible that DMU$_0$ has improved its relative efficiency. On the other hand, it is possible that the available technology has been improved.

Färe, Grosskopf, Lindgren, and Roos (1992) proposed a decomposition of the Malmquist index which allows us to separate it into two terms, both related to the sources of productivity change:

$$M_0 = \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t}(x_0^{t}, y_0^{t})}\left[\frac{D_0^{t}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}\,\frac{D_0^{t}(x_0^{t}, y_0^{t})}{D_0^{t+1}(x_0^{t}, y_0^{t})}\right]^{1/2} \tag{4}$$

where:

$\Delta EF_0^{t,t+1} = \dfrac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t}(x_0^{t}, y_0^{t})}$ measures the technical efficiency change of DMU$_0$ between time period t and t + 1, and $\Delta T_0^{t,t+1} = \left[\dfrac{D_0^{t}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}\,\dfrac{D_0^{t}(x_0^{t}, y_0^{t})}{D_0^{t+1}(x_0^{t}, y_0^{t})}\right]^{1/2}$ measures the technological change of DMU$_0$ between time period t and t + 1.

$\Delta EF_0^{t,t+1}$ reflects the change that has occurred in the relative efficiency of the DMU (variation in the distance that separates it from its current frontier), while $\Delta T_0^{t,t+1}$ reflects the productivity change that can be attributed to the shift of the frontier between time period t and t + 1. Hence, the index of technical change measures the shift of the frontier caused by the evaluated DMU (defined as a geometric mean in order to avoid choosing an activity level).

4. Factors considered for the analysis

The efficiency analysis performed for the dehydration process of apples considered each production lot produced in the season of 2010 as a DMU. Because each variety requires a different treatment, it is not possible to consider the processed lots of different varieties of apples as homogeneous. Specifically, this is due to the fact that these varieties have different organoleptic, quality, and origin characteristics and, hence, they show different behaviours during the process. For this reason, an efficiency analysis by variety, origin, and type of processed apple was made. Table 1 depicts the number of DMUs analysed by variety, origin, and type.

Table 1
Number of DMUs analyzed by variety, origin, and type

Segregation	**Variety**		**Fruit Origin**		**Fruit Type**	
	Fuji	**Granny Smith**	**Orchard**	**Packing Plant**	**Ordinary**	**Organic**
Nº of Analyzed Lots	660	700	637	1131	205	660

Segregations by variety, origin, and fruit type were conducted for the efficiency analysis. Regarding the segregation by variety, the varieties named as Fuji and Granny Smith were used; this happens because these are the main varieties used for the production of dried apple cubes; additionally, they have different industrial performances and agronomic characteristics. Regarding the segregation by origin, it is interesting to analyse this factor because the fruit, either from the packing plant or from the orchard, has different treatments and, mainly, storage times. The latter could affect the quality of the final product because, the longer the storage time, the higher the sugar content of the fruit or the lower the turgor of the fruit (more likely to be damaged).

On the other hand, the segregation by fruit type, either ordinary or organic, could affect the caliber or size, the sweetness, or other agronomic characteristics of the fruit that, finally, could affect the industrial performance and, thus, the efficiency of the entire production process of the dried apple. For analytical purposes, we have used at least 205 DMUs or lots in the case of the ordinary fruit, and at most 1131 DMUs in the case of the fruit from the packing plant.

Regarding the above table, for a better analysis and representation of the current situation of the company, we conducted a segregation of the data with respect to the variety, fruit origin, and fruit type.

Additionally, in order to evaluate the efficiency of each lot, we considered six inputs and one output for each studied segregation.

The inputs used in the analysis were as follows:

Storage: Corresponds to the period of time, in days, in which the fruit remained in the cellars of controlled atmosphere.

Caliber B: This variable corresponds to the percentage of fruit which has a Caliber B size within a quality sample of a production lot.

Turgor: This variable corresponds to the average pressure in the fruit, measured in pounds, within a quality sample of a production lot.

Sugar content: This variable represents the degree of average sweetness at which the apple arrives before entering the process, measured in degrees Brix, within a quality sample of a production lot.

Strong bruise: This variable corresponds to the percentage of fruit which shows bruises before entering the process, within a quality sample of a production lot.

Wet kilograms: Corresponds to the total number of fruits which enter the process, measured in kilograms, of a given lot.

The identified output in the study was:

Dried kilograms: This variable represents the total number of dried apples, measured in kilograms, at the end of the overall process.

For this case, the variables explained above have been included because of their practical relevance. Each of these corresponds to a performance indicator of the control operations from the major dried food companies. While some of these represent agronomic characteristics, like raw materials, and others represent operational characteristics, there is a direct relationship between them. For example, when the storage time increases, then the fruit quality decreases and, thus, the fruit turgor decreases, affecting the peeling and cutting processes. Also, some of these variables were selected from statistical studies carried out by the research department of the company which provided the data.

According to the incorporation of these variables into the models presented above, all of them were used as DVs in the DVM. For the NDM, only the variables “Caliber B”, “Turgor”, “Sugar Content”, and “Strong Bruise” were considered as NDVs; this happens because the main objective was the comparison of the current situation against a new proposal, which requires changes in the decision making process.

The following section presents a summary of the main results obtained after applying the models defined in the theoretical background section.

5. Main results

5.1. Comparisons between DVMs and NDMs and recognition of the improvement sources

In this subsection, Tables 2, 3, and 4 present the efficiency analysis results, segregated and explained by factor. These tables show the comparisons between DVMs and NDMs (current situation). For these tables, on one hand, all the inputs were used as DVs in the DVM and, on the other hand, only the variables “Caliber B”, “Turgor”, “Sugar Content”, and “Strong Bruise” were considered as NDVs in the NDM.

Table 2
Main results of the efficiency analysis by fruit variety.

Variety	NDM			DVM		
	N° of Efficient Lots	**Average Efficiency (%)**	**Coefficient of Variation (%)**	**N° of Efficient Lots**	**Average Efficiency (%)**	**Coefficient of Variation (%)**
Fuji	63	80.95	20.87	64	92.48	7.37
Granny Smith	76	66.69	26.50	87	89.07	7.65

In the above table, for both models, we can observe that the lots, which processed the variety named as Fuji, obtained higher average efficiency, lower quantity of efficient lots, and, thus, lower coefficient of variation, which indicates that there is a more homogeneous behaviour of the lots around the average efficiency. However, if we analyse both varieties by model, the DVM reaches higher efficiencies. The latter indicates that if the company had considered within its decision-making process some efficiency analysis and fruit segregation, by factor analyzed in this research, it could have improved its operational performance.

Similarly, Table 3 shows the results of the efficiency analysis by fruit origin. In this case, the efficient lots and the coefficient of variation have increased, however, the average efficiency has decreased. As in the previous case, the DVM shows the best performance of the process, so that the efficiency analysis and the segregation by fruit origin would allow to increase the average efficiency by at least 30% and have a coefficient of variation less than 9%, which means that the lots could improve their performance and perform homogeneously. In this situation, the average efficiency is 89% approximately.

Table 3
Main results of the efficiency analysis by fruit origin.

Origin	NDM			DVM		
	N° of Efficient Lots	**Average Efficiency (%)**	**Coefficient of Variation (%)**	**N° of Efficient Lots**	**Average Efficiency (%)**	**Coefficient of Variation (%)**
Orchard	81	57.34	37.56	89	88.32	8.04
Packing Plant	86	58.89	39.40	95	88.98	8.36

Finally, Table 4 shows the results of the efficiency analysis by fruit type, either ordinary or organic. In this case, the DVM (variables modified by the decision maker) achieves the highest efficiency. This is relevant because an organic orchard requires special treatment and, therefore, generates fruits with different agronomic characteristics, such as sweetness, size, or pressure.

Table 4
Main results of the efficiency analysis by fruit type.

Type	NDM			DVM		
	N° of Efficient Lots	Average Efficiency (%)	Coefficient of Variation (%)	N° of Efficient Lots	Average Efficiency (%)	Coefficient of Variation (%)
Ordinary	113	51.43	44.70	137	87.60	8.59
Organic	56	79.19	22.35	56	92.33	7.28

In conclusion, whichever the factor is, the situations in which the decision maker can make changes, *i.e.*, DVMs, suggest higher levels of efficiency. The following figure presents the potential goals suggested by the efficiency analysis in order to achieve the relative efficiency for the overall segregations.

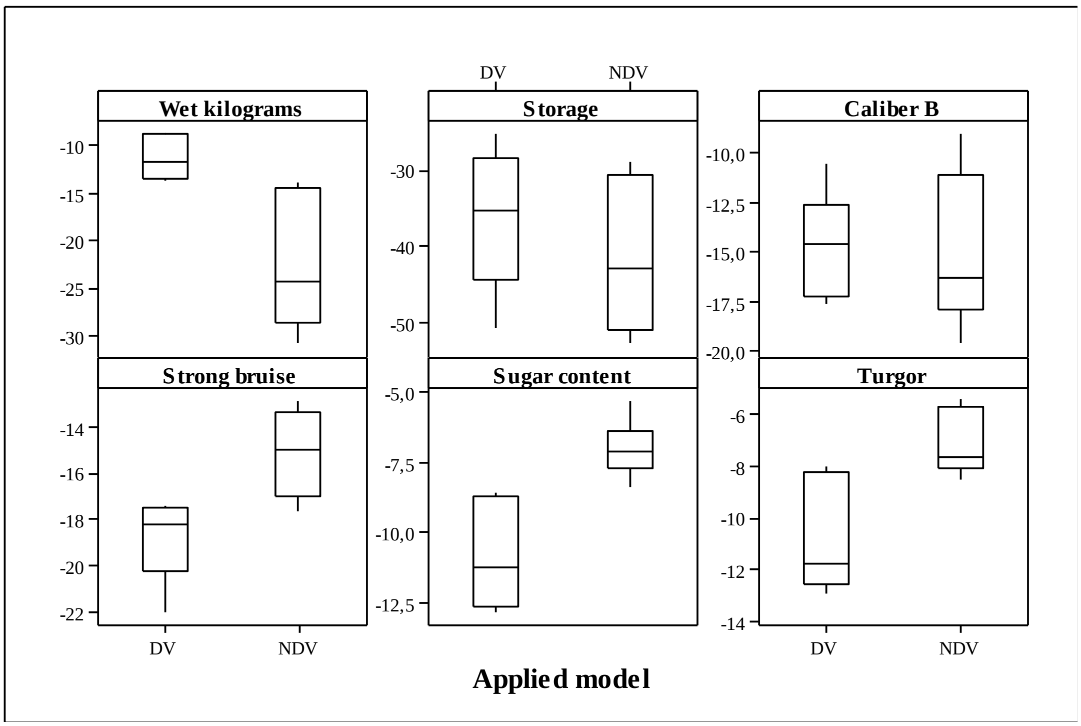

Fig. 4. Goals of resource reduction: average values in percentage for the overall segregations.

Fig. 4 shows a comparative analysis of the goals of resource reduction for every variable considered in the efficiency studies. In this case, the results were averaged according to the model utilized, either NDM or DVM[2], because the aim of this research is to show the effect of the decision-making process on the production process performance. Hence, in the case of fresh fruit consumption (wet kilograms), the gap between the current

[2] For Fig. 4, on one hand, all of the inputs were used as DVs in the DVM and, on the other hand, only the variables "Caliber B", "Turgor", "Sugar Content", and "Strong Bruise" were considered as NDVs in the NDM.

consumption and the efficiency goal is lower for the DVM, as it can be reduced, on average, by 12%. In the case of the storage time variable (storage), the goal indicates an average reduction of 35% for the DVM. Thus, both variables are very important for the production process, because they represent the highest costs for this kind of companies. This is very important because the cost of a ton of fruit stored in an external warehouse is 11.0 US$/month approximately. In general, an averaged dried apple company maintains its fresh fruit stored for approximately 6 months (*i.e.*, 66.0 US$/ton). Hence, a reduction of 3.8 US$/month means a potential saving of 23.1 US$/year per ton of fresh fruit, approximately.

According to the NDM in Fig. 4, the “Storage” variable shows the highest potential improvements, *i.e.*, an average reduction of approximately 40% in the storage time, for the overall segregations. Additionally, the consumption of fresh fruit, represented by the “Wet kilograms” variable, can be reduced by approximately 23%, considering the average value for the overall segregations. Hence, according to the obtained data, this model could get a reduction of 4.4 US$/month, which means a potential saving of 26.4 US$/year per ton of fresh fruit, approximately.

In consequence, although the NDM gives higher potential savings for the variables “Storage” and “Wet kilograms” (variables which represent the highest costs for this kind of companies), it is more important to consider the results of the average efficiencies, in order to determine the most appropriate model for the operations management of the dehydration plant; because the average efficiencies are applied to the overall model, while the potential savings are applied only to some variables.

Additionally, the results obtained with respect to the improvements in the use of resources employed for the process of apple segregation are summarized in Fig. 5. In this figure, we show the average percentage reduction of inputs (Storage, Caliber B, Turgor, Sugar content, Strong bruise, and Wet kilograms); so the inefficient lots can achieve the efficiency, according to the segregation of the processed fruit and considering the average values between DVMs and NDMs.[3]

[3] For Fig. 5, on one hand, all of the inputs were used as DVs in the DVM and, on the other hand, only the variables “Caliber B”, “Turgor”, “Sugar Content”, and “Strong Bruise” were considered as NDVs in the NDM.

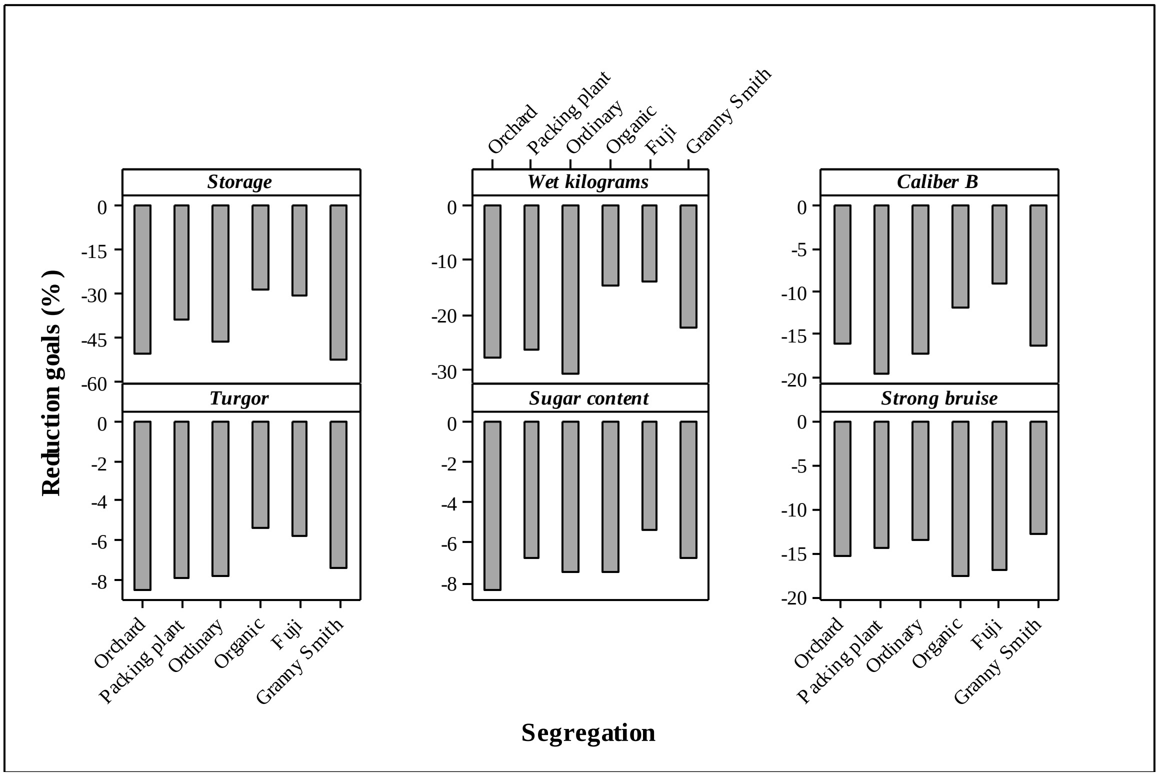

Fig. 5. Estimated percentage reductions for inputs by fruit segregation: average values between DVMs and NDMs.

According to Fig. 5, the main goals of resource reduction are related to the variables "Storage" and "Wet kilograms", reaching values of up to 50% and 30%, respectively. This is very interesting because those factors can be directly controlled by the decision maker and, thus, can improve the operations management; they can also promote and improve competitiveness, from a resource point of view.

5.2. Analysis of the impact of technological change

Based on the efficiency analysis, we found potential improvements in relation to variables associated with production and agronomic decisions. Thus, the efficiency analysis provides to the decision maker potential areas for improvement, which allows achieving the efficient frontier. Similarly, this type of calculation methodology can be used to study the effect of a technological change on the productivity. In this case, the company in which the research was conducted made some changes in the production system. In the following table, we present the results of the analysis of technological change, through the Malmquist index, specifically by using the Total Factor Productivity change and considering the overall segregations as an aggregated data set, *i.e.*, we have not considered any distinction between segregations. A value of less than 1 of the Malmquist index and of any of its components implies a deterioration in the performance, whereas a value greater than 1 implies an improvement in the relevant performance (Kumar and Charles, 2009, p. 78).

Table 5
Results of the analysis of technological change using the Malmquist index methodology.

Time Period	Technical Efficiency Change	Technological Change	Pure Technical Efficiency Change	Scale Efficiency Change	Total Factor Productivity (TFP) Change
2004 - 2006	0.910	0.870	0.973	0.935	0.792
2004 - 2010	1.017	1.009	1.013	1.003	1.025
2006 - 2010	1.117	1.180	1.041	1.073	1.317

The analysis of technological change was made using the DEAP V2.1 software and the DMUs were considered to be the lots aggregated between March and September of each year. Additionally, this analysis used the variables, on one hand, "Dried kilograms" as the output and, on the other hand, "Wet kilograms" and "Labor" as the inputs; considering only the DVM. The experiments were conducted in the periods 2004-2006, 2004-2010, and 2006-2010. The most significant change in the productivity was obtained in the period 2006-2010 (1.317). Specifically, the TFP in experiment 1 was 0.792, in experiment 2 was 1.025, and in experiment 3 was 1.317. The results give a positive gesture, because the decision to make improvements to the process was taken in 2006 and these improvements[4] began to be implemented in 2007. Hence, according to the obtained indicators, we can say that the most relevant change, which had an effect on the productivity, was generated between 2006 and 2010. Furthermore, in the period 2006-2010, the technological change contributed to the TFP change more than the pure technical efficiency change and the scale efficiency change.

Similarly, to the aforementioned analysis, we found that the highest growth in the productivity was obtained in the month of July, in the period 2006-2010.

Table 6
TFP change by month and time period.

Month	2004 - 2006	2004 - 2010	2006 – 2010
March	0.916	1.010	1.117
April	0.905	0.938	1.058
May	0.868	1.008	1.276
June	0.774	1.028	1.319
July	0.641	1.082	1.684
August	0.687	0.985	1.427
September	0.794	1.138	1.441

As it has been indicated previously, the production process of dried apples is cyclic, because it increases in the first trimester of the year and reaches its peak at the beginning of the third trimester. By observing the values in the above table, a positive variation can be

[4] These improvements are related to changes in the production lines on a technical level, including machinery renovation and a new selection process of the fruit.

seen in the TFP, as this indicator achieves the best values in the referred periods. Hence, this could mean that the modified production system was gradually adjusting to the changes, as it achieves better returns and operational results at the end of the period.

6. Conclusions

DEA models have been proven to be a reliable, flexible, and efficient tool in measuring the performance of the dehydration process. This work examines two input-oriented BCC-DEA models, with DVs and NDVs. Thus, the NDM provides the technical efficiency measurement in the current decision process of the company, while the DVM provides the measurement in a proposed strategic decision process. The information obtained from both models helps managers to identify the inefficient lots and helps to take the corrective actions in order to continue the improvement.

Through the BCC-DEA models, it was possible to: calculate an efficiency measure for each processed lot, identify the efficient lots, and provide benchmarks for the inefficient lots according to the segregation or classification performed. This fact is highly relevant for a company, as it allows to determine the possible causes of inefficiencies and to estimate the possible improvements in the use of resources.

In general, irrespective of fruit segregation (variety, origin, or type), the application of the DVM shows better results, higher efficiency indices, and lower variability coefficients than the NDM. However, regardless of fruit origin, the production process reaches similar efficiency levels with both models. This information could help solve bottlenecks in the buying process and improve the logistics process. Additionally, processing organic apples allows higher efficiency levels than processing ordinary apples. This result could be used to promote the consumption of the organic apple varieties in the dehydration process, and to increase the commercial prices of products labelled as organic.

Considering the efficiency analysis for the overall segregations (as an aggregated data set), it could be observed that the relative efficiency frontier obtained by applying a DVM is higher, by approximately 13%, than the relative efficiency frontier of the current situation, which is represented by a NDM. This implies that a change in the decision process, either in the selection of the fruit or in the setting process of the machinery, could allow a cost reduction. At the same time, according to the DVM in Fig. 4, we have found potential reductions in the storage time, by approximately 35%, which results in savings and better efficiency levels.

Additionally, by analysing the results obtained through the input-oriented BCC-DEA model, showed in Tables 2, 3, and 4, we can observe that the lots involved in the production process of the Fuji apple variety and of the organic apples showed a greater average of technical efficiency with 92.48% of average efficiency, followed by the organic fruit with 92.33%. It is interesting to note that these lots show segregations and a low dispersion in the efficiency, which indicates that the analysed sample had a homogeneous performance with respect to the production levels. On the other hand, the least efficient lots were related to the ordinary fruit and the fruit from the orchard, which showed average efficiencies of 87.60% and 88.32%, respectively. We can observe that although the efficiency is below the best practices, the efficiency dispersion and the number of efficient lots is similar to those of the lots with better performance.

As initially stated, in this research we analysed two situations related to the production process management and their impact in the operational efficiency. The results indicate that variables related to fruit characteristics are relevant for a better efficiency of the dehydration process, which has an impact on the reduction of fuel costs and fresh fruit consumption per kilogram of dried product. For this reason, it was found that the longer the storage time of the fresh fruit, the worse the quality indicators of the fruit at the beginning of the process, negatively affecting the efficiency results of the production.

According to this research, a manager could use these methodologies and results to promote better practices within the decision making process, regarding the consumption of fresh fruit or the storage time; also, the selection of these segregations could be used to increase the production or generate higher efficiencies. Hence, we can say that the DVM is the most appropriate model for the operations management of this dehydration plant of apples, because it reaches the highest efficiencies.

In this paper, we also analyzed the impact of technological change in the same plant, through the Malmquist index, and we found that the most relevant change, which had an effect on the efficiency, was generated between 2006 and 2010. Furthermore, in this period, the technological change contributed to the TFP change more than the pure technical efficiency change and the scale efficiency change. Also, we found that the production process of dried apples is cyclic, because it increases in the first trimester of the year and reaches its peak at the beginning of the third trimester.

Given the utility of the results obtained through the DEA models, the management of the company has implemented this methodology in the processing plant of apples and furthermore plans to extend this type of efficiency analysis to the rest of the plants in the company.

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