MEASURING AND IMPROVING THE ECO-EFFICIENCY USING DATA ENVELOPMENT ANALYSIS. A CASE STUDY OF MAHON-MENORCA CHEESE

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Keywords: Cost assessment, Data Envelopment Analysis, Life Cycle Assessment, price simulation**,** scenario building

Summary

The concept of eco-efficiency can be defined by using the "product value/environmental influence" ratio. Different models have been proposed to measure eco-efficiency. The main difference among them is the weighting system used to aggregate the environmental results. Data Envelopment Analysis (DEA) permits this aggregation without requiring a subjective judgment about the weights. In this study, a DEA model was applied to Spanish Mahón-Menorca cheese production to determine the most eco-efficient production techniques.

To this end, 16 scenarios of Mahón-Menorca cheese production were built regarding technical (degree of automation) and cleaner production criteria. The environmental impacts were assessed by means of the Life Cycle Assessment. An economic assessment was carried out by determining the economic value added and the net income for each scenario. The results are referred to as 1 kg cheese ripened over 105 days. By using DEA, an eco-efficiency ratio lying between 0 and 1 was obtained. Three scenarios were found to be eco-efficient, using a high degree of automation (enclosed vat and molding and demolding machines) and accelerated cheese ripening.

The Montecarlo simulation was used to carry out a sensitivity analysis to compare the influence of price changes on the eco-efficiency ratio. The results emphasized the consistency and stability of the eco-efficient scenarios.

<heading level 1> **Introduction**

According to the results from a study financed by the European Union (EU), one of the product groups with the highest environmental impact throughout its entire life cycle is foods, especially dairy and meat products (Tukker et al. 2006). For this reason, food production systems need to be rethought in order to be more environmentally friendly. The food industry is one of the main contributors to discovering new solutions and, therefore is highly relevant. In this context the role of cleaner production techniques must be emphasized since they have a pro-active focus instead of a reactive one. They have the potential to reduce emissions and waste produced in the production process and, consequently waste treatment. Nevertheless, establishing the best available techniques requires that not only the environmental aspects, but also the economical ones, be taken into account. The eco-efficiency concept embraces these two aspects.

Eco-efficiency of production concerns the capability to produce goods and services while causing minimal environmental degradation. According to World Business Council for Sustainable development (WBCSD 2000), eco-efficiency is represented by the ratio "Product or service value/Environmental influence".

Kuosmanen and Kortelainen (2005) consider the eco-efficiency concept to be critically important for at least two reasons: (1) it is often the most effective way of reducing environmental pressures; (2) policies targeted at efficiency improvements tend to be easier to adopt than policies that restrict the level of economic activity. The eco-efficiency concept and the search for eco-efficient processes are justified by the need to reach a positive environmental objective at a micro-economic level, either by means of public policy or by means of instructions or demonstrations to people and firms. An eco-efficiency analysis makes it possible to set priorities in purchasing decisions and can be used to show optimization potentials in product development processes (Rüdenauer et al. 2005).

Although the eco-efficiency concept is well defined, it is not easy to quantify and different models have been proposed to measure the eco-efficiency of processes (Saling et al. 2002; Hellweg et al. 2005; Korhonen and Luptacik 2004; Kuosmanen and Kortelainen 2005; Nieuwlaar et al. 2005; Rüdenauer et al. 2005; Lauwers 2009). The aggregation of the results of the impact categories into a single environmental damage index is a challenge of eco-efficiency measurement (Tyteca 1996). The aggregation can be carried out in two generic ways, either on the basis of a specific weighting method, or by the "expert judgment" of the decision makers (Rüdenauer et al. 2005). Data Envelopment Analysis (DEA) has been proposed as a method for aggregating the impact categories to construct an eco-efficiency index. The first proposal of aggregation using DEA to quantify eco-efficiency according to its definition (Economic value added/Environmental damage) comes from Kuosmanen and Kortelainen (2005). Nevertheless, DEA models have been widely applied to integrate undesirable outputs in measuring the technical efficiency of productive processes.

Färe and colleagues (1989) are the first to show the importance of including undesirable outputs in efficiency analysis, finding that efficiency rankings turned out to be very sensitive to whether or not undesirable outputs were included in DEA models. Färe and colleagues (1996) build an environmental performance indicator using a pollution index and a productive efficiency index to measure the environmental performance of electric utilities. Tyteca (1996) shows several ways to measure environmental efficiency that include undesirable outputs. Among them, two ratios to minimize defined as "undesirable outputs/(outputs-inputs)"and "(inputs+undesirable outputs)/outputs", and a third ratio with undesirable outputs in the numerator and a quantity measuring the firm's activity in the denominator. Scheel (2001) analyzes different approaches to model undesirable outputs and builds an example comparing the different efficient frontiers. He shows three alternatives to model undesirable outputs: as negative outputs (output<0), as inputs, and as outputs using the inverse of undesirable outputs. Korhonen and Luptacik (2004) use several DEA models to analyze the eco-efficiency of power plants. Their modeling of undesirable outputs is similar to Tyteca (1996) and Scheel (2001).

Dyckoff and Allen (2001) say that ecological efficiency is usually measured comparing environmental performance indexes. In this context DEA has great potential because it allows different indexes to be aggregated avoiding explicit weights.

Food production processes should be concerned in the search for eco-efficiency. In this context, the Kuosmanen and Kortelainen model for measuring eco-efficiency (2005) is applied to food processing systems.

The model integrates both the economic results of the production process and its environmental impact in an eco-efficiency index. This model has been applied to Mahón-Menorca cheese production in order to determine the most eco-efficient production techniques. Specifically, sixteen production scenarios were measured using the economic result of the production process and the related environmental impacts, assessed through the Life Cycle Assessment (LCA). Both kinds of measurements are integrated in an eco-efficiency (EE) ratio through a model of weight estimation based on DEA. DEA provides different weights for each evaluated scenario.

<heading level 1> **Methodology**

This methodology begins with the definition of the goal and scope of the study. The next step is to perform an economic assessment of the production process by means of an economical result function, then an environmental assessment is carried out by using LCA. Finally the results of the two assessments are aggregated by means of DEA.

Classical applications of DEA examine decision making units (DMU), that is, autonomous production units (firms or production plants or departments) whereas LCA works with a functional unit that reflects different ways of manufacturing a product by considering its environmental impacts. The applied model in this study comes close to the latter approach and hence differs from usual DEA approaches and from the original work by Kuosmanen and Kortelainen (2005). The applied model is based on 16 scenarios, with each scenario representing a way of making a product using different combinations of inputs, generating different impact categories, and obtaining a different net income. Studying actual production plants provides access to data of production processes over long periods of time and thus average consumption and costs are more reliable and variability estimations can be made. However, plants often produce several products and the age and use of equipment varies, making it difficult to accurately allocate consumption and costs for a specific product. Analyzing scenarios allows us to more accurately define representative systems and build future scenarios, but there is a lack of information about the variability of the processes. This means that estimating the consumption and impacts of some processes must be modeled or interpolated.

In the following paragraphs the steps of the eco-efficiency analysis are described.

<heading level 2> **Goal and scope**.

This step is equivalent to that of an LCA. It includes the definition of the goal of the study, a description of the scenarios to be assessed, and the definition of both the functional unit and the system boundaries. The data sources are explained in detail below.

<heading level 2> **Economic assessment**.

In this step a single measure that represents the economic result of the production process was obtained. Kuosmanen and Kortelainen (2005) use the economic value added, which implies a social point of view. The total economic value added by all firms represents the gross national product (GNP). The GNP is used to measure the wealth and creation of value of the society of a country, thus the economic value added measures the creation of value for society at a firm level. The value of the raw material increases as a consequence of the production process and is meaningful in quantifying eco-efficiency. Nevertheless, the production processes are carried out by firms which are more concerned with profit than with the value added, as value added does not include all production costs. Indeed, capital and labor costs are not calculated to quantify economic value added. Not taking all the production costs into account will make it more difficult to drive firms towards eco-efficiency. For this reason a second variable of economic result is calculated representing the production net income. The production net income comes from the production process and therefore no commercial or administrative costs are accounted for.

Using the variable "economic value added" is to choose the economic result of the production process for the society and we named it the social model (SM). Using the variable "net income" is to choose the firm point of view and we named it the firm model (FM).

<heading level 2> **Environmental assessment.**

The aim of this step of the methodology is to quantify the environmental impact of the scenarios by means of LCA. LCA is a well established and accepted tool to analyze the environmental impact caused by a product during its entire life cycle in an objective, methodical, systematic, and scientific way.

By paying attention to the data availability and the importance of both the life cycle stages and the impact categories, a streamlined LCA was performed (Todd and Curran 1999).

In the study performed by Kuosmanen and Kortelainen (2005) it should be noted that they take into consideration "environmental pressures", as they do not attempt to measure the ultimate impact, as it is very complex and difficult to predict. In this study, we have referred to the same concept although we have named it by using the term "impact category" as in the terminology proposed by the ISO 14042 (2000). According to these standards, an impact category can be defined as a class representing environmental issues of concern to which life cycle inventory results may be assigned.

<heading level 2> **Integration of results**.

The objective of this step is to obtain an index that serves as a basis to compare products or processes in terms of both environmental and economic aspects. A key point when integrating the results is that there are several impact categories expressed with different measurement units. To solve this aspect, the use of a weighting method is needed. The weights given to the impact categories will be crucial in the final obtained value. DEA was used in this study to integrate the results.

As previously mentioned, DEA is usually used to estimate technical efficiency measures. The definition of efficiency in DEA is based on the engineering concept of total factor productivity and is specified as the ratio of the weighted sum of outputs to the weighted sum of inputs of a production unit or scenario (Allen et al. 1997).

As previously mentioned, the model from Kuosmanen and Kortelainen (2005) was the first proposal using DEA to quantify eco-efficiency according to its definition. For the numerator of the ratio, the authors suggest, as an output, a global measure of the production process value as the economic value added. For the denominator, the authors define as input a linear function of the environmental damage $D(z) = w_1 \cdot z_1 + w_2 \cdot z_2 + \ldots + w_n \cdot z_n$ with the problem of determining the weights (*w*) of the different environmental impact categories (*z*). The variable *z* means environmental impact categories, not an undesirable output measure as is usual when measuring technical efficiency. In contrast to economic inputs and outputs, environmental impact categories do not have prices or other unambiguous weights.

The model implies solving an optimization program for every scenario resulting in the same number of programs as scenarios. For a given scenario, the program calculates a set of weights for the environmental impact categories that maximize the EE ratio, subject to that the same set of weights is applied to the rest of the scenarios and will not allow an EE ratio greater than 1 in any of them. The EE ratio always lies between 0 and 1, where high values indicate good performance. An EE ratio equal to 1 means that the scenario is relatively eco-efficient within the group of scenarios. Scenarios with an EE=1 are not necessarily equal in terms of eco-efficiency, it means that each scenario is not dominated by any other when using the most favorable set of weights. On the contrary the non eco-efficient scenarios underperform (EE < 1) even with their own set of weights (the most favorable). Kuosmanen and Kortelainen (2005) warn that the model measures eco-efficiency relative to the "best practice" in the sample, which is not necessarily the same as best available technology.

The fractional problem for scenario *i*, considering *m* scenarios and *n* environmental impact categories would be as follows:

$$\max_{w} EE_i = \frac{V_i}{w_1 \cdot z_{i1} + w_2 \cdot z_{i2} + \ldots + w_n \cdot z_{in}}$$
$$s.t.$$
$$\frac{V_1}{w_1 \cdot z_{11} + w_2 \cdot z_{12} + \ldots + w_n \cdot z_{1n}} \leq 1$$
$$\frac{V_2}{w_1 \cdot z_{21} + w_2 \cdot z_{22} + \ldots + w_n \cdot z_{2n}} \leq 1$$
$$\ldots$$
$$\frac{V_m}{w_1 \cdot z_{m1} + w_2 \cdot z_{m2} + \ldots + w_n \cdot z_{mn}} \leq 1$$
$$w_1, w_2, \ldots, w_n \geq 0$$

Where:

V_q: economic value added per functional unit for scenario $i=1..m$

w_j: weight of the environmental impact category j $=1..n$

z_{ij}: value of the environmental impact category $j=1..$n per functional unit for scenario $i=1..m$

This program is easy to linearize by taking the inverse of the EE ratio (Kuosmanen and Kortelainen 2005).

A minor transformation of this program, not considering the economic dimension, would allow ranking the production scenarios regarding only the environmental impacts.

<heading level 1> Case study: Eco-efficiency improvement of the production of Mahón-Menorca cheese

Mahón-Menorca cheese is a traditional cheese manufactured on the Island of Menorca (Spain). Menorca has a microclimate different than the other Balearic Islands, with relatively high precipitation for a Mediterranean region (around 600 mm yearly) from autumn to spring. The rain and the typical Mediterranean temperatures make the area suitable for growing forage plants and, consequently, for grazing. The dairy cows of Menorca give a milk production of around 60,000 tonnes per year, of which, 45% is used for making cheese under the Appellation of Origin Mahón-Menorca, with a production of 2,875 tonnes in the year 2008.

According to the Appellation of Origin, the cheese can be made with raw milk or with pasteurized milk. Furthermore, it can also be classified according to the ripening time of *tierno* (between 21 and 60 days), *semi-maduro* (between 60 and 150 days), and *maduro* (more than 150 days).

<heading level 2> Goal and scope of the study.

The goal of this case study is to compare different cheese-making scenarios using environmental and economic criteria. The analysis is performed considering a small production scale, with an average processing capacity of between 3 and 4 million liters (L) milk/year. That is 10,000 L milk/day is representative of most of the dairies on the island.

The sixteen scenarios were built by following technical (degree of automation) and cleaner production criteria. Figure 1 shows the scenario tree. The main criteria used to build the scenarios are described below.

Scenarios 1 to 4 correspond to a process with a low degree of automation, with an open vat, hand molding, and hand washing of the molds and the vat. Scenarios 9 to 16 have a closed vat. Closed vats allow cleaning in place (CIP) systems to be used, thus reducing the consumption of water and cleaning agents. The power requirements are the same as with an open vat. Although automatic molding and mold emptying increase power consumption, they reduce manpower and processing time and allow CIP systems to be used.

Ripening is the highest energy consuming stage in cheese processing. The BAT reference document (BREF) for dairy products (MAPA 2003) proposes reducing energy consumption in ripening chambers by using ionized air at 16ºC and 85% relative humidity. According to the BREF, these conditions allow the ripening time to be reduced by 50%.

The use of a mold washing machine results in a reduction of water consumption and cleaning agents, since the cleaning solution can be reused for one week, and a decrease in manpower and an increase in energy consumption. It also requires changing the cleaning agent.

Automated processes allow CIP systems to be used to clean the entire process line, recycling the cleaning solutions throughout all the equipment. Classical 2-stage CIP consists of a pre-rinse with water, a caustic cleaning, an intermediate rinse, an acid cleaning step (normally on alternate days), and a final rinse. The use of 1-stage CIP implies the use of only one cleaning solution, removing the acidic cleaning agent, and reducing water consumption.

As the main function of the systems studied is to produce cheese, the functional unit is 1 kilogram (kg) of *semi-curado* cheese ripened for 105 days, packaged and ready–for-shipment. A ripening time of 105 days was chosen because it is the average time of a *semi-curado* cheese, the most widely sold.

With respect to the system boundaries, the following operations have been included: milk reception, milk pasteurization and the cheese making process, cheese drying and ripening, cheese packaging, cleaning of the facilities, and electricity production. Upstream (i.e. cow farming) and downstream stages (i.e. transport, retailing, consumption, and waste management) are the same, regardless of the scenario, and may therefore be omitted from the comparison. Mold manufacturing was not included because it uses durable goods. The manufacturing of cleaning agents was not included due to lack of data. To be able to assess the order of magnitude of capital goods production (machinery and buildings) and to decide if it was to be included or not, a raw calculation of the global warming impact category was carried out by using the Economic Input-Output Life Cycle Assessment (EIO-LCA) (Carnegie Mellon University Green Design Institute, 2008).

Taking into account that the goal of the study is to assess cheese production scenarios, data sources and data quality are two important aspects to be defined. The data sources used to characterize the scenarios are:

- Data that referred to raw material consumption (milk, cleaning agents) and amount of final product (cheese) was provided by cheese production companies.
- Machinery characteristics were provided from both cheese production companies and cheese equipment manufacturers.
- Electricity consumption of machinery and facilities was obtained in production plants by using a power analyzer. Two replications were made.
- Steam and hot water required for production were estimated from energy balances supposing 95% heat transfer efficiency.
- Data on water abstraction for cleaning was provided by the cleaning protocol of the firms.
- Wastewater characterization was carried out taking into account the composition and amount of the cleaning agents.

Due to the fact that some of the inventory data were theoretical (e.g. wastewater composition) it was not possible to calculate standard deviation and to carry out an uncertainty analysis of the impact results.

<heading level 2> **Economic assessment.**

In the economic assessment, the variables related to revenues and costs were obtained in order to estimate economic value added and net income for the year 2008.

Revenues come from cheese selling. As the kilogram of cheese is the functional unit, the revenues per functional unit are determined by the price of cheese. In order to avoid any bias due to commercial agreements, the official price of one kilogram of cheese was obtained from the Appellation of Origin Mahón-Menorca. For Coelli and colleagues (2005), quality is a multi-dimensional phenomenon that is associated with a commodity produced for a given enterprise. In our case, the quality of the product is assumed to be the same because we are not taking into account the changes in the quality of the raw materials or in the formulation of the product.

Production costs can be broken down into capital, labor , energy , material inputs , and purchased services.

The amortization cost was determined by the capital stock of each scenario. To quantify this stock, the machinery of each scenario was valued using a new replacement value and a straight-line depreciation model, where value declines by a fixed amount each year. Information about the value of new equipment and length of lifetime was provided by machinery suppliers.

Labor costs were estimated by considering the number of working hours of specialized workers in each shift. Wages were fixed as the average wage of specialized workers and included the firm's social security expenses which increased the cost by 29.90%.

The main cost of energy comes from the electricity used by engines and pumps. This cost was calculated through direct measures of electricity consumption, using the electricity tariff and a fixed fee. The fixed fee was determined by the quantity of power used by the production equipment. Another energy expense is the boiler fuel that is used to heat water, the cost of which was determined by the price of fuel and the consumption of the boiler.

In many enterprises labor constitutes a major component of the total expenditure of inputs, however in this case milk is the main contributor. The price of raw milk used in this study was 0.37 Euros/liter (€/L) of milk, although it is very volatile. Besides milk, the production process uses salt, additives, cleaning water, and other materials, such as antifungal paint and packaging materials.

The services purchased only include the maintenance of equipment as a percentage of the value of each machine at point of purchase.

Cheese production firms are unable to control the price components of these costs. Therefore, in order to determine the influence of price changes on the eco-efficiency index, a sensitivity analysis was carried out.

Figure 2 shows the distribution of the production costs of each scenario. As has been mentioned, due to the large quantity of milk that is used, raw materials account for a significant share of input costs. As expected, highly automated scenarios (9 to 16) present a lower cost of production than the rest (1 to 8).

<heading level 2> **Environmental assessment.**

The environmental assessment was carried out using LCA software Gabi 4 (PE International GmbH, Stuttgart). The life cycle inventory and the impact assessment were carried out using the aforementioned data sources and the inventory database of the software.

The following impact categories were chosen: global warming, eutrophication, and water abstracted for cleaning. Other impact categories such as ozone layer depletion, acidification, photochemical ozone formation, and abiotic resource depletion were not considered because, in this study, all of them depend directly on energy consumption, like the global warming, hence the environmental impact for each scenario presents the same trend. Toxicity related impact categories caused by the cleaning agents were not considered due to a lack of data and for this reason the toxicity impacts are also aligned with energy consumption.

The EDIP 2003 methodology was used (Potting and Hauschild 2004) to assess the global warming and eutrophication impacts and the results were expressed as kilograms of CO_2equivalents (kg CO_2 eq.)and kg NO_3^- eq., respectively. The water abstracted was expressed as litres of water. No distinction between evaporative and non-evaporative use of water was made (Milà i Canals et al. 2009) because the amount of evaporated water must be proportional to the water abstracted irrespective of the scenario.

To estimate the order of magnitude of the impact of the machinery production by the EIO-LCA we used the US2002 benchmark producer price model for the sector '33329A: Other industrial machinery' which includes Food product machinery manufacturing (Carnegie Mellon University Green Design Institute, 2008). For the scenario with the greatest capital investment, considering the average lifetime of machinery provided by machinery suppliers (15-20 years) and the production of cheese for the aforementioned lifetime, we arrived at 0.01 kg-eq CO_2 /kg of cheese. The total amount of kg CO_2 eq. for the different scenarios varies between 0.5-0.8 kg CO_2 eq./kg of cheese. Taking into account the different order of magnitude and the other sources of uncertainty of this case study, the impact of the capital goods can be ruled out.

The results of global warming potential are shown in figure 3. This impact category is directly related to energy consumption. As can be observed in the figure, ripening represents around 70% of total global warming in scenarios with conventional ripening (1, 3, 5, 7, 9, 11, 13 and 15) and approximately 50% in scenarios with accelerated ripening (2, 4, 6, 8, 10, 12, 14 and 16), since, in the latter, the ripening time is shorter. Pasteurization is another step in the production process that greatly contributes to global warming due to the steam generated from fossil fuels. With respect to milk tank and process line cleaning, those scenarios in which 2-stage CIP is carried out contribute more greatly to global warming than the ones with 1-stage CIP because, in the former system, two cleaning solutions must be heated. Hand washing the molds requires less energy than the washing machine. For this reason, the potential contribution to global warming associated with this operation in scenarios 1, 2, 3, 4, 9, 10, 11, 12 is lower than in scenarios 5, 6, 7, 8, 13, 14, 15 and 16. As expected, automated scenarios (from 9 to 16) have a higher potential contribution to global warming in this processing step than scenarios 1 to 8.

Eutrophication is mainly due to process line cleaning and the use of a washing machine for molds, although power generation also contributes greatly to this impact category in those scenarios with conventional ripening (Figure 4). Process line cleaning impact is higher in scenarios 1 to 8, which do not have automatic molding and demolding machines, than in the equivalent automated scenarios (9 to 16), since in the latter scenarios the cleaning of the vat is included in CIP system and smaller amounts of cleaning agents are used. Furthermore, 2-stage CIP has a lower eutrophication impact than 1-stage CIP due to the composition of the cleaning agents used in each case. Eutrophication is higher in those scenarios with a washing machine (5, 6, 7, 8, 13, 14, 15, 16) than in the ones where the molds are handwashed (1, 2, 3, 4, 9, 10, 11, 12) due to the fact that the cleaning agents have a higher chemical oxygen demand and nitrogen and phosphorus content, which cause eutrophication.

Water abstraction is related to the cleaning operation (figure 5), since the steam used in the pasteurizer and the vat is in a closed cycle. When comparing scenarios, water abstraction is higher in scenarios with an open vat (1 to 8) than in the ones with a closed vat (9 to 16) because enclosed vats allow CIP systems to be used in all the processing equipment, thus reducing the water abstraction. The use of a mold washing machine (scenarios 5, 6, 7, 8, 13, 14, 15, 16) results in a reduction of water abstraction because the cleaning solution is reused for six days. With respect to the CIP system, the use of a 1-stage system (scenarios 3, 4, 7, 8, 11, 12, 15, 16) represents water savings of 40% in comparison with the 2-stage CIP scenarios (1, 2, 5, 6, 9, 10, 13, 14). For the same reason, the cleaning of the reception tank in 1-stage CIP needs 60% more water than the 2-stage CIP.

<heading level 2> **Integration of results.**

The model presented by Kuosmanen and Kortelainen (2005), described above, was applied to the 16 defined production scenarios. Two different economic measures were calculated for every scenario leading to two models, the SM, with economic value added in the numerator of the EE ratio, and the FM, with net income in the numerator. The environmental impact categories placed in the denominator of the EE ratio remain equal for both models.

Thus, each scenario includes an economic measure in the numerator of the ratio of eco-efficiency and three environmental impact categories in the denominator. Working with 4 variables and 16 scenarios could cause a dimensionality problem (few observations compared with the number of restrictions). Dyson and colleagues (2001) refer to problems of discrimination in cases with a low value of the ratio of observations/variables. To achieve a reasonable level of discrimination, they suggest that the number of observations must be at least 2 x number of inputs x number of outputs. In this case study: Scenarios = 16 ≥ 2 x 3 x 1 = 6. Bowlin (1998) suggested a rule of at least 3 observations for every input and output considered. In this case study: Scenarios = 16 ≥ 3 x (3+1) = 12.

Table 1 gathers the EE ratio for every scenario and economic model. SM shows 5 eco-efficient scenarios, that is to say with an EE ratio equal to 1, (2, 4, 10, 12 and 16), while FM has 3 eco-efficient scenarios (10, 12 and 16).

The average EE ratio of scenarios 9 to 12 is 0.97 for both EE models and for scenarios 13 to 16 is 0.96 and 0.95 for FM and SM, respectively. These values are higher than for the rest of scenarios. These scenarios have a higher degree of automation and are more eco-efficient than the average EE ratio of scenarios 1 to 4 and 5 to 8. SM obtains an average EE ratio of 0.89 compared with an average EE ratio of 0.85 in the FM. This result could be expected because the only difference between models is the value of the numerator and the fact that labor and amortization costs are not included in SM, which reduces variability in the economic result, that is in the numerator, and therefore, it reduces the discrimination power of the model (5 eco-efficient scenarios in SM as opposed to 3 in FM).

The FM eco-efficient scenarios (10, 12 and 16) present a high degree of automation (enclosed vat plus molding and demolding machines) and use the accelerated ripening of cheese. Nevertheless, scenario 10 does not incorporate a washing machine for molds. The use of a washing machine reduces water consumption and the costs of labor but it increases the eutrophication and global warming impact categories. In this trade-off the washing machine is not a decisive feature.

Classical DEA models build an efficient frontier with the efficient units analyzed. In this case, the eco-efficient scenarios constitute an eco-efficient frontier, so the EE ratio could be read as a distance to this frontier. The EE ratio shows the maximum equiproportionate reduction in all the impact categories that is technically possible with the present economic result. For example, the EE ratio of scenario 3 FM is 0.64, which means that for this scenario, it is feasible to reduce the values of the impact categories by 36% while maintaining its net income.

Another way to analyze the results is to look at the multiplications of weight by impact category, which we could name "virtual impact", as an analogy to DEA jargon "virtual input" (Ray 2004). The models do not need any kind of normalization of the environmental impacts assessed through LCA since they are scale invariant (Ray 2004). This means that a change in the unit of measurement of the economic result or of any environmental impact category does not alter the EE ratio obtained or the relative composition of the denominator. Therefore, the shares of the denominator are not affected by the choice of the units of measurement of the environmental impacts (for instance g-eq of CO_2 instead of kg-eq of CO_2). The analysis of the composition of the virtual impact makes more sense than the direct analysis of the single weights.

Looking over these virtual impacts (figure 6), it is easy to notice a dominant component in each scenario; the shares of the components of the virtual impact are unbalanced. The reason for this is that the weights assigned by means of the linear program are specific for every resolution, thus the weights of the environmental impacts that we have used to estimate the EE ratio of a given scenario are specific to that scenario. In this way, a large weight may be assigned to an environmental impact category where a scenario performs well. This will favor a high EE score although that same scenario performs poorly in the rest of the categories. In order to avoid unbalanced virtual impact, Wong and Beasley (1990) suggest restricting the weight flexibility by fixing the minimum share of each component of the virtual impact over the entire virtual impact. The fact that the model does not estimate a common set of weights for the environmental impacts is a controversial point since people usually employ a fixed framework. Although a common set of weights could be easier to understand by stakeholders, a disadvantage is that the methods to obtain these common weights are often subjective. For this reason another possibility would be to restrict the weights of the environmental impacts eliciting the opinion of experts by using multiple criteria decision making techniques, such as the Analytic Hierarchy Process (AHP). In this sense, the new model would include agreed restrictions and although it would not estimate a common set of weights either, it would ensure that the weights would be within a fixed range. Furthermore the fact of considering human views could give decision-makers more confidence in the results as it would be close to an agreed common set of weights keeping the objectivity feature.

Despite this drawback, the main feature of using DEA techniques should not be forgotten: a scenario is eco-efficient because no other scenario with any combination of weights can beat it. On the contrary, and more importantly, one eco-inefficient scenario, even using the most favorable weight allocation, is not able to achieve an EE ratio equal to one. In this sense, the model would be useful to detect eco-inefficient scenarios. A second phase would be needed to rank the difference between the eco-efficient scenarios.

Although DEA models are scale invariant, they are not translation invariant. This means that adding or subtracting a constant in the economic result or in any environmental impact can alter the eco-efficiency measure. In our case study we did not take into account the amortization of buildings, considering that this cost is the same for every scenario. To test the influence of leaving out a parameter with a constant value, we recalculated both models, FM and SM, leaving out the highest cost, milk consumption. For both models, the eco-efficient scenarios (EE ratio=1) remain eco-efficient, although there are some small variations in the EE ratio of the rest.

The proximity of the EE ratios might cast doubts on the stability of the solutions. In other words, how is the eco-efficiency ratio influenced by changes in the non-controllable variables, that is to say prices? In competitive markets, firms do not control the level of prices, neither that of inputs, nor that of outputs. In order to test the influence of price changes on the EE ratio, a sensitivity analysis was carried out using the Montecarlo simulation. The sensitivity analysis entails simulating the different prices of the production costs and the price of the cheese. In each simulation run each cost can vary between 0.5 times and 1.5 times the fixed price. No correlation conditions were imposed between the different prices. We carried out 10,000 simulation runs, resulting in 10,000 prices for each input and 10,000 prices for 1 kg of cheese, that is 10,000 sets of prices and 10,000 sets of measures of net income (each set gathers 16 scenarios). For every set of measures of net income we applied the firm model (FM) to calculate the EE ratio of every scenario. Thus, the linear program has been solved 16 x 10,000 times.

Prices vary between simulation runs but not between scenarios in each simulation run. This means that each simulation run represents a state of nature, which producers cannot control.

Table 2 shows the descriptive statistics of the simulation process. The EE ratio of the scenarios previously estimated as eco-efficient (10, 12 and 16) seems very robust; as a result of the simulation process, they have been found as eco-efficient in at least 97.87% of the simulation runs. Only scenarios 4 and 14, not previously found as eco-efficient, are now eco-efficient in a small percentage of the simulations. The rest of the scenarios not previously scored as eco-efficient do not reach eco-efficiency in any of the simulation runs. The scenarios with a low degree of automation show a higher variability (higher coefficient of variation and range of EE ratio) than the rest, since their greater dependence on labor input make them more sensitive to changes in wages.

Summarizing the simulation's analysis, the most determinant prices in eco-efficiency are wages and cheese price. Low wages and high prices of cheese favor those scenarios with a low degree of automation, while high wages and low cheese prices favor those scenarios with a high degree of automation. Due to the fact that scenarios 1 to 8 are labor intensive and their net income is lower than the automated ones, only extreme conditions of very low wages and high cheese prices can move them closer to eco-efficiency.

<heading level 1> **Conclusions**

From the LCA results it can be concluded that the conventional ripening step is the greatest contributor to global warming, while accelerated ripening decreases this impact by 50%. Cleaning the molds and process line implies high water consumption and also eutrophication. Although the use of a washing machine for mold cleaning and a 1-stage CIP system decreases this consumption, the cleaning agents used in both cases contribute more heavily to the eutrophication impact category. For these reasons, it is difficult to establish which are the best practices of all the scenarios studied.

The use of DEA techniques to measure eco-efficiency provides an objective method of weighting the environmental impacts, irrespective of individual thoughts and preference. This is important in cases such as this study, in which the techniques that perform well in one impact category perform poorly in another.

For the WBCSD, the numerator of the EE ratio is made by the product value. Product value is a broad concept so it could be read in different ways. We used the economic value added, considering a social point of view, and the net income, from the firms' point of view. Small differences between the results of eco-efficiency were found in both approaches. Taking into account that eco-efficiency is the firms' contribution to sustainability, net income is preferable since it is closer to the real economic result of the process than the value added.

In regards to the results of the case study, three scenarios have been found to be eco-efficient, using a high degree of automation (enclosed vat plus molding and demolding machines) and accelerated cheese ripening. These scenarios are eco-efficient from both the social and the firm's point of view. These results could be extrapolated to other food industries, since automation decreases production costs. Furthermore it is also important to focus on improving unit operations with high energy consumption such as ripening.

Since producers have no control over the prices of inputs, a sensitivity analysis was carried out to contrast the influence of price changes on the EE ratio using the Montecarlo simulation. The results show the consistency and stability of those scenarios scored as eco-efficient.

DEA techniques allocate the weights of the impact categories in the best possible way in order to obtain the most favorable EE ratio, thus, the scenarios not scored as eco-efficient are always overtaken by other scenarios. DEA does not discriminate among eco-efficient scenarios and, in this sense, it would be useful to apply a second model to the eco-efficient ones.

Finally, it is important to stress the need to develop and establish methodologies for evaluating the eco-efficiency of food production systems.

These methodologies would help firms in their decision making processes about how to incorporate new techniques because both the economic and environmental perspectives would be considered. Furthermore, broadening the scenarios to consider other stages of the life cycle, such as product use or waste management, would increase the possibility of reaching the goal of eco-efficient food production.

<heading level 1> **ACKNOWLEDGEMENTS**

We gratefully acknowledge the financial support from the Spanish Ministry of Education and Science, project CTM2006-12328/TECNO, the Universidad Politécnica de Valencia, project PAID-05-06-6733, and also the help of the Consell Regulador de la Denominació d'Origen Mahón-Menorca, Alcaidús S.A.T., Cooperativa Insular Ganadera (Coinga), Hort de Sant Patrici, S.L., and Iberlact S.L.

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Table 1. Eco-efficiency ratio

Scenario	Firm Model EE	Social Model EE
1	0.60	0.69
2	0.89	**1.00**
3	0.64	0.73
4	0.91	**1.00**
5	0.59	0.66
6	0.81	0.88
7	0.64	0.71
8	0.85	0.92
9	0.94	0.94
10	**1.00**	**1.00**
11	0.95	0.96
12	**1.00**	**1.00**
13	0.91	0.89
14	0.97	0.94
15	0.98	0.98
16	**1.00**	**1.00**

Note: EE= eco-efficiency

Table 2. Descriptive statistics of eco-efficiency (EE) ratio in firm model after 10,000 simulations

Scenario	EE Mean	EE Std. Dev.	EE cv	EE Min	EE Max	Times EE=1*
1	0.57	0.12	0.22	0.001	0.970	0
2	0.85	0.16	0.19	0.012	0.988	0
3	0.61	0.12	0.20	0.027	0.716	0
4	0.87	0.16	0.18	0.059	1.000	174
5	0.57	0.10	0.18	0.068	0.659	0
6	0.78	0.12	0.16	0.131	0.887	0
7	0.61	0.10	0.17	0.134	0.707	0
8	0.82	0.12	0.14	0.203	0.922	0
9	0.93	0.04	0.04	0.664	0.958	0
10	1.00	0.00	0.00	0.896	1.000	9994
11	0.94	0.04	0.04	0.682	0.969	0
12	1.00	0.00	0.00	0.940	1.000	9787
13	0.91	0.02	0.02	0.721	0.952	0
14	0.97	0.02	0.02	0.879	1.000	885
15	0.97	0.03	0.03	0.746	0.996	0
16	1.00	0.00	0.00	1.000	1.000	10000

* Number of times each scenario obtains an eco-efficiency ratio = 1

EE = eco-efficiency; Std. Dev. = standard deviation; cv = coefficient of variation; Min = minimum; Max = maximum

Figure Captions

Figure 1. Cheese making scenarios

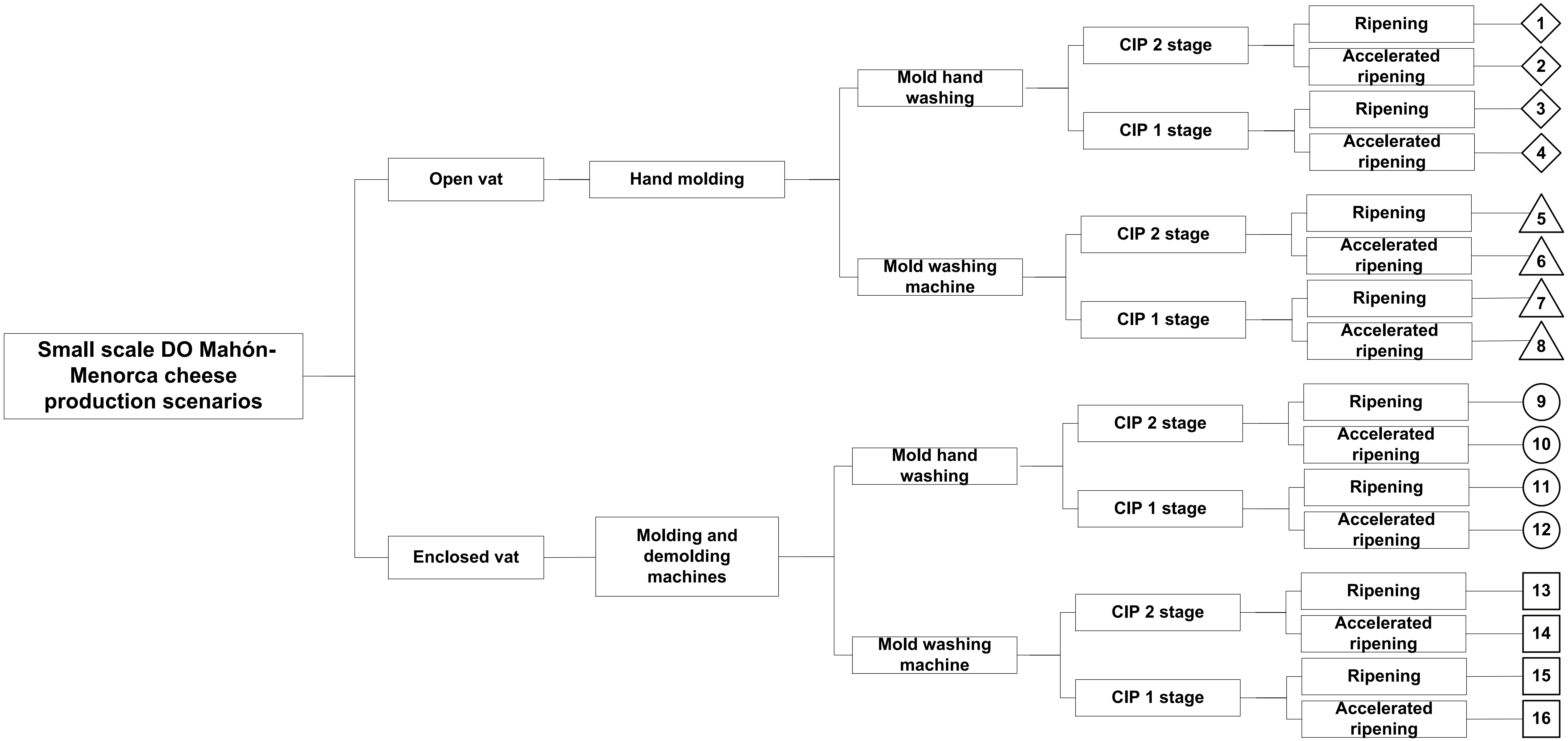
Figure 2. Cost categories for each production scenario (Euros/kilogram of cheese)

Figure 3. Global warming of the scenarios (kilogram-equivalents of CO_2/kilogram cheese)

Figure 4. Eutrophication of the scenarios (kilogram PO_4^{-3} equivalents/kilogram cheese)

Figure 5. Water abstraction of the scenarios (liters of water/kilogram of cheese)

Figure 6. Share of virtual impact per scenario


Small scale DO Mahón-Menorca cheese production scenarios
Open vat
Hand molding
Enclosed vat
Molding and demolding machines
Mold hand washing
Mold washing machine
Mold hand washing
Mold washing machine
CIP 2 stage
CIP 1 stage
CIP 2 stage
CIP 1 stage
CIP 2 stage
CIP 1 stage
CIP 2 stage
CIP 1 stage
Ripening
Accelerated ripening
Ripening
Accelerated ripening
Ripening
Accelerated ripening
Ripening
Accelerated ripening
Ripening
Accelerated ripening
Ripening
Accelerated ripening
Ripening
Accelerated ripening
Ripening
Accelerated ripening
1
2
3
4
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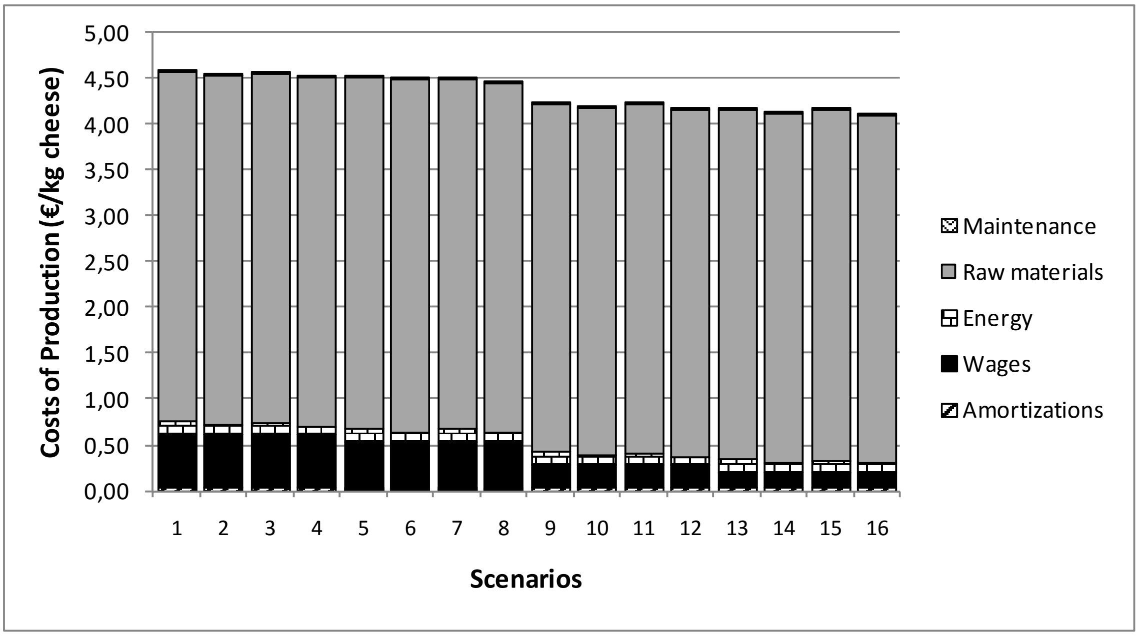
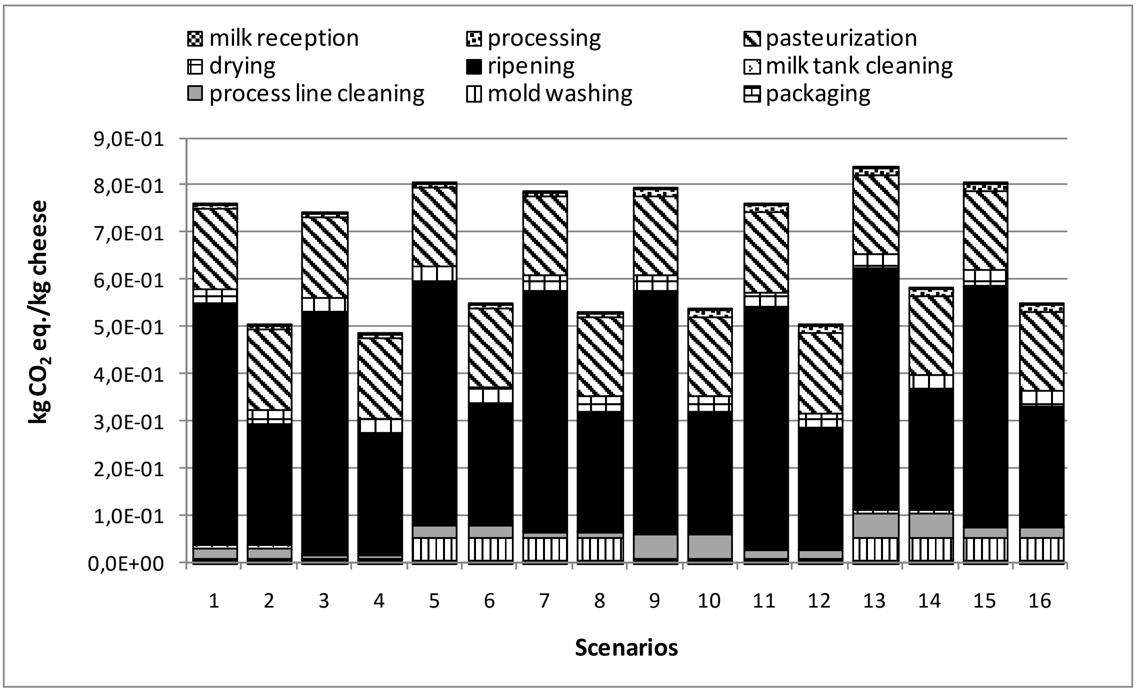
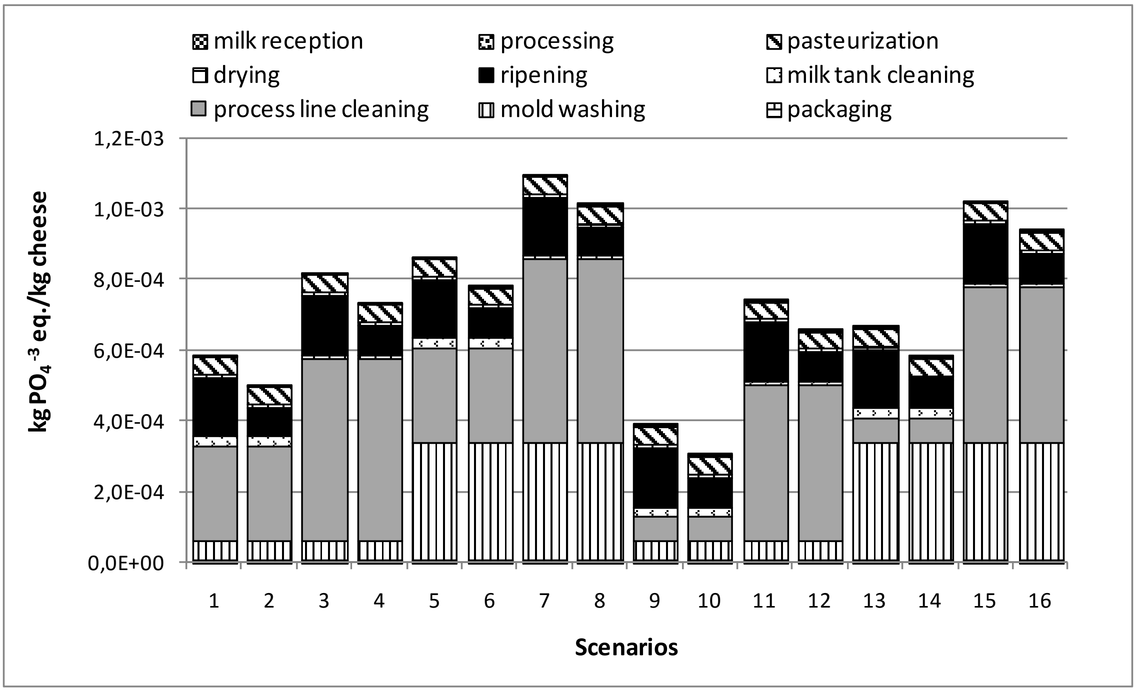
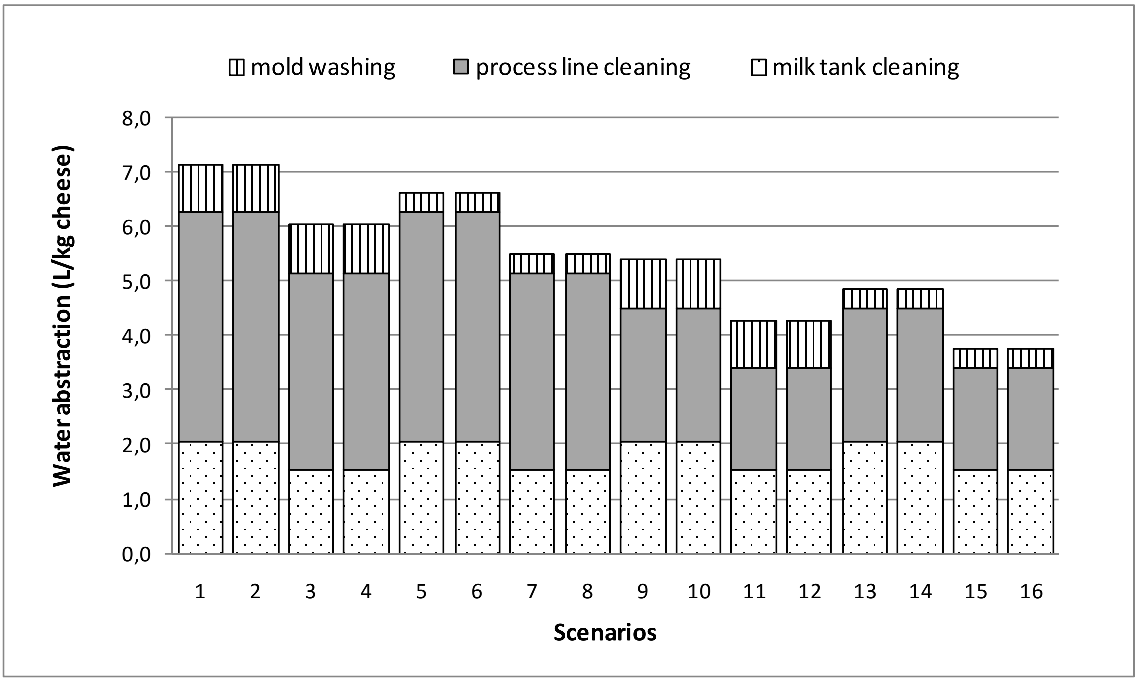
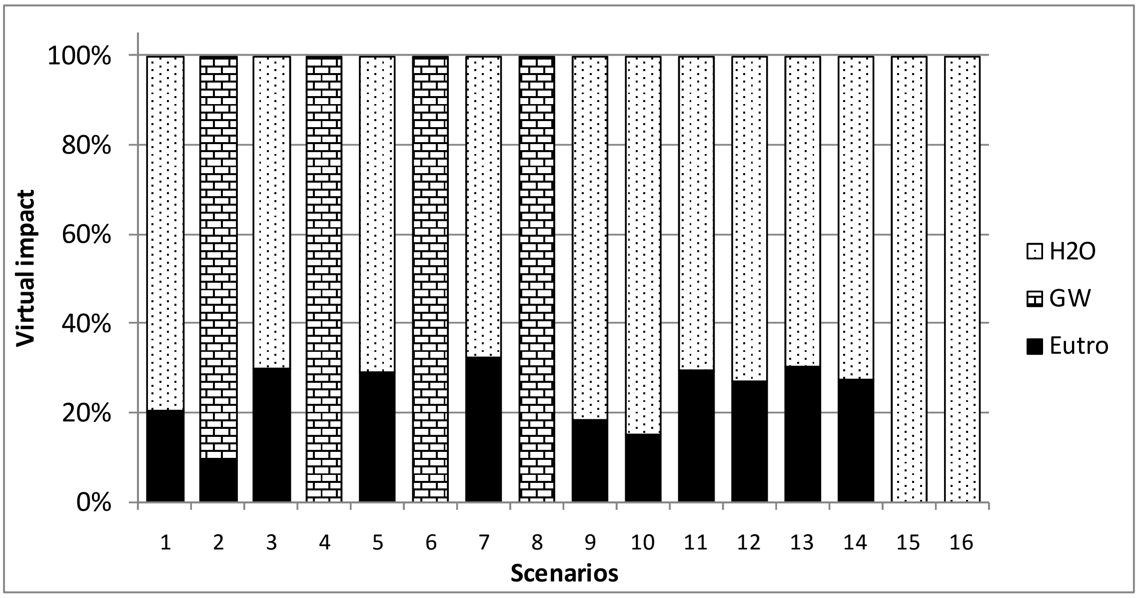
6
7
8
9
10
11
12
13
14
15
16


Costs of Production (€/kg cheese)
5,00
4,50
4,00
3,50
3,00
2,50
2,00
1,50
1,00
0,50
0,00
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Scenarios
Maintenance
Raw materials
Energy
Wages
Amortizations


milk reception
processing
pasteurization
drying
ripening
milk tank cleaning
process line cleaning
mold washing
packaging
kg CO_2 eq./kg cheese
9,0E-01
8,0E-01
7,0E-01
6,0E-01
5,0E-01
4,0E-01
3,0E-01
2,0E-01
1,0E-01
0,0E+00
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Scenarios


milk reception
processing
pasteurization
drying
ripening
milk tank cleaning
process line cleaning
mold washing
packaging
kg PO4 -3 eq./kg cheese
1,2E-03
1,0E-03
8,0E-04
6,0E-04
4,0E-04
2,0E-04
0,0E+00
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Scenarios


mold washing
process line cleaning
milk tank cleaning
Water abstraction (L/kg cheese)
8,0
7,0
6,0
5,0
4,0
3,0
2,0
1,0
0,0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Scenarios



100%
80%
60%
40%
20%
0%
Virtual impact
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Scenarios
H2O
GW
Eutro