Available online at www.elixirpublishers.com (Elixir International Journal)

Agriculture

Elixir Agriculture 84 (2015) 33630-33634

ISSN: 2229-712X

Optimization of Energy Consumption in Peach Fridges by Dea Approach (Case Study: Mazandaran Province, Iran)

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ARTICLE INFO

Article history:

Received: 12 May 2015;

Received in revised form: 20 June 2015;

Accepted: 6 July 2015;

Keywords

Energy Use,
Technically Efficient,
Peach Fridge,
Optimization,
Mazandaran Province.

ABSTRACT

This study utilizes a data envelopment analysis approach to survey the technical and scale efficiencies of peach fridges with respect to energy consumption conservation of products in Mazandaran province of Iran. The study also helps to recognize the wasteful uses of energy by incompetent units and to establish the optimum level of energy from different inputs. Data used in this study were collected from 18 peach fridges in Mazandaran province, Iran. The results showed that, the total energy of 3363344 MJ/1000kg capacity was consumed for peach fridges and about 23% of peach fridges were found to be technically efficient and the technical, pure technical and scale efficiency scores of units were found to be 0.78, 0.86 and 0.90, respectively. The results also expressed that on average, a potential 645762 MJ/1000kg capacity (about 19.2%) reduction in total energy input could be acceded provided all units operated efficiently, assuming no other constraints on this adjustment.

Introduction

There are several parametric and non-parametric techniques to measure the efficiency in production. Data Envelopment Analysis (DEA) technique is a non-parametric linear programming (LP) based technique of frontier estimation for measuring the relative efficiency of a number of decision making units (DMUs) on the basis of multiple inputs and outputs (Zhang et al., 2009). In this case, the efficiency of a unit is defined as the ratio of weighted sum of its outputs to the weighted sum of its inputs and it is measured on a bounded ratio scale. The weights for inputs and outputs are determined to the best advantage for each unit so that to maximize its relative efficiency (Despotis et al., 2010).

A main advantage of non-parametric method of DEA compared to parametric approaches is that it does not require any prior assumption on the underlying functional relationships between inputs and outputs. It is, therefore, a non-parametric approach. In addition, DEA is a data-driven frontier analysis technique that floats a piecewise linear surface to rest on top of the observations (Zhou et al., 2008).

Due to the high advantages of DEA, there are a large number of its applications for evaluating the performances of DMUs in different study areas. In an earlier and related study, DEA was utilized to evaluate the technical efficiency of irrigated dairy farms in Australia. The results from this study proposed that DEA was a useful tool in helping to benchmark the dairy industry, which is continually striving to improve the productive efficiency of farms (Fraser and Cordina, 1999). In another study, DEA was applied to investigate the efficiency of individual units and to identify the efficient units for citrus production in Spain (Reig-Martinez and Picazo-Tadeo, 2004). Barnes (2006) identified the technical efficiency scores of Scottish dairy farms by applying the DEA approach. Malana and Malano (2006) employed the DEA technique to benchmark the productive efficiency of irrigated wheat area in Pakistan and India. Finally, Omid et al. (2010) employed a DEA method to analyze technical and scale efficiencies of cucumber producers.

The main objectives of the present study are to investigate the energy use for peach fridges in Mazandaran province, Iran, and to analyze the technical and scale efficiencies of units based on energy inputs of and the output of peach processing. Moreover, this study helps to identify the wasteful usage of energy by inefficient units and to establish the optimum level of energy from different sources.

Materials and methods

Data collection and processing

The study was carried out in some peach fridges in Mazandaran Province, Iran. Data were collected from the peach fridges by using a face-to-face questionnaire. Total peach fridges in the region were investigated. The inputs used in the preservation process were in the form of human labor, electricity, equipment and fuels. The energy equivalents of these inputs were calculated using the energy equivalent coefficients. The selected fridges were predominantly working and have a similar climatic conditions and environment. There were temperate climatic conditions. The data were included the amount of all direct and indirect energy inputs used in different operations and amount of peach fruit preserved in the process. The size of each sample was determined using a simple random sampling method. This method was described by Loghmanpour zarini (2014):

$$n = \frac{N(s \times t)^2}{(N-1)d^2 + (s \times t)^2} \qquad (1)$$

Where n is the required sample size; s is the standard deviation; t is the value at 95% confidence limit (1.96); N is the number of olding in the target population and d is the acceptable error (permissible error 5%). For the calculation of sample size,

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criteria of 5% deviation from population mean and 95% confidence level were used. The sample size was calculated as 15 but for precision competition 18 units were selected randomly.

Energy balance analysis method

A standard procedure was used to convert each input into energy equivalents. The inputs may be in the form of chemicals, diesel fuel, electricity, human labor and equipment. The energy equivalent may thus be defined as the energy input taking into account all forms of energy in preservation process. The energy equivalents were computed for all inputs using the conversion factors for machinery and diesel fuel (Canakci et al., 2005), human labor (Rafiee et al., 2010; Erdal et al., 2007), and electricity (Mobtaker et al., 2010); multiplying the quantity of the inputs used per 1000 kg of preservation fruit with their conversion factors gave the energy equivalents reported in mega joule per 1000 kg of preservation fruit. Embodied energy in equipment is measured in terms of MJ kg^{-1}.

Data envelopment analysis technique (DEA)

In this study, a non-parametric method of DEA is employed to evaluate the technical, pure technical and scale efficiencies of individual industries which use similar inputs, preserve the same fruit (peach) and operate in a relatively homogenous region (e. g. climatic conditions, etc.). So, the energy consumed from different energy sources including: human labor, equipment, diesel fuel and electricity energy inputs, in terms of MJ per 1000 kg of fruit, were defined as the input variables; while, the processed fruit (kg) was the output; also each fridge called a DMU.

In DEA an inefficient DMU can be made efficient either by minimizing the input levels while maintaining the same level of outputs (input oriented), or, symmetrically, by reducing the output levels while holding the inputs constant (output oriented). Fruit preservation process relies on finite and scarce resources; therefore the use of input-oriented DEA models is more appropriate to reduce inputs consumed in the preservation process. In order to evaluate the energy use efficiencies of apple fridges, the technical, and pure technical and scale efficiency indices were investigated (Nassiri and Singh, 2009):

Technical efficiency (TE)

Technical efficiency (TE) can be defined as the ability of a DMU (e.g. an peach fridge) to produce maximum output given a set of inputs and technology level. The TE score (θ) in the presence of multiple-input and output factor can be calculated by the ratio of sum of weighted outputs to the sum of weighted inputs or in a mathematical expression as follows (Cooper et al., 2004):

$$TE_j = \frac{u_1 y_{1j} + u_2 y_{2j} + \ldots + u_n y_{nj}}{v_1 x_{1j} + v_2 x_{2j} + \ldots + v_m x_{mj}} = \frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{s=1}^{m} v_s x_{sj}} \qquad (2)$$

Where, u_r is the weight given to output n; y_r is the amount of output n; v_s is the weight given to input n; x_s is the amount of input n; r, is the number of outputs ($r = 1, 2 \ldots n$); s is the number of inputs ($s = 1, 2\ldots m$) and j represents j^{th} of DMUs ($j = 1, 2 \ldots k$).

Pure technical efficiency (PTE)

In DEA, the technical efficiency can be divided into scale efficiency for scale factors and pure technical efficiency for non-scale factors; the pure technical efficiency is the technical efficiency that has the effect of scale efficiency removed. The model for calculating the PTE was introduced by Banker et al. (1984), which was called BCC model. The BCC model is provided by adding a restriction on λ (λ =1) in the model, resulted to no condition on the allowable returns to scale. It assumes variable returns to scale (VRS), indicating that a change in inputs is expected to result in a disproportionate change in output.

Scale efficiency

Scale efficiency (SE) relates to the most efficient scale of operations in the sense of maximizing the average productivity. A scale efficient unit has the same level of technical and pure technical efficiency scores. It can be calculated as below (Nassiri and Singh, 2009):

$$SE = \frac{TE}{PTE} \qquad (2)$$

SE gives quantitative information of scale characteristics. It is the potential productivity gained from achieving optimum size of a DMU. However, scale inefficiency can be due to the existence of either IRS or DRS. A shortcoming of the SE score is that it does not indicate if a DMU is operating under IRS or DRS. This is resolvable by simply imposing a non-increasing return of scale (NIRS) condition in the DEA model (Scheel, 2000). IRS and DRS can be determined by comparing the efficiency scores obtained by the BCC and NIRS models; so that, if the two efficiency scores are equal, then DRS apply; else IRS prevail (Omid et al., 2010). The information on whether a unit operates at IRS, CRS or DRS is particularly helpful in indicating the potential redistribution of resources between the units, and thus, enables them to achieve to the higher yield value (Chauhan et al., 2006).

The results of standard DEA models divide the DMUs into two sets of efficient and inefficient units; the inefficient units can be ranked according to their efficiency scores; while, DEA lacks the capacity to discriminate among efficient units. A number of methods are in use to enhance the discriminating capacity of DEA (Adler et al., 2008). In this study, the benchmarking method was applied to overcome this problem. In this method, an efficient unit which is chosen as a useful target for many inefficient DMUs, and so appears frequently in the reference sets, is highly ranked. In this study for data analysis, the Microsoft Excel spreadsheet and the DEA-solver software were employed.

Results and Discussion

Efficiency estimation

In this study, 18 peach fridges from surveyed region were selected to benchmark the productive efficiency of this food processing industry. In Table 1 the energy analysis of peach fridges are presented. The last row of Table 1 gives the standard deviation of various energy inputs and output for peach fridges in the study area. As it is seen, the human labor energy in the surveyed farms was 17863 (MJ/1000kg capacity); also, it varied from 7508 to 301128 (MJ/1000kg capacity). Moreover, depreciation cost of equipment was calculated as 335681 (MJ/1000kg capacity) with the standard deviation of 159921. On the other hand, total peach fruit processed was found to be 919 (kg/1000kg capacity), with the standard deviation of 153. The variation in both the levels of input energies and output is noticeable; such variations were mainly due to the mismanagement of resource usage between the units, indicating that there is a great scope for improving the energy productivity of peach fridges in the region.

Initially we applied the CCR model to evaluate the technical or overall efficiencies of all DMUs. Additionally, we used the BCC model to evaluate the pure technical efficiency and scale efficiency.

Table 1. Statistics on input/output data for efficiency measurement of peach fridges in Mazandaran, Iran.

Statistics	Equipment (MJ/1000kg capacity)	Labor (MJ/1000kg capacity)	Electricity (MJ/1000kg capacity)	Fuel (MJ/1000kg capacity)	Fruit (kg/1000kg capacity)
Max	710125	301128	5001215	142422	1319
Min	171012	7508	810258	8908	621
Average	335681	17863	2958968	49913	919
SD	159921	11125	921255	2771	153

Table 2. Three types of efficiencies of individual peach fridges in Mazandaran, Iran.

DMU	Technical efficiency	Pure technical efficiency	Scale efficiency	RTS
1	0.71	0.78	0.90	Decreasing
2	1	1	1	Constant
3	0.81	0.81	1	Constant
4	0.90	1	0.90	Increasing
5	0.42	0.54	0.78	Decreasing
6	1	1	1	Constant
7	0.69	1	0.69	Increasing
8	1	1	1	Constant
9	0.49	0.85	0.58	Decreasing
10	0.52	0.55	0.93	Decreasing
11	0.71	0.78	0.91	Decreasing
12	1	1	1	Constant
13	0.62	0.65	0.97	Decreasing
14	1	1	1	Constant
15	0.95	1	0.95	Decreasing
16	0.84	1	0.84	Decreasing

Table 3. Average efficiencies of peach fridges in Mazandaran, Iran.

	Technical efficiency	Pure technical efficiency	Scale efficiency
Max	1.00	1.00	1.00
Min	0.42	0.54	0.58
Average	0.78	0.86	0.90
SD	0.20	0.18	0.12

The results of the CCR and BCC models are shown in Fig. 1 and Table 2. Based on CCR results, this study shows that only 18 growers were relatively efficient and the remaining 42 were inefficient, i.e., their efficiency scores are below 1; while from the results of BCC model, 43 growers (out of total 60 growers) were found as efficient garlic producers, meaning they have an efficiency score of 1. The scale efficiency was calculated as 1 for 18 farms. In other word the all efficient units of the CCR model were efficient in BCC model.

For investigating the efficiency scores of units, both the constant and variable returns to scale DEA models were applied to the specified input and output variables. The summarized information for the distribution of efficiency scores of units are presented in Table 2. The results revealed that, from the total of 16 units considered for the analysis, 6 and 8 units were identified as efficient units on the basis of constant and variable returns to scale assumptions, respectively. Moreover, from these efficient units 5 units were fully efficient in both the technical and pure technical efficiency scores, indicating that they were globally efficient and operating at the most productive scale size of production; while, the remainder of 2 efficient units were only locally not globally efficient; implying that, they have not used the correct level of inputs in the period; however, they moved toward the BCC efficient frontier when the effect of scale size was omitted. The results of returns to scale indicated that 6 units were operating at constant returns to scale, showing the optimum scale of their practices; whereas, 8 units were found to be operating at decreasing returns to scale and the remainder of 2 units were operating at increasing returns to scale. This indicates that the majority of peach fridges in the region were operating upon their optimal scale; therefore, a proportionate decrease in all inputs leads to more than the proportionate decrease in outputs. Also, and some of them were operating at their optimal scale.

The summarized statistics for the three estimated measures of efficiency based on the results of the DEA models are presented in Table 3. The results revealed that the average values of technical and pure technical efficiency scores were 0.78 and 0.86, respectively. Also, the technical efficiency varied from 0.42 to 1 range. The wide variation in the technical efficiency implies that all the units were not fully aware of the right production techniques or did not apply them properly. Based on the literature, the technical efficiency scores of 0.7720 for paddy production (Chauhan et al., 2006), 0.75 for tomato, 0.81 for asparagus production (Iraizoz et al., 2003) and 0.782 for pig farming (Galanopoulos et al., 2006) were reported.

The average scale efficiency score was 0.90, indicating the disadvantageous conditions of scale size; so, if inefficient units utilize their inputs efficiently, 10% savings in energy use from different sources is possible without any change in technological practices.

Conclusions

In this study energy use for peach fridges in Mazandaran province of Iran was investigated; also an input-oriented DEA model was subjected to the data of 18 peach fridges to investigate the degree of technical and scale efficiency of units. Based on the results of the study the following conclusions are drawn:

1. Peach fridges in the region were dependent mainly on the non-renewable energy resources, which can create serious consequences on human health and ecosystems.
2. The results showed substantial inefficiency for units and therefore, a potential 19.2% reduction in total energy input use may be achieved provided all units operated efficiently and assuming no other constraints on this adjustment.
3. Electricity and diesel fuel energy inputs had the highest potential for saving energy; so, they should be considered as priorities.
4. Applying a better management technique, application of inputs by performance monitoring and utilization of alternative sources of energy may be also the pathways to make energy usage more environmental friendly, and thus to reduce their environmental footprints.

Acknowledgment

The authors would like to thanks all the peach fridges managers who are participated in this research.

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