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Application of Data Envelopment Analysis for Performance Assessment and Energy Efficiency Improvement Opportunities in Greenhouses Cucumber Production

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ABSTRACT

In the present study, an attempt has been made to use Data Envelopment Analysis (DEA) for assessing the technical efficiency and return-to-scale for greenhouse cucumber production in Iran. For this purpose, the data from greenhouses in Esfahan province, during one period of plant cultivation in one year including spring plants were randomly collected. The results indicated that total input energy, total output energy and energy ratio were 436,824 MJ ha^{-1}, 128,532 MJ ha^{-1} and 0.29, respectively. *DEA* can be used to optimize the performance of any cucumber greenhouse. Based on input-oriented *CRS* and *VRS* models of *DEA*, the average values of pure technical efficiency, technical efficiency and scale efficiency were found to be 0.95, 0.83 and 0.88, respectively. Also the results revealed that, on average, about 30.27% of the total input energy could be saved without reducing the cucumber yield from its present level by adopting the recommendations based on the present study.

Keywords: Cucumber, Data envelopment analysis, Technical efficiency, Yield.

INTRODUCTION

Greenhouse production is now an important sector in Iran (Samadi, 2011). Cucumber is one of the major greenhouse vegetable products worldwide. In Iran, cucumber production was 1.46 million tones in 2008. From 2002 to 2008, greenhouse areas of Iran increased from 3,380 to 7,000 ha (FAO, 2008). The share of greenhouse production was as follows: vegetables 59.3%, flowers 39.81%, fruits 0.54% and mushroom 0.35% (Anonymous, 2008).

Agriculture itself is an energy user and energy supplier in the form of bio-energy (Alam *et al.,* 2005). Energy is used in every form of inputs such as human, seeds, fertilizers, pesticides, diesel fuel, electricity and machinery to perform various operations for crop production. Energy use in agriculture has increased in response to increasing populations, limited supply of arable land and desire for an increasing standard of living. In all societies, these factors have encouraged an increase in energy inputs to maximize yields, minimize labor-intensive practices, or both (Esengun *et al.,* 2007b). Effective energy use in agriculture is one of the prerequisites for sustainable agricultural production, since it provides financial savings, fossil resources preservation and air pollution reduction (Uhlin, 1998).

There are several studies on the energy use pattern and benchmarking of greenhouse crops production. Energy use for greenhouse vegetables (tomato, cucumber, eggplant and pepper) production were investigated

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(Ozkan *et al.,* 2004b; Canakci and Akinci, 2006; Omid *et al.,* 2011). Hatirli *et al.* (2006) and Mohammadi and Omid (2010) investigated energy inputs and crop yield relationship to develop and estimate an econometric model for greenhouse tomato and cucumber productions, respectively.

The present study differs from all previous researches since it explores data envelopment analysis (DEA) which permits efficiency estimation of greenhouses without assuming an a priori functional form for frontier production. The *DEA* is an analysis method to measure the relative efficiency of a homogeneous number of units that essentially perform the same tasks (Seiford and Thrall, 1990). In the present study, they are greenhouses that produce cucumber. Basically, this methodology is centered in determining the most efficient producers of the sample to be used as a reference, with which the efficiency of the rest of the producers is compared. The most efficient greenhouses are those for which there is no other greenhouse or linear combination of greenhouses that produces more of a product (given the inputs) or use less of each input (given the Cucumber products). A product can be the cucumber yield or sold value and an input could be human labor or the fuel consumed. *DEA* has been accepted as a major frontier technique for benchmarking energy sectors in many countries. *DEA* is a well established methodology to evaluate the relative efficiencies of a set of comparable entities by some specific mathematical programming models. These entities (greenhouses in this case) are often called decision making units (DMUs) and perform the same function by transforming multiple inputs into multiple outputs. Given a sample of the *DMUs*, the purpose of the *DEA* is to establish the relative efficiency of each *DMU* within a sample. The main advantage of *DEA* is that it does not require any prior assumptions on the underlying functional relationships between inputs and outputs (Seiford and Thrall, 1990). It is therefore a nonparametric approach. In addition, *DEA* is a data-driven frontier analysis technique that floats a piecewise linear surface to rest on top of the empirical observations.

DEA method was used to determine the efficiency of *DMUs* in different energy systems. Malana and Malano (2006) studied benchmarking productive efficiency of selected wheat areas in Pakistan and India using *DEA* based on three inputs: water for irrigation (m^3 ha^{-1}), seeds (kg ha^{-1}) and fertilizer use (kg ha^{-1}). The results of the analysis showed that *DEA* was an effective tool for analysis and benchmarking productive efficiency of agricultural units. Nassiri and Singh compared two methods of parametric (Cobb-Douglas production function) and non-parametric (DEA) energy use efficiency in paddy production in India (Nassiri and Singh, 2010).

This paper presents an application of DEA to discriminate efficient greenhouse cucumber producers in Esfahan Province from inefficient ones, pinpoint best operating practices of energy usage, recognize wasteful uses of energy inputs by inefficient farmers and suggest necessary quantities of different inputs to be used by each inefficient farmer from every energy source.

MATERIALS AND METHODS

Data Collection and Processing

The study was carried out on 26 greenhouse cucumber producers in Esfahan Province. Data were collected from the farmers by using a face-to-face questionnaire. The data collected belonged to the production period of 2009–2010. The size of each sample was determined using the Neyman technique (Esengun *et al.,* 2007b; Mohammadi and Omid, 2010). The input energy (MJ ha^{-1}) was from various input sources including human, diesel, farm yard manure (FYM), fertilizer, electricity, chemicals, and transportation. Previous studies were used to determine the energy equivalents' coefficients (Shrestha, 1998; Nagy, 1999; Singh, 2002; Mandal *et al.,*

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2002; Ozkan *et al.,* 2004b; Hatirli *et al.,* 2006; Esengun *et al.,* 2007b). The total input equivalent can be calculated by adding up the energy equivalents of all inputs in Mega Joule (MJ). Energy equivalents shown in Table 1 were used for the estimation. Cucumber yield (kg ha^{-1}) was used as the output.

The energy use efficiency (output energy to input energy ratio) and energy productivity of farmers in crop production systems can define the performance of farms (Acaroglu, 1998). Output yield values of cucumber were used to estimate the energy ratio, energy productivity, net energy, etc. Based on the energy equivalents of the inputs and output (Table 1), the energy ratio (energy use efficiency), energy productivity and net energy were calculated (Zangeneh *et al.,* 2010; Mohammadi and Omid, 2010):

Energy use efficiency= Energy output (MJ ha^{-1})/Energy input (MJ ha^{-1}) (1)

Energy productivity= Cucumber output (kg ha^{-1})/Energy input (MJ ha^{-1}) (2)

Net energy = Energy output (MJ ha^{-1})-Energy input (MJ ha^{-1}) (3)

For the growth and development, energy demands in agriculture can be divided into direct and indirect or renewable and non-renewable forms (Zangeneh *et al.,* 2010). Direct energy (DE) covers human labor, diesel, electricity and transportation, while indirect energy (IDE) includes energy embodied in fertilizers and chemicals used in the cucumber production. Renewable energy (RNE) consists of human labor and FYM, whereas non-renewable energy (NRE) includes diesel, electricity, fertilizers and chemicals.

Data Envelopment Analysis

DEA allows for the measurement of relative efficiency for a group of units that use various inputs to produce outputs. It is a non-parametric approach based on mathematical linear programming techniques. Unlike parametric methods, *DEA* does not require a function to relate inputs and outputs (Seiford and Thrall, 1990).

DEA is used for the estimation of resource use efficiency and ranking of production units on the basis of their performance. Production units are termed decision making units (DMUs) in DEA terminology. The term *DMU* in the context of this study applies to any scale of measurement ranging from individual entities to the entire economic sectors. *DEA* determines the efficiency of *DMUs* relative to others in the group, evaluates inefficient units and can identify the levels as well as sources of inefficiency. The performance of inputs depends on cucumber yields achieved in

Table 1. Energy coefficients of different inputs and outputs used.

Input & output	Units	Energy coefficient, (MJ $unit^{-1}$)	Reference
A. Input			
1. Human labor	h	1.96	(Mohammadi *et al.,* 2010)
2. Diesel fuel	L	56.31	(Mohammadi *et al.,* 2010)
3. Electricity	kW	11.93	(Banaeian *et al.,* 2011)
4. Fertilizers	kg		
(a) FYM [a]		0.30	(Mohammadi *et al.,* 2010)
(b) Nitrogen		66.14	(Mohammadi *et al.,* 2010)
(c) P_2O_5		12.44	(*Mohammadi et al.* 2010)
(d) K_2O		11.15	(Mohammadi *et al.,* 2010)
(e) Micro		120	(Canakci and Akinci, 2006)
5. Chemicals	kg	120	(Mohammadi *et al.,* 2010)
B. Output			
1. Cucumber	kg	0.80	(Canakci and Akinci, 2006)

[a] Farm yard manure.

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relation to resources consumed in the process. In general, the performance assessment may be carried out by comparing a particular system with key competitors having best performance within the same group or another group performing similar functions (Malana and Malano, 2006). This process is called benchmarking.

Farrell (1957) proposed a new approach to efficiency measurement and the production frontier at the micro level. He divided economic efficiency into resource use (technical) and allocative (price) components. He proposed a piecewise linear envelopment of data as the conservative estimate of the production frontier which envelopes observation points as closely as possible which was estimated by solving a system of linear equations. Technical efficiency (TE) is defined as the *DMU's* ability to achieve maximum output from given inputs, while allocative efficiency is defined as the *DMU's* success in selecting inputs in optimal proportions with respect to price.

There are two kinds of *DEA* models included: *CCR* and *BCC* models. The *CCR* model (Charnes *et al.,* 1978) is built on the assumption of constant returns to scale (CRS) of activities, but the BCC model (Banker, Charnes and Cooper, 1984) is built on the assumption of variable returns to scale (VRS) of activities. The DEA models have been described in detail by several authors (Charnes *et al.,* 1978; Banker *et al.,* 1984), thus a detailed description is not provided here. The dual (envelopment) form of the DEA linear programming problem is simpler to solve than the ratio and multiplier forms due to fewer constraints.

Efficiency by *DEA* is defined in three different forms: overall technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE).

The first development of *DEA* was by Charnes, Cooper and Rhodes (CCR) who measured the efficiency of individual DMUs. Mathematically, the CCR DEA model for measuring the input-oriented TE of a DMU is written as follows (Charnes *et al.,* 1994):

$$\begin{aligned} &\max \theta \\ &s.t.: \\ &Y\lambda \geq Y_o \\ &\theta X_o - X\lambda \geq 0, \\ &\theta\ free,\ \lambda \geq 0. \end{aligned} \tag{4}$$

Where θ is the *TE* of *DMU* to be evaluated, DMU_o and λ represents the intensity of the efficient *DMUs* in projecting inefficient *DMUs* onto the efficient frontier, also called the convexity constant. The optimal efficiency of a *DMU*, θ^*, will be less than or equal to 1. *DMUs* with $\theta^* < 1$ are inefficient while *DMUs* with $\theta^* = 1$ form a set of boundary (frontier) points. The envelopment problem (Equation (4)) evaluates a DMU_o by comparing it with other *DMUs* in the group. The model allocates a minimum value to DMU_o provided that a combination of other *DMUs* does not consume more inputs and outputs (at least equal to DMU_o). The linear programming problem must be repeated for each DMU_j, such that $(X_o, Y_o) = (X_j, Y_j)$ for $j = 1,2,\ldots, n$, where X_o and Y_o are inputs and outputs of the DMU to be evaluated, and n is the total number of *DMUs* considered in the *DEA* analysis(Malana and Malano, 2006).

Constant and Variable Return to Scale

If there is no restriction on λ ($\lambda \geq 0$), the solution to Equation (4) represents constant returns to scale (Seiford and Thrall, 1990). Constant returns to scale (CRS) imply that a given increase in inputs would result in a proportionate increase in outputs and the feasible region of the envelopment problem becomes a conical hull. A restriction on λ ($\lambda = 1$) leads to no condition on the allowable returns to scale, also called variable returns to scale (VRS). Under this condition, the performance frontier line or hyperplanes are not then restricted to pass through the origin (Charnes *et al.,* 1994). An increase in inputs may not result in a proportionate increase in outputs in this case. Due to convexity, the efficient *DMUs* form a convex hull on which all inefficient points are projected.

Banker (1984) extended the *CCR* (after Charnes *et al.,* 1978) model to the estimation of the most productive scale size (MPSS). The *MPSS* was defined as the scale where constant returns to scale (CRS) prevail and the slope of outputs to inputs is 1. Increasing returns to scale (IRS) exist if the slope exceeds 1 and decreasing returns to scale (DRS) occur when the slope of the line is less than 1. *IRS* indicates that an increase in the input resources produces more than proportionate increase in outputs. Similarly, *DRS* suggests a less than proportionate increase in the outputs in response to an increase in inputs.

Because the *VRS* is more flexible and envelops the data in a tighter way than the *CRS*, the score of pure *TE* (θ_{VRS}) is equal to or greater than the *CRS* or overall TE score (θ_{CRS}). The relationship can be used to measure scale efficiency (SE) of the farmers as (Omid *et al.,* 2011):

$$SE = \frac{\theta^*_{CRS}}{\theta^*_{VRS}} \tag{5}$$

Where *SE= 1* implies scale efficiency (or CRS) and *SE< 1* indicates scale inefficiency. A shortcoming of the SE score (5) is that it does not indicate if a *DMU* is operating under *IRS* or *DRS* (Omid *et al.,* 2011). This is resolvable by simply imposing a non-increasing return of scale (NIRS) condition in the *DEA* model, i.e. changing the convexity constraint $\lambda = 1$ of the *VRS* model with $\lambda \le 1$. Let θ_{NIRS} be the efficiency of DMU_i obtained with the *NIRS* model. One then compares the value of TE_{NIRS} with the value of θ_{VRS}. If $\theta_{NIRS} \ne \theta_{VRS}$, then *IRS* applies to DMU_i; if, however, $\theta_{NIRS} = \theta_{VRS}$, then the DRS exists for DMU_i. The information on whether a greenhouse operates at increasing, constant or decreasing returns to scale is particularly helpful in indicating the potential redistribution of resources among the greenhouse and, thus, enables the grower to attain a higher yield.

In this study, we used DEA-solver software to calculate *CRS* and *VRS* with radial distances to the efficient frontier and determine the amount of energy loss and energy savings of inefficient farmers. *NIRS* was calculated with the help of EMS software (Scheel, 2000).

RESULTS AND DISCUSSION

Energy Use Pattern

Table 2 summarizes the energy use pattern and the yield for the 26 farmers. The energy use pattern indicated that diesel, electricity and chemical fertilizers were the major sources of energy for greenhouse cucumber production in the region. Farmers were using different technologies, standards as well as practices. For example, some farmers were replacing chemical fertilizers with FYM, some farmers were using heaters with low efficiency, therefore the production and yield differences were noticeable between the farmers who were using advanced technologies and those practicing haphazardly. The averages of human, diesel,

Table 2. Summary of inputs (source wise energy use, MJ ha^{-1}) and output (yield, kg ha^{-1}).

Particular	Labor	Diesel	Electricity	Transportation	FYM	Chemical fertilizers	Chemicals	Yield
Max	17640	337985	299702	91222	78000	136351	22350	333333
Min	7317	45116	45432	2703	0	10719	3172	55556
Average	9935	192798	121856	31942	28412	41023	10860	160666
SD	2132	72726	65198	23391	18440	26461	5968	58471

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electricity, transportation, FYM, chemical fertilizers and chemicals energy were 9,935, 192,798, 121,856, 31,942, 28,412, 41,023 and 10,860 MJ ha^{-1}, respectively. The energy consumptions of diesel and electricity were very high in the studied area mainly due to use of heaters and pumps with low efficiency and also low price of diesel fuel and electricity in Iran. Also, the high contribution of chemical fertilizer energy showed that not all farmers were fully aware of proper time and quantity of fertilizers application.

The cucumber yield, energy use efficiency (output–input ratio), energy productivity, and net energy of cucumber production are shown in Table 3. The average yield in cucumber production was determined to be 160666 kg ha^{-1}. Energy use efficiency (Equation (1)) was calculated as 0.29. Other results such as 0.76 for cucumber, 0.61 for eggplant, 0.99 for pepper (Ozkan *et al.,* 2004b), 0.32 for tomato, 0.31 for cucumber, 0.23 for eggplant, 0.19 for pepper (Canakci and Akinci, 2006) and 0.74 for cotton (Yilmaz *et al.,* 2005), have been reported, showing the inefficient use of energy in the cucumber production in the region. The average energy productivity of cucumber (Equation (2)) was 0.37 kg MJ^{-1}. The calculation of energy productivity rate is well documented in the literature such as; soybean (0.18) (De *et al.,* 2001), tomato (0.40), cucumber (0.39), eggplant (0.29), and pepper (0.23) (Canakci and Akinci, 2006). The net energy (Equation (3)) of cucumber production was -308,292 MJ ha^{-1}, therefore, it can be concluded that in cucumber production, energy is being lost. Mohammadi and Omid (2010) found a negative value for the net energy of greenhouse cucumber production.

In addition to high consumption of diesel and electricity, due to the lack of soil analysis, chemical fertilizers energy was high in the studied area and therefore, energy use efficiency, energy productivity and net energy in this study were low.

Energy forms used in cucumber production were also investigated (Table 3). The distribution of inputs used in the production of cucumber according to the direct (DE), indirect (IDE), renewable (RE) and non-renewable (NRE) energy groups is indicated in Table 3. The total energy input consumed could be classified as *DE* (81.62%), *IDE* (18.38%), *RE* (8.78%) and *NRE* (91.22%), indicating that greenhouse cucumber production depends mainly on fossil fuels. Several researchers have found that the ratio of *DE* was higher than that of *IDE*, and the rate of *NRE* was much greater than that of *RE* consumption in cropping systems (Hatirli *et al.,* 2006; Ozkan *et al.,* 2004a; Esengun *et al.,* 2007a). The high ratio of *NRE* in the total used energy inputs causes negative effects on the sustainability in vegetable production. Therefore, it is important to better utilize the *RE* sources to make up for the increasing energy deficit, as

Table 3. Energy output–input ratio and forms in cucumber production.

Items	Unit	Cucumber	%
Cucumber yield	kg ha^{-1}	160666	
Energy use efficiency	-	0.29	
Energy productivity	kg MJ^{-1}	0.37	
Net energy	MJ ha^{-1}	-308292	
Direct energy[a]	MJ ha^{-1}	356531	81.62
Indirect energy[b]	MJ ha^{-1}	80294	18.38
Renewable energy[c]	MJ ha^{-1}	38346	8.78
Non-renewable energy[d]	MJ ha^{-1}	398478	91.22
Total input energy	MJ ha^{-1}	436824	100

[a] Includes human labor, diesel, electricity and transportation; [b] Includes fertilizers and chemicals; [c] Includes human labor and farm yard manure, [d] Includes diesel, chemical fertilizers, chemicals and electricity.

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they represent an effective alternative to fossil fuels for preventing resources depletion and for reducing air pollution. Agriculture has the potential to become an increasingly important source of *RE* and provide significant economic opportunities for producers. *RE* production stimulates the agricultural and rural economy, improves the environment and enhances national energy security.

Identifying Efficient and Inefficient Farmers

The results of the analysis are discussed under the following headings:

• Identifying efficient and inefficient farmers and determining *RTS*,

• Adopting efficient operating practices,

• Setting realistic input levels for inefficient farmers.

The *BCC* model results indicated that of the total of 26 greenhouses considered for the analysis, 17 farmers had efficiency score of unity. Thus, they were efficient. On the other hand, the remaining 9 farmers who secured efficiency scores less than one were relatively inefficient in energy use from the different sources. However, the technical efficiency estimation indicates that only 11 farmers were efficient. The average values of the *PTE, TE* and *SE* are summarized in Table 4.

The average values (for all 26 farmers considered) of *PTE, TE* and *SE* were found to be 0.95, 0.83 and 0.88, respectively. The results of the *RTS* indicate that all efficient farmers (based on PTE) were operating at *CRS*, whereas all inefficient farmers were found to be operating at *IRS*. The average of *SEs* was as low as 0.88, which indicates that if the scale size of *DMU* were moved toward the best size, the scale efficiency could be improved.

Table 4. Technical efficiency, reference set inefficient farmers and return to scale.

DMU	Technical efficiency		*SE*	Frequency in reference set	Benchmarks	*RTS*
	CRS	*VRS*				
1	1.00	1.00	1.00	0		Constant
2	1.00	1.00	1.00	13		Constant
3	1.00	1.00	1.00	3		Constant
4	0.67	0.98	0.68		2(0.39)11(0.03)13(0.19)	Increasing
5	1.00	1.00	1.00	2		Constant
6	0.83	0.86	0.97		13(0.83)	Increasing
7	1.00	1.00	1.00	2		Constant
8	1.00	1.00	1.00	0		Constant
9	0.62	0.83	0.75		2(0.30)3(0.09)5(0.16)7(0.00)13(0.12)	Increasing
10	0.62	1.00	0.62		3(0.09)5(0.10)7(0.03)13(0.24)	Increasing
11	1.00	1.00	1.00	3		Constant
12	0.60	0.81	0.74		2(0.12)13(0.42)20(0.01)	Increasing
13	1.00	1.00	1.00	14		Constant
14	0.70	1.00	0.70		2(0.27)11(0.03)13(0.02)	Increasing
15	1.00	1.00	1.00	0		Constant
16	0.98	1.00	0.98		2(0.02)11(0.06)13(0.51)20(0.17)	Increasing
17	1.00	1.00	1.00	0		Constant
18	0.74	0.90	0.82		2(0.22)13(0.20)20(0.23)	Increasing
19	0.57	1.00	0.57		2(0.15)13(0.23)	Increasing
20	1.00	1.00	1.00	7		Constant
21	0.94	1.00	0.94		2(0.16)13(0.53)20(0.12)	Increasing
22	0.72	1.00	0.72		2(0.27)13(0.27)20(0.03)	Increasing
23	0.64	0.98	0.65		2(0.22)3(0.20)13(0.21)	Increasing
24	0.67	0.80	0.84		2(0.35)13(0.34)	Increasing
25	0.68	0.70	0.97		2(0.67)20(0.20)	Constant
26	0.63	0.74	0.86		2(0.28)13(0.01)20(0.37)	Increasing
Average	0.83	0.95	0.88			
SD	0.17	0.09	0.15			

Benchmarking

Table 4 shows the results of technical efficiency analysis for the 26 greenhouse cucumber production units (DMUs). The *VRS* analysis (BCC model) showed that 17 out of 26 *DMUs* were efficient. These efficient *DMUs* can be selected by inefficient *DMUs* as best practice *DMUs*, making them a composite *DMU* instead of using a single *DMU* as a benchmark.

A composite *DMU* is formed by multiplying the intensity vector λ by the inputs and outputs of the respective efficient *DMUs*. For example, for *DMU4*, the composite *DMU* that represents the best practice or reference composite benchmark *DMU* is formed by the combination of *DMUs* 2, 11 and 13. This means that *DMU4* is close to the efficient frontier segment formed by these efficient *DMUs*, represented in the composite *DMU*. The selection of these efficient *DMUs* is made on the basis of their comparable level of inputs and output yield to *DMU4*. In Table 4, the benchmark *DMU* for unit 4 is expressed as 2(0.39) 11(0.03) 13(0.19), where 2, 11 and 13 are the *DMU* numbers while the values between brackets are the intensity vector λ for the respective *DMUs*. The higher value of the intensity vector λ for unit 2 (= 0.39) indicates that its level of inputs and output is closer to *DMU4* compared to other *DMUs*. The summation of all intensity vectors in a benchmark *DMU* must equal 1. On the other hand, the unit 13 appears 14 times in the reference set of inefficient *DMUs*. This places unit 13 closest to the input and output levels of most of the inefficient *DMUs* but uses fewer inputs.

While the *DEA* results highlight the lower yield of inefficient units, a more detailed analysis by including the effects of uncontrollable exogenous variables, such climatic conditions and soil fertility as well as agricultural practices, ownership, producer's experience and education should be incorporated in future studies in order to investigate the causes of inefficiency. Furthermore, these units are not perfectly competitive and therefore cannot be treated on equal grounds. However, by identifying those units with lower yield, this analysis provides a quantification of the yield in these units in relation to those performing at the frontier of high yield, thus enabling producers and scientists to focus their attention on those units with lower performance to determine the actual underlying causes of that under performance.

Returns to Scale

The analysis shows that the efficient units under the *CRS* model are both technically and scale efficient (Table 4). The *RTS* analysis indicated that efficient and inefficient units (based on pure technical efficiency) were operating at *CRS* and *IRS*. In the units with *IRS*, technological change is required to attain considerable changes in yield (Omid *et al.,* 2011).

Setting Realistic Input Levels for Inefficient Farmers

The pure technical efficiency score of a greenhouse that is less than one indicates that, at present, the farmer is using more energy than required from the different sources. Therefore, it is desired to suggest realistic levels of energy to be used from each source for every inefficient farmer in order to avert wastage of energy without reducing the yield level. Using the information in Table 5, it is possible to advise a farmer on the better operating practices followed by his peers in order to reduce the input energy level to the target values indicated in the analysis while achieving the output level presently achieved by him. This gives the average energy spent and targeted (MJ ha^{-1}), possible energy savings and percent of energy saving from each source. The amount of diesel, electricity, chemical fertilizer, FYM,

Table 5. Energy savings from different sources if recommendations of the study are followed.

Inputs	Present use (MJ ha^{-1})	Target use (MJ ha^{-1})	Energy saving (MJ ha^{-1})	Savings (%)
Chemicals	10860	6306	4554	41.93
Farm yard manure	28412	16145	12267	43.18
Chemical fertilizers	41023	23837	17186	41.89
Labor	9935	7593	2342	23.58
Diesel	192798	137476	55322	28.69
Transportation	31942	23080	8862	27.74
Electricity	121856	90148	31708	26.02
Total input energy	436824	304584	132240	30.27

transportation, chemicals and human energy saving were 55,322, 31,708, 17,186, 12,267, 8,862, 4,554 and 2,342 MJ ha^{-1}, respectively.

Results show that reductions in diesel fuel, electricity and fertilizers consumptions are important for energy saving and decreasing the environmental risk problem in the area. A saving in diesel fuel and electricity by improving heaters and pumps performance and in fertilizer by soil analysis may be possible. We note from Table 5 that the possible overall energy saving is 30.27%.

CONCLUSIONS

In this research, the energy requirements of inputs and output for greenhouse cucumber production were examined. The results indicated that total input energy, total output energy and energy use efficiency were 436,824 MJ ha^{-1}, 128,532 MJ ha^{-1} and 0.29, respectively.

Also the paper describes the application of *DEA* to the study for improving the energy use efficiency in greenhouse cucumber production in Esfahan province. Based on the results, the following conclusions may be drawn:

- *DEA* is highly suitable to analyze these data and extract many distinctive features of their practices. *DEA* has helped in segregating efficient farmers from inefficient farmers. It has also helped in finding the wasteful uses of energy by inefficient farmers, and ranking energy sources by using the distribution of virtual inputs. The practices followed by the truly efficient farmers form a set of recommendations in terms of efficient operating practices for the inefficient farmers.
- The average values (for all 26 farmers considered) of *PTE*, *TE* and *SE* were found to be 0.95, 0.83 and 0.88, respectively.
- On the average, about 30.27% of the total input energy could be saved without reducing the cucumber yield from its present level by adopting the recommendations based on the present study.
- The energy use pattern indicates that diesel, electricity and chemical fertilizers are the major sources of energy for greenhouse cucumber production in the studied area. Therefore, inefficient farmers should strive to utilize such energy saving devices. A saving in diesel fuel and electricity by improving heaters and pumps performance and in fertilizer by soil analysis may be possible.

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کاربرد تحلیل پوششی داده‌ها برای تعیین کارایی و فرصت بهبود کارایی انرژی در گلخانه‌های تولید خیار

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چکیده

در این مطالعه سعی شد تا از روش تحلیل پوششی داده‌ها در جهت تخمین کارایی فنی و بازگشت به مقیاس برای گلخانه‌های تولید خیار در ایران استفاده شود. برای این کار داده‌ها از گلخانه‌های استان اصفهان در دوره کشت بهاره، به روش تصادفی جمع‌آوری شدند. نتایج نشان دادند که کل انرژی ورودی، کل انرژی خروجی و نسبت انرژی به ترتیب برابر ۴۳۶۸۲۴ مگاژول بر هکتار، ۱۲۸۵۳۴ مگاژول بر هکتار و ۰.۲۹ بودند. تحلیل پوششی داده‌ها می‌تواند برای بهینه‌کردن کارایی هر گلخانه استفاده شود. بر اساس مدل‌های بازگشت به مقیاس ثابت و متغیر ورودی محور، مقادیر متوسط کارایی فنی خالص، کارایی فنی و کارایی مقیاس به ترتیب برابر با ۰.۹۵، ۰.۸۳ و ۰.۸۸ به‌دست آمدند. همچنین نتایج مشخص کردند که با کارا شدن همه‌ی گلخانه‌ها، به طور متوسط حدود ۳۰.۲۷ درصد از کل انرژی‌های ورودی بدون تغییر در عملکرد، کاهش خواهد یافت.