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Energy efficiency and congestion considering Data Envelopment Analysis and Bounded Adjusted Measure: A case of tomato production

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Abstract

Auditing energy usage of farming operations is a key step towards agricultural sustainability. The current systems of tomato production use a considerable quantity of energy. As a result, improving energy efficiency is a crucial stage in decreasing energy consumption in tomato production. Data envelopment analysis (DEA) model is an established methodology to assess energy efficiency in crop production. In this study, the bounded adjusted measure (BAM) is applied for improving the efficiency of tomato production as well as decreasing the carbon footprint. In this regard, the overall, environmental, production, and pure emission efficiency of tomato production in 24 provinces of Iran are investigated. The nine overall efficient tomato producing provinces recognized that showed they had no input excesses and/or output shortfalls. Also, similar to the overall efficiency, nine out of the 24 DMUs were recognized as environmental, production, and pure emission efficient. Finally, in order to measure the probable amounts of excessive investments in inputs, with the aim of obtaining more outputs, a new approach of determining congestion is proposed based on BAM model.

Keywords: Data Envelopment Analysis (DEA), Bounded Adjusted Measure (BAM), Congestion, Tomato production, Energy efficiency.

1 Introduction

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Modern agriculture is closely related to energy. A variety of novel methodologies of agricultural production consume a considerable quantity of energy. Auditing energy use of farming operations to improve efficiency and decrease environmental impacts is a key step towards agricultural sustainability (Erdal et al., 2007). Mathematical models have shown that they can be an effective tool for evaluating the performance of different organizations. Accordingly, the design of an appropriate mathematical model to evaluate the performance of farms that are active in tomato production and, also, to identify their strengths and weaknesses in energy consumption is the primary motivation of the present study. Previous studies indicate that, among the existing mathematical models and methods, data envelopment analysis has a special place in the field of performance evaluation (Emrouznejad and Yang, 2018) and can be employed to measure the efficiency of DMUs (Aliakbarpoor and Izadikhah, 2012). DEA is a non-parametric mathematical programming technique proposed by Charnes et al. (1978) for evaluating the relative efficiency of decision making units (DMUs) . One of the problems of some traditional DEA models like CCR, is the inability to recognize the weak efficiency. This difficulty is due to the radial form of these models (Izadikhah and Farzipoor Saen, 2016). However, non-radial DEA models overcome this problem, and in general, they have some priorities over radial DEA models. This paper applies the Bounded-Adjusted Measure (BAM) model, a non-radial DEA based model, to determine tomato farms' Overall Efficiency (OE), Environmental Efficiency (EE), Production Efficiency (PE) and Pure Emission Efficiency (PEE). BAM model is a non-radial DEA model with linear objective function and proposed by Cooper et al. (2011). The linearity of the objective function makes it possible to easily calculate the linear form of the dual of BAM model. Furthermore, the BAM model can be used under any of the standard returns to scale models, provided the corresponding bounded additive model is considered (Cooper et al., 2011). However, since in this study, the increase in inputs does not result in a proportional change in the outputs, the BAM model is considered under variable return to scale technology.

DEA is used to calculate the performance efficiency of various agricultural products such as maize (Mulwa et al., 2009; Mwambo et al., 2021), tomato (Murthy et al., 2009; Platis et al., 2021), cucumber (Omid et al., 2011), grape (Khoshroo et al., 2013), walnut (Khoshroo and Mulwa, 2014), watermelon (Khoshroo and Izadikhah, 2019) and dairy products (Cortés et al., 2021). Sueyoshi et al. (2017) systematically reviewed application of data envelopment analysis in energy sector and environmental related studies.

The concept of congestion is used in various fields such as medicine, traffic, agriculture and population. A good example of congestion is mines. When the number of workers in a mine increases, the amount of ore extracted decreases. Also, increasing the number of workers in a small production causes them to collide with each other. This is an example of congestion in which reducing the number of workers increases output and production (Cooper et al., 2000). In other words, increasing at least one input without improving other inputs and outputs reduces the number of outputs from its maximum value (or vice versa, a decrease in one or more inputs leads to an increase in some outputs), thus, congestion occurs (Wei and Yan, 2004).

Agricultural policymakers aim to determine the probable amount of excessive investments in inputs to get more outputs. Thus, the measurement of congestion in inputs can be helpful in measuring the performance of crop production. From the econometric point of view, congestion in DEA that was proposed by Fare and Svensson (1980) is an economic condition that results from excessive investments in one or some input resources (Karimi et al., 2016). Therefore, the second goal in this study is to design a model to calculate the congestion in each tomato production farm. Such management will lead to more control over energy consumption.

Recently, the policy of Iran’s government has been to optimize energy demands in all economic sectors. Therefore, an important issue in Iran’s agriculture is efficient use of finite energy resources.

This study investigates the performance of tomato farms in Iran’s provinces by using a DEA-BAM methodology to determine the efficient or inefficient tomato farms and suggest inefficiency sources. As far as we know, this is the first application of BAM model in efficiency estimation of agricultural products. Because BAM model integrates lower bounds for inputs and upper bounds for outputs, BAM has more discriminatory power in comparison to other DEA models like RAM (Range Adjusted Measure). Therefore, better estimation of efficiency in agricultural products is assumed. Due to the fact that, so far, no mathematical model has been used to determine congestion in crop production for energy management, this study also intends to evaluate congestion of tomato production by using the proposed DEA-BAM model. This paper, also, presents the link between DEA-based congestion and crop physiology.

The remaining part unfolds as follows: section 2 provides the Literature review; the developed methodology is described in section 3; the case study is introduced in section 4; and, section 5 presents the conclusions.

2 Literature Review

2.1 DEA models to measure Farming's efficiency

Since 1978 that the DEA was initially introduced by Charnes-Cooper-Rhodes, it has become an efficient tool for productivity estimation in agriculture. using the DEA technique and Tobit regression, Khoshroo et al. (2013) proposed that education level of farmers had a significant effect on efficiency of grape production. Masuda (2016) applied a DEA-LCA technique to determine the eco-efficiency of wheat farms in Japan. Izadikhah and Khoshroo (2018) evaluated the performance of 22 barley production farms in Iran in a fuzzy environment. For this purpose, they introduced a modified Enhanced Russell DEA Model with undesirable output. Arabi et al. (2016) presented DEA models to find efficient power plants based on less fuel consumption, combusting less polluting fuel types, and incorporating emission factors in order to measure the ecological efficiency trend during an eight-year period of power industry restructuring in Iran.

Recently, Feng and Wang (2017) used the meta-frontier DEA approach to evaluate the efficiency and possible energy savings in industrial sectors of China. Guo et al. (2017) estimated the inter-temporal efficiency using a dynamic DEA model based on fossil-fuel carbon dioxide pollution. Gong et al. (2017) introduced a model based on DEA methodology and factor analysis to increase the accuracy of determining the productivity under different operating conditions in the production of ethylene.

Vlontzos and Pardalos (2017) implemented a DEA-ANN technique to investigate the efficiency and environmental performance of agricultural production in the European Union. Tahmasebi et al. (2018) evaluated environmental sustainability in wheat production in Iran. Khoshroo et al. (2018) developed a non-radial DEA model by considering undesirable outputs to assess the performance of 30 turnip farms in Iran.

Yang and Wei (2019) estimated energy efficiency of 26 Chinese cities during 2005-2015 using a DEA model. Their results implied that economic growth has an important role in promoting energy efficiency. Geng et al. (2019) developed a new DEA model for assessment and optimization of efficiency in petrochemical industries. The proposed model identifies the most significant factors affecting energy efficiency. Ezici et al. (2020) developed a combined time series MRIO and DEA model to examine the sustainability indices based on utilization of renewable and non-renewable energies and economic returns of manufacturing industries in the United States. For a deep review of applying DEA methodologies on energy efficiency see Mardani et al. (2017) and Yu and He (2020). Although all of the above models have used data envelopment analysis models to evaluate the performance of agricultural industry, none of them have used the BAM model for their evaluation. On the other hand, none of the mentioned studies have calculated the congestion of resources in the agricultural industry. This indicates the importance of using the proposed method in this study.

2.2 Backgrounds on the Bounded Adjusted Measure model

Cooper et al. (2011) introduced the Bounded Adjusted Measure (BAM) for the additive model to improve the Range Adjusted Measure (RAM) model which was defined by Cooper et al. (1999). Rashidi and Farzipoor Saen (2015) developed a BAM model based on green factors to determine the eco-efficiency of DMUs. Haghighi and Rostamy-Malkhalifeh (2017) applied the BAM model for investigating the environmental efficiency of organizations. The above methods have mainly used and developed the BAM model to evaluate the performance of the units. A noteworthy point about the present study is that with the help of the proposed model based on the BAM model, four criteria, i.e. overall efficiency (OE), environmental efficiency (EE), production efficiency (PE), and pure emission efficiency (PEE), have been suggested for evaluating the tomato farms. Moreover, the proposed BAM model is further extended to measure the amount of possible congestion.

2.3 Review of existing DEA models for measuring congestion

Congestion is a well-known economic concept which shows that reductions in any inputs lead to increase in outputs (Cooper et al., 2001). Fare and Svensson (1980) introduced another aspect of congestion based on the law of variable proportions. Färe and Grosskopf (1983) introduced a new definition of congestion based on DEA models that makes the Fare-Svensson idea more operational. Table 1 summarizes the existing method of measuring the congestion based on data envelopment analysis.

Table 1: Existing DEA methods for measuring the congestion

	Reference	**Description**	**Property**
1	(Cooper et al., 2000); (Wei and Yan, 2004)	They developed required condition for determining (input) congestion.	Identifying congestion
2	(Brockett et al., 2004)	They proposed a methodology that dealt with identifying and managing congestion.	
3	(Khodabakhshi, 2009)	They provided a one-model congestion model	Input relaxation
4	(Noura et al., 2010)	They proposed a way to reduce the computational process	Less computation
5	(Sharma and Yu, 2013)	They developed a multi-stage DEA to obtain congestion	Multi-stage DEA
6	(Khoveyni et al., 2013)	They presented a slacks-based model to measure the congestion	Strong and Weak Congestion
7	(Wu et al., 2013); ; (Chen et al., 2019)	They considered undesirable outputs to calculate congestion	Undesirable outputs
8	(Meng et al., 2014)	They proposed RAM model for measuring the energy performance and congestion	RAM model
9	(Reza Salehizadeh et al., 2015)	They calculated the congestion based on multi-objective model	Multi-objective congestion
10	(Sueyoshi and Yuan, 2016)	They measured the returns to damage and damages to return based on DEA approaches	Returns to damage and damages to return
11	(Chen et al., 2016)	They employed economic, environmental and the economic-environmental congestion aspects	Three policy objectives
12	(Khoveyni et al., 2017)	They considered negative data to measure the congestion	Negative data
13	(Karimi et al., 2016); (Khoveyni et al., 2019)	They took into account integer data to obtain congestion	Integer-valued data
14	(Zhou et al., 2017)	They measured congestion by using a two-stage DEA	Two-stage DEA
15	(Mehdiloozad et al., 2018)	They proposed a single-stage LP model to determine the congestion status	Weak and strong congestion; Negative data
16	(Zhang et al., 2020); (Chen et al., 2020)	They proposed models to measure the carbon congestion	Carbon Congestion

The models presented in Table 1 calculate the amount of congestion in different modes. Nevertheless, the distinguishing features of the proposed model in this study are: i: congestion measurement based on the BAM model for the first time, ii: considering the undesirable data, and iii: application in the field of agriculture.

3. Proposed methodology

The main motivation of this study originates from the need to develop and apply a reliable approach to manage energy consumption in tomato production. Recent methods of tomato production use considerable quantity of energy, thus, decreasing energy consumption in tomato production is an important stage in improving energy efficiency. Data envelopment analysis can be considered as one of the most effective approach to evaluate the performance of firms, especially in assessing energy efficiency. Therefore, new insights based on DEA models are discussed in this section.

3.1 Efficiency measures

This study uses BAM model to evaluate efficiency measures. There are n DMUs as $DMU_j, j = 1, \dots, n$ which DMU_j produces s_1 desirable outputs $y_{rj}^g,\ (r = 1, \dots, s_1)$ and s_2 undesirable outputs $y_{fj}^u, (f = 1, \dots, s_2)$ by consuming m inputs $x_{ij},\ (i = 1, \dots, m)$. The main purpose of this paper is to measure the effect of emission on performance and also to discuss managing the amount of produced emission's level. In order to treat the undesirable outputs as desirable inputs, inspiring from (Iqbal Ali and Seiford, 1990), (Pastor, 1996), (Seiford and Zhu, 2002), and (Sahoo et al., 2011) we consider the extended strong disposability assumption and define M_f as a positive and big enough number where ensures that the value of y_{fj}^b is always non-negative. Hence, we set $y_{fj}^u < M_f$, and $y_{fj}^b = M_f - y_{fj}^u > 0$. Thus, the following unified DEA-BAM model (1) is proposed:

$$
\begin{aligned}
&\max \sum_{i=1}^{m} H_{ip}\gamma_i + \sum_{r=1}^{s_1} H_{rp}^g \sigma_r^g + \sum_{f=1}^{s_2} H_{fp}^b \sigma_f^b \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{ij} + \gamma_i = x_{ip}, \quad i = 1, \dots, m, \\
&\sum_{j=1}^{n} \lambda_j y_{rj}^g - \sigma_r^g = y_{rp}^g, \quad r = 1, \dots, s_1, \\
&\sum_{j=1}^{n} \lambda_j y_{fj}^b - \sigma_f^b = y_{fp}^b, \quad f = 1, \dots, s_2, \\
&y_{fj}^b = M_f - y_{fj}^u, \quad \forall f, j,
\end{aligned} \tag{1}
$$

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

$$\gamma_i, \sigma_r^g, \sigma_f^b, \lambda_j \geq 0, \ \ \forall i, r, f, j$$

Where M_f is a positive and big enough number and ensures that the value of y_{fj}^b is always non-negative. In the fourth constraint, the large positive number M_f is used to convert the undesirable output to the desired one. In model (1), γ_i, σ_r^g, and σ_f^b are all slack variables and

$$\begin{aligned} &H_{ip} = 1/\left\{(m+s_1+s_2)(x_{ip} - \min_j\{x_{ij}\})\right\}, \ \ (i=1,\dots,m), \text{ and} \\ &H_{rp}^g = 1/\left\{(m+s_1+s_2)(\max_j\{y_{rj}^g\} - y_{rp}^g)\right\}, \ \ (r=1,\dots,s_1), \text{ and} \\ &H_{fp}^b = 1/\left\{(m+s_1+s_2)(\max_j\{y_{fj}^b\} - y_{fp}^b)\right\}, \ \ (f=1,\dots,s_2) \end{aligned} \tag{2}$$

Based on the unified model (1), the overall efficiency (OE) score for DMU_p can be defined as follows:

$$\theta_p^o = 1 - \left[\sum_{i=1}^{m} H_{ip}\gamma_i^* + \sum_{r=1}^{s_1} H_{rp}^g \sigma_r^{g*} + \sum_{f=1}^{s_2} H_{fp}^b \sigma_f^{b*}\right] \tag{3}$$

Where γ_i^*, σ_r^{g*}, and $\sigma_f^{b*}$are the optimal values based on model (1).

An important feature of a performance assessment model is that it provides a performance measure, usually between zero and one, to determine efficient and inefficient units. The following proposition guarantees that the overall efficiency is always between zero and one, and as a result, it is a convenient criterion for measuring the performance efficiency. For convenience, we provide its proof in the appendix.

Proposition 1: For each DMU_p we have $0 \leq \theta_p^o \leq 1$.

Definition 1: If $\theta_p^o = 1$, DMU_p is called overall efficient, and otherwise it is called overall inefficient.

Inspired from Wang et al. (2013) and based on the optimum solution of Model (1), the environmental efficiency (EE) score can be measured by

$$\theta_p^e = 1 - \left[\sum_{i=1}^{m} H_{ip} \gamma_i^* + \sum_{f=1}^{s_2} H_{fp}^b \sigma_f^{b*} \right] \tag{4}$$

Clearly, in each optimal solution, we always have $\theta_p^e \geq \theta_p^o$. The overall efficiency measure incorporates the inputs and, both, the good and bad outputs; however, environmental efficiency does not consider the good outputs. Production efficiency (PE) score is measured by

$$\theta_p^p = 1 - \left[\sum_{i=1}^{m} H_{ip} \gamma_i^* + \sum_{r=1}^{s_1} H_{rp}^g \sigma_r^{g*} \right] \tag{5}$$

Again, in each optimal solution, we always have $\theta_p^p \geq \theta_p^o$. The production efficiency does not consider the undesirable emission outputs.

According to the works of Iftikhar et al. (2016), Chang et al. (2013), Hu and Wang (2006) and Zhou et al. (2008) the pure emission efficiency (PEE) can be obtained by dividing target emissions with actual emissions as follow:

$$\theta_p^{PEE} = \frac{y_p^b - \sigma_p^b}{y_p^b} \tag{6}$$

By solving model (1), the optimal level of inputs and outputs that are known as target values can be calculated using equations (7), (8) and (9). These equations determine the position of the *p*-th (inefficient) DMU on the efficiency frontier by eliminating the slacks as follows:

Optimal level of i^{th} input: $$\hat{x}_{ip} = \sum_{j=1}^{n} \lambda_j^* x_{ij} = x_{ip} - \gamma_i^*, \qquad i = 1, \ldots, m, \tag{7}$$

Optimal level of r^{th} desirable output: $$\hat{y}_{rp}^g = \sum_{j=1}^{n} \lambda_j^* y_{rj}^g = y_{rp}^g + \sigma_r^{g*}, \qquad r = 1, \ldots, s_1, \tag{8}$$

Optimal level of f^{th} undesirable output: $$\hat{y}_{fp}^b = \sum_{j=1}^{n} \lambda_j^* y_{fj}^b = y_{fp}^b - \sigma_f^{b*}, \quad f = 1 \ldots, s_2, \tag{9}$$

The value of λ_k^* shows the intensity value, and, $\hat{x}_p$ and $\hat{y}_p$ are the projection of DMU_p on the efficiency frontier.

3.2 Analyzing Congestion

Congestion is one of the concepts that has attracted a remarkable attention in the production area. Existence of extra inputs can lead to recognizing congestion in a DMU and causes to reduce the efficiency of the DMU by increasing the costs and decreasing outputs. As a result, finding the congestion status can give important information to the decision makers and help them to make appropriate decisions about DMUs. Based on the definition of congestion, if a DMU has congestion, then the decision maker can reduce its inputs for the purpose of increasing its outputs (Khoveyni et al., 2017).

Traditional approaches are only designed to detect undesirable congestion. Most often, both desirable and undesirable outputs can be produced during a real problem process. Since, in reality, not usually can all outputs be expected to increase, in the case of undesirable outputs these models fail to give a correct efficiency score. In this case, authors often suggest methods to enhance the amount of the desirable outputs as much as possible, and decrease the values of inputs and undesirable outputs, that is, they recommend decision makers to remove the undesirable congestion and improve the desirable congestion (Chen et al., 2016). In the case of an undesirable output, like emission, pollution, etc., determining the existence and amount of congestion can help decision makers to take appropriate action to increase the efficiency of firms.

As a result, this paper simultaneously considers the environmental and economic effects to develop a methodology for protecting the environment and improving the economy status. Based on the congestion definition both desirable and undesirable congestion caused by extra inputs should be considered, and decision makers must modify the inputs level for the purpose of maximizing the efficiency score without decreasing the desirable outputs or increasing undesirable outputs. Therefore, in order to measure the amount of congestion in inputs, inspired by Chen et al. (2016) and based on the capabilities of the BAM model, the following DEA mathematical model (10) is proposed:

$$\max \sum_{r=1}^{s_1} \sigma_r^g + \sum_{f=1}^{s_2} \sigma_f^b + \varepsilon\left(\sum_{i=1}^{m} -s_i^{-c}\right)$$

s.t.

(10)

$$\sum_{j=1}^{n} \lambda_j x_{ij} = x_{ip} - s_i^{-c}, \quad i = 1, \dots, m,$$

$$\sum_{j=1}^{n} \lambda_j y_{rj}^{g} = y_{rp}^{g} + \sigma_r^{g}, \quad r = 1, \dots, s_1,$$

$$\sum_{j=1}^{n} \lambda_j y_{fj}^{b} = y_{fp}^{b} + \sigma_f^{b}, \quad f = 1, \dots, s_2,$$

$$y_{fj}^{b} = M_f - y_{fj}^{u}, \quad \forall f, j,$$

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

$$s_i^{-c}, \sigma_r^{g}, \sigma_f^{b}, \lambda_j \geq 0, \ \forall i, r, f, j$$

Where $s_i^{-c^*}$ denotes the congestion value for the i^{th} input. With a simple investigation, it can be understood that model (10) always has feasible solution.

According to Cooper et al. (2002), $\varepsilon > 0$ in model (10), is formulated as a "non-Archimedean infinitesimal, i.e. $\varepsilon > 0$ is smaller than *any* positive real number and, also, the product of ε by *any* real number. This means that $\varepsilon > 0$ is not a real number because it has the Archimedean property. However, it is not necessary to specify a value of $\varepsilon > 0$ explicitly. The two-phase procedure accomplishes all that is required. Phase I accords priority to max $\sum_{r=1}^{s_1} \sigma_r^{g} + \sum_{f=1}^{s_2} \sigma_f^{b}$, and according to the optimal solution of phase I, in phase II the objective max $\sum_{i=1}^{m} -s_i^{-c}$ is solved (see Amin and Toloo (2004) for more details).

4 An application

Tomato is the second most consumed vegetable in the world. Tomato is a valuable source of vitamin A, vitamin C and several minerals, including calcium, iron, manganese, and, particularly, potassium (Gould, 1992). In 2019, world's production of tomato was approximately 180.7 Mt. The leading tomato producing countries are China, India, Turkey, USA, Egypt, Italy, Iran, and Spain. Tomato production in Iran exceeds 5.25 Mt with the cultivation area of 121,000 hectares (FAO, 2019) . Murthy et. al (2009) studied technical and scale efficiencies of tomato-producing farms in Karnataka, India, using data envelopment analysis approach. Results showed that improving labor and land efficiencies would provide the higher tomato yields. Jung and Yang (2016) evaluated economic efficiency of tomato farms using DEA approach. They studied how production characteristics and farm size affect overall efficiency, allocative efficiency, and technological efficiency.

4.1 Data set

This research intends to measure the performance efficiency of tomato production in Iran. Therefore, data of tomato production in 24 provinces of Iran during 2014-2015† is taken into account. Energy inputs in the developed DEA model are labor, machinery, fertilizers, biocides and electricity. In this study two outputs are considered: TPV (Total Production Value) of tomato farms as desirable output and environmental emission as undesirable output. Table 2 shows the statistical description of data variables. Production, storage and distribution of agricultural inputs lead to the combustion of fossil fuel that emits CO_2 and other greenhouse gases into atmosphere. Congestion, which reduces the use of excessive agricultural inputs, decreases pollution and greenhouse gas emissions of crop production.

Table 2: Statistical measures of inputs and outputs of tomato production in Iran

Statistical measure	Inputs					Outputs	
						Good output	Bad output
	Labor (MJ)	Machinery (MJ)	Fertilizers (MJ)	Biocides (MJ)	Electricity (MJ)	TPV (10000 Rial)	Emission (kg)
Average	571.81	564.35	6255.06	533.08	740.91	18868.80	1357.68
Std. Deviation	248.37	1525.16	1393.71	0.00	472.57	10413.71	432.72
Min	3355.99	3544.36	28005.77	2640.00	3506.62	4476.19	780.70
Max	571.81	564.35	6255.06	533.08	740.91	42422.68	2319.10

4.2 Results and discussion

The results of running the proposed models on the tomato farms in 24 provinces of Iran at the time period of 2014-2015 are presented in Table 3. Here, the efficiency of tomato farms is measured by the model (3) and the overall, environmental, production and pure emission efficiency are calculated by Models (4-6). Where 'OE', 'EE', 'PE' and 'PEE' stand for overall, environmental, production and pure emission efficiency, respectively. In Table 3 there are nine

†Annual agricultural statistics. Ministry of Agriculture of Iran [in Persian], www.maj.ir; 2015. [accessed 22.03.21].

overall efficient tomato producing provinces including ‘Isfahan’, ‘Bushehr’, ‘South of Kerman’, ‘Khuzestan’, ‘Lorestan’, ‘Mazandaran’, ‘Markazi’, ‘Kordestan’ and ‘Kohgilouyeh-BoyerAhmad’. It means that that these provinces have no input excesses and/or output shortfalls. However, the rest of the provinces are not on the efficiency frontier. The higher score implies better performance.

Table 3: Efficiency scores of tomato production in Iran (in percent)

DMU	Province	OE	EE	PE	PEE
1	Ardebil	82.17	86.64	87.76	91.50
2	Bushehr	100.00	100.00	100.00	100.00
3	East Azarbayejan	43.05	54.55	55.31	0.07
4	Fars	60.37	74.66	66.88	84.69
5	Ghazvin	48.51	54.41	60.86	3.64
6	Golestan	71.25	83.85	76.92	88.94
7	Hamedan	58.44	64.65	71.38	16.62
8	Hormozgan	68.91	79.64	75.69	86.76
9	Isfahan	100.00	100.00	100.00	100.00
10	Kermanshah	53.16	57.16	65.48	51.91
11	Khorasan Razavi	56.90	62.19	69.36	38.80
12	Khuzestan	100.00	100.00	100.00	100.00
13	Kohgilouyeh-BoyerAhmad	100.00	100.00	100.00	100.00
14	Kordestan	100.00	100.00	100.00	100.00
15	Lorestan	100.00	100.00	100.00	100.00
16	Markazi	100.00	100.00	100.00	100.00
17	Mazandaran	100.00	100.00	100.00	100.00
18	North Khorasan	79.36	82.52	85.63	85.02
19	Sistan-Balouchestan	56.00	56.06	68.74	75.67
20	South of Kerman	100.00	100.00	100.00	100.00
21	Tehran	69.79	77.52	72.93	96.81
22	West Azarbayejan	73.88	78.62	83.29	72.38
23	Yazd	56.00	56.85	68.68	48.33
24	Zanjan	66.00	72.63	76.78	60.80

The second column of Table 3 indicates the environmental efficiency score of each DMU. Again, same as overall efficiency, nine out of 24 DMUs are environmentally efficient. Moreover, the third column of Table 3 represents production efficiency scores. And the fourth column presents the pure emission efficiency scores. Results show that nine DMUs are efficient with respect to all efficiency scores. Also, the tomato farms of ‘East Azarbayejan’ have the worst performance with respect to all efficiency measures.

In Table 3, a very low score in pure emission efficiency can be seen for ‘East Azarbayejan’, i.e. 0.07. This score means, the tomato farms in ‘East Azarbayejan’ produce a huge amount of emission that is very far from the standard target. Another instance is the pure emission efficiency of ‘Isfahan’, that is 100%. This value indicates that the tomato farms in ‘Isfahan’ produce a standard amount of emission as the expected target value. As expected from the models (4-6), the environmental efficiency scores and production efficiency scores are greater than or equal to overall efficiency scores. Figure 1 also illustrates trends of each DMU with respect to the average of all efficiency measures. Clearly, the average of production efficiency scores is greater than others and the average of pure emission efficiency scores is less than others.

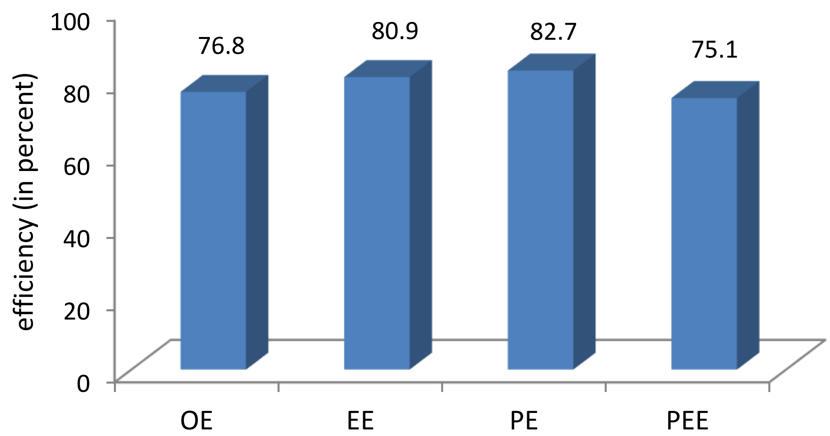

Figure 1. Trends of efficiency scores in tomato farms of Iran

Table 4 shows the present energy consumption, optimum energy consumption and potential values for energy saving in tomato production. According to the findings, if all DMUs operate efficiently, the reduction of labor, machinery, fertilizers, biocides and electricity would be possible by 14.37%, 11.22%, 35.06%, 19.42% and 6.85%, respectively, without influencing the production level. By considering these values of reductions in inputs' level, the amount of input energy reduction would be 5661.57 MJ (27.63%). The last column of Table 4 shows each input's contribution percentage in this amount of energy saving.

Table 4. Optimum energy consumption of tomato production in Iran

Inputs (MJ)	Current Use	Optimum Use	Saving Amount	Percentage of energy Saving	Percentage of total energy saving
Labor	1397.32	1196.57	200.75	14.37	3.55
Machinery	2742.95	2435.17	307.78	11.22	5.44
Fertilizers	14029.39	9111.23	4918.16	35.06	86.87
Biocides	605.14	487.63	117.51	19.42	2.08
Electricity	1713.93	1596.56	117.37	6.85	2.07
Total Input energy	20488.73	14827.15	5661.58	27.63	100

Additionally, according to the results, there is a good opportunity for improving the energy efficiency of tomato production in Iran. Developing training programs can help the farmers to improve the technical efficiency of tomato production.

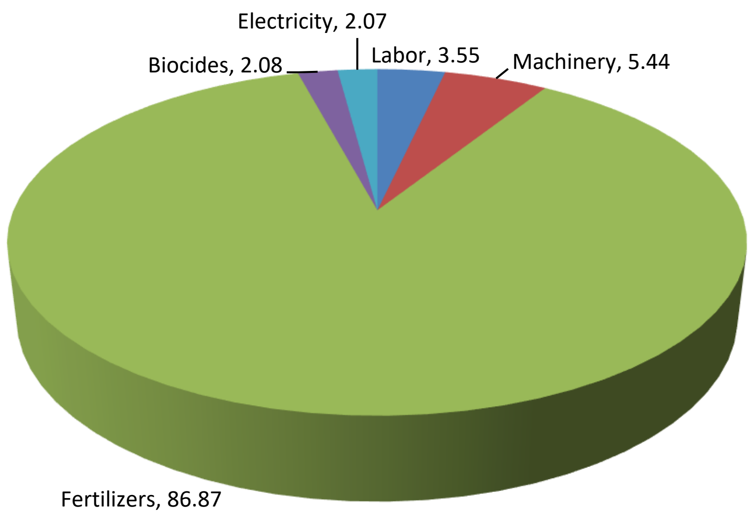

Figure 2. The proportion of each input of saving energy in tomato production

Figure 2 illustrates the proportion of each input in energy saving. The results show that the fertilizers have the highest effect in energy saving. Thus, the agricultural managers should pay more attention to the use of fertilizers.

The next aim is to determine the probable amount of excessive investments in inputs to get more outputs. In this section, the amount of congestion in tomato farms in Iran is measured during 2014-2015 by means of the proposed BAM model. Results of the amount of congestion are shown in Table 5.

Table 5. Congestion in tomato farms of Iran's provinces

DMU	Province	Labor	Machinery	Fertilizers	Biocides	Electricity
1	Ardebil	0.00	86.48	165.22	0.00	0.00
2	Bushehr	0.00	0.00	0.00	0.00	0.00
3	East Azarbayejan	58.18	38.67	1692.67	98.10	0.00
4	Fars	74.64	229.69	239.80	50.58	7.54
5	Ghazvin	766.44	201.38	1548.35	0.00	221.18
6	Golestan	323.83	0.00	205.39	0.00	21.12
7	Hamedan	0.00	152.41	1826.26	0.00	0.00
8	Hormozgan	96.94	0.00	293.61	67.24	0.00
9	Isfahan	0.00	0.00	0.00	0.00	0.00
10	Kermanshah	55.19	118.78	1015.62	0.00	0.00
11	Khorasan Razavi	0.00	254.00	1270.04	0.00	0.00
12	Khuzestan	0.00	0.00	0.00	0.00	0.00
13	Kohgilouyeh-BoyerAhmad	0.00	0.00	0.00	0.00	0.00
14	Kordestan	0.00	0.00	0.00	0.00	0.00
15	Lorestan	0.00	0.00	0.00	0.00	0.00
16	Markazi	0.00	0.00	0.00	0.00	0.00
17	Mazandaran	0.00	0.00	0.00	0.00	0.00
18	North Khorasan	0.00	109.42	306.15	0.00	0.00
19	Sistan-Balouchestan	0.00	140.55	526.68	0.00	0.00
20	South of Kerman	0.00	0.00	0.00	0.00	0.00
21	Tehran	388.69	164.27	0.00	0.00	0.00
22	West Azarbayejan	0.00	191.25	559.42	0.00	0.00
23	Yazd	314.65	0.00	1319.31	0.00	0.00
24	Zanjan	44.83	0.00	835.07	0.00	0.00
	Average	58.79	62.12	440.31	9.00	10.41

Based on the proposed DEA-BAM model, 'Isfahan', 'Bushehr', 'South of Kerman', 'Khuzestan', 'Lorestan', 'Mazandaran', 'Markazi', 'Kordestan' and 'Kohgilouyeh-BoyerAhmad' are efficient, with no congestion. These results indicate that there are not any excessive investments in inputs. Clearly, existing excessive inputs lead to inefficiency. However, inefficiency does not necessarily lead to congestion. For example, see the results of congestion for 'Ardebil'. Also, although 'Ardebil' is inefficient, it has no congestion in labor, biocides and electricity. On the other hand, 'Ardebil' has congestion in machinery and fertilizers which show that the tomato farms in 'Ardebil' have some excessive amounts in machinery and fertilizers, and thus, their reduction can lead to increase in outputs and the efficiency performance. Figure 3 illustrates the average amounts of congestion in each input.

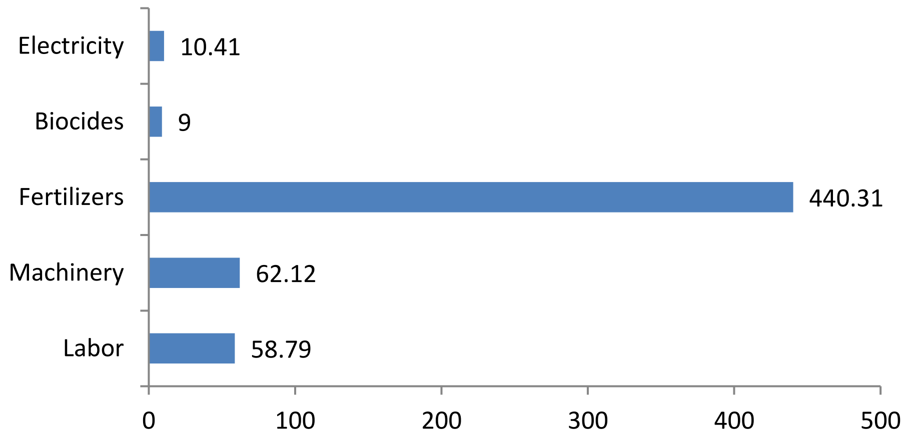

Figure 3. Average amounts of congestion in tomato production in Iran (in MJ)

From the results of Table 5, it can be seen that the most amount of observed congestion is related to fertilizers and the least amount is related to biocides. This indicates that the excessive use of fertilizers is also a serious problem. Based on the amount of congestion shown in Table 5, these inefficient regions can decrease their inputs to increase desirable outputs and decrease emission.

Among the different inputs, the excessive use of chemical fertilizers has the highest impact on tomato yield reduction. The link between congestion and crop physiology can be described by Misterlich law of diminishing returns. This law is applied to determine the effect of levels of fertilizers on crop yield. This law states that after a proportional increase of crop yield due to increasing the amount of fertilizers, extra amount of fertilizer does not increase the yield, but it reaches a level that decreases the yield. Excessive use of fertilizers especially nitrogen fertilizer in tomato increases vegetative growth and decreases reproductive growth, which delays flowering stage. Therefore; crop encounters the cold phase, which leads to reduced tomato yield.

4.3 Policy recommendation

The agricultural market is very competitive. Production of agricultural commodities requires intensive use of energy resources. Proper management and optimal use of the energy resources is important. Mathematical models can help policy makers in agriculture to assess productivity of crop production. Estimating productivity of various crop products such as tomato in provinces of Iran shows the relative advantage of production in different provinces, which is useful in design of the planting pattern.

In this study, the results obtained by implementing the DEA-BAM model have shown that only nine out of 24 tomato producing provinces are efficient. This fact gives the policy-makers opportunity to have information about provinces that need to be developed to trigger innovation and growth in tomato production. It also enables policy-makers to determine productive investment and proper managerial decisions. Also, the efficient provinces can be selected as a benchmark for other DMUs.

Based on the obtained results, the policy-makers and managers in agriculture can use the results of the proposed modeling as following:

1. The results reveal that ‘Isfahan’, ‘Bushehr’, ‘South of Kerman’, ‘Khuzestan’, ‘Lorestan’, ‘Mazandaran’, ‘Markazi’, ‘Kordestan’ and ‘Kohgilouyeh-BoyerAhmad’ are efficient in tomato production, with no congestion. Then policy-makers have the opportunity to increase tomato production levels in these provinces.
2. The results show that ‘East Azarbayjan’ and ‘Ghazvin’ are least efficient provinces in tomato production.
3. The results show that the highest amount of observed congestion is related to fertilizers. Policymakers, using educational and extension programs and making sample pattern farms in different areas of the country, should teach farmers the optimal consumption of various inputs, especially chemical fertilizers to reduce the level of congestion.
4. Plans for decreasing fertilizers subsides especially nitrogen fertilizers decrease consumption and congestion of fertilizers.

5 Conclusion and direction for future research

The various modern methods of crop production use considerable quantity of energy. Thus, improving energy consumption and decreasing greenhouse gas emission have become vital subjects in reducing the environmental risks in crop production process. The main purpose of the current study is to measure the efficiency and of Iranian tomato farms and to determine the optimum consumption of the input resources. Energy inputs included labor, machinery, fertilizers, biocides and electricity. Total production value of tomato was a desirable output and emission was an undesirable output. By means of the bounded adjusted model, four efficiency scores of tomato farms, i.e. overall, environmental, production and pure emission efficiency were calculated. The nine overall efficient tomato producing provinces recognized that they had no input excesses and/or output shortfalls. Also, like overall efficiency, nine out of 24 DMUs were recognized as environmental, production and pure emission efficient. Meanwhile, the tomato farms of 'East Azarbayejan' had the worst performance with respect to the efficiency measures of other provinces. As expected from the proposed models, the environmental efficiency scores and production efficiency scores were greater than or equal to overall efficiency scores. In the next step, congestion in tomato farms was measured by means of the proposed BAM model. Results showed that fertilizers has the highest contribution in the congestion.

The proposed approach in this study can be used in two stage and network DEA models. The developed model in this study can be extended to use stochastic and fuzzy data. Extending a super SBM model (Tone et al., 2020) to evaluate the congestion can be considered as another interesting research direction. Furthermore, the proposed formulated model in this study can be extended to determine the status of returns to scale in farming industries. In addition, BAM based inverse DEA model can be another interesting topic for future researches.

Appendix

Proof of the Proposition 1:

Obviously, $0 \le \theta_p^o$. Now, since $\sum_{j=1}^{n} \lambda_j = 1, \ \ \lambda_j \ge 0 \ (j = 1,...,n)$, then

$\min_i \{x_{ij}\} \le \sum_{j=1}^{n} \lambda_j x_{ij} \le \max_r \{x_{ij}\}$. Therefore, from the first constraint of Model (1):

$$\gamma_i^* = x_{ip} - \sum_{j=1}^{n} \lambda_j^* x_{ij}; \quad \Rightarrow \gamma_i^* \le x_{ip} - \min_i \{x_{ij}\};$$

$$\Rightarrow \; H_{ip}^{*}\gamma_i^{*} \le \left\{x_{ip} - \min_i\{x_{ij}\}\right\} / \left\{(m+s_1+s_2)(x_{ip} - \min_j\{x_{ij}\})\right\} = 1/(m+s_1+s_2);$$

$$\Rightarrow \; \sum_{i=1}^{m} H_{ip}\gamma_i^{*} \le \sum_{i=1}^{m} 1/(m+s_1+s_2) = m/(m+s_1+s_2);$$

Similarly, it can be proved that $\sum_{r=1}^{s_1} H_{rp}^{g}\sigma_r^{g*} \le s_1/(m+s_1+s_2)$ and $\sum_{f=1}^{s_2} H_{fp}^{b}\sigma_f^{b*} \le s_2/(m+s_1+s_2)$.

Thus, $\theta_p^{o} = 1 - \left[\sum_{i=1}^{m} H_{ip}\gamma_i^{*} + \sum_{r=1}^{s_1} H_{rp}^{g}\sigma_r^{g*} + \sum_{f=1}^{s_2} H_{fp}^{b}\sigma_f^{b*}\right] \le 1$. □

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