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Improving energy efficiency considering reduction of CO_2 emission of turnip production: A novel data envelopment analysis model with undesirable output approach

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Abstract

Modern Turnip production methods need significant amount of direct and indirect energy. The optimum use of agricultural input resources results in the increase of efficiency and the decrease of the carbon footprint of turnip production. Data Envelopment Analysis (DEA) approach is a well-known technique utilized to evaluate the efficiency for peer units compared with the best practice frontier, widely used by researches to analyze the performance of agricultural sector. In this regard, a new non-radial DEA-based efficiency model is designed to investigate the efficiency of turnip farms. For this purpose, five inputs and two outputs are considered. The outputs consist turnip yield as a desirable output and greenhouse gas emission as an undesirable output. The new model projects each DMU on the strong efficient frontier. Several important properties are stated and proved which show the capabilities of our proposed model. The new models are applied in evaluating 30 turnip farms in Fars, Iran. This case study demonstrates the efficiency of our proposed models. The target inputs and outputs for these farms are also calculated and the benchmark farm for each DMU is determined. Finally, the reduction of CO_2 emission for each turnip farm is evaluated. Compared with other factors like human labor, diesel fuel, seed and fertilizers, one of the most important findings is that machinery has the highest contribution to the total target energy saving. Besides, the average target emission of turnip production in the region is 7% less than the current emission.

Keywords: Data envelopment analysis (DEA); Undesirable output; Energy saving; benchmarking.

1. Introduction

Agriculture contributes to the global greenhouse gas emission significantly ((Lozano et al., 2009); (Wu et al., 2017); (Vetter et al., 2017)) and crop production requires a large quantity of energy, directly and indirectly (Khoshroo and Mulwa, 2014). Reducing greenhouse gas

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emission and the efficient use of the finite energy resources is a necessary step towards increasing agricultural sustainability and reducing environmental problems ((Erdal et al., 2007); (Theurl et al., 2017); (Zare and Izadikhah, 2017); (Wang et al., 2017, Yue et al., 2017)).

Li and Tao (2017) have presented a systematical review of methodologies proposed for energy demand management in order to measure the energy efficiency performance accurately. Cai et al. (2016) have also proposed a new concept of fine energy consumption allowance for workpieces contributing to the strengthening of energy monitoring and management which improves energy efficiency in the mechanical manufacturing industries. ElMaraghy et al. (2016) proposed a methodology for energy use analysis and benchmarking of manufacturing lines. Bukarica and Tomšić (2017) have proposed a methodology related to the concept of energy efficiency market that discusses the fundamental aim of energy efficiency policy and presents market barriers that call for policy interventions.

Efficiency can be measured using mathematical programming techniques. Data envelopment analysis (DEA) is a nonparametric mathematical programming approach to calculate the relative efficiency of decision making units (DMUs). The first DEA model, i.e. CCR model, was proposed by Charnes et al. (1978) and is based on the work of Farrell (1957). The CCR model beside the BCC model presented by Banker, Charnes andCooper (Banker et al., 1984) are the most popular classic DEA radial models. The BCC model is an extension of constant returns to scale model of CCR to allow for variable returns to scale (VRS) that is stated as follows:

$$
\begin{aligned}
&\min \ \theta \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ip}, \qquad i = 1,\dots,m, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp}, \qquad r = 1,\dots,s, \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0, \qquad\qquad j = 1,\dots,n.
\end{aligned}
\tag{1}
$$

Where, there are n DMUs where each $DMU_j\,(j=1,\dots,n)$ uses m inputs, $x_{ij}\,(i=1,\dots,m)$ to produce s outputs, $y_{rj}\,(r=1,\dots,s)$. Model (1) is called BCC model and evaluates efficiency of DMU under evaluation, DMU_p . Radial models, like BCC model, have some disadvantages like failure to recognize weak efficient DMUs, see (Izadikhah and Farzipoor Saen, 2016b, Izadikhah and Farzipoor Saen, 2016a). Another type of DEA models are non-radial DEA models. These models have some advantages over radial DEA models and have , thus, been extensively used in agricultural and energy efficiency related studies. Mardani et al. (2017) have reviewed some articles that adopted DEA in energy and environmental studies.

Khoshroo et al. (2013) have investigated the factors influencing energy efficiency in grape production in Iran using the DEA approach and Tobit regression. Malana and Malano (2006) have applied DEA to evaluate and rank productivity performance of wheat growing area in selected regions of Pakistan and India. Yaqubi et al. (2016) have evaluated the marginal abatement cost of the main agricultural pollutants using DEA. The results showed that DEA was useful for benchmarking and analyzing the efficiency of agricultural units.

The efficient use of farms' finite energy resources is an important issue for policy makers in Iran. Hence, this study estimates the energy efficiency of turnip production in Iran and suggests the optimum use of agricultural inputs to improve efficiency.

In this paper, inspired by the generic directional distance model of Chambers et al. (1998), a new non-oriented model is proposed. This model is an upgraded form of the Allahyar and Rostamy-Malkhalifeh (2015) model. However, as formerly mentioned in Koopmans (1951), the production process may also generate undesirable outputs like smoke pollution or waste. Take into consideration a paper mill production where paper is produced with the undesirable outputs of pollutants such as biochemical oxygen demand, suspended solids, and particulate and sulfur oxides (Sueyoshi and Goto, 2016, Wang et al., 2016, Zhang et al., 2016, Liu et al., 2017). If inefficiency exists in the production, the undesirable pollutants should be reduced to improve the inefficiency, i.e., during the evaluation process of the production performance of paper mills, the undesirable and desirable outputs should be treated differently. The Combination of life cycle analysis (LCA) with optimization techniques connects operational input efficiency and environmental impacts (Lozano et al., 2009); (Zare and Izadikhah, 2017); (Iribarren et al., 2015, Mohammadi et al., 2015, Beltrán-Esteve et al., 2017). Mulwa et al. (2012) have used undesirable pollutant output in both hyperbolic and directional distance function DEA models to measure the total factor productivity in sugarcane farming in Kenya.

The aim of this paper is to evaluate the efficiency of turnip farms in Fars, Iran. Therefore, in this study, the proposed DEA model is used to model efficiency as an explicit function of human labor, machinery, seed, chemical fertilizers and irrigation energies. These turnip farms produce emission as undesirable output. Thus, our proposed DEA model evaluates DMUs in the presence of undesirable data. A number of useful and interesting properties of the proposed model are stated and proved in this paper. Our model is applied on real data in evaluating turnip farms. The results show that all of the properties are held and the efficient and inefficient farms are also determined in the proposed model.

The main contributions of this paper are as follows: This paper proposes a new non-radial DEA efficiency model in the presence of undesirable outputs. The capabilities of our new proposed model are illustrated by stating and proving some important theorems. The proposed model is applied to evaluate the efficiencies of the 30 turnip farms.

This paper unfolds as follows: In Secton 2 the literature review is presented. Section 3 proposes our new DEA models in the presence of undesirable output. In Section 4, a case study is presented and the final conclusion appears in Section 5.

2. Literature review

In this section, some important related works are reviewed.

2.1 Energy efficiency using DEA

Energy efficiency is an important step to reduce the amount of required energy for providing products and services. Since introducing the CCR model by Charnes et al. (1978), DEA models have been applied to measure the energy efficiency. Reinhard et al. (2000), using DEA models, estimated comprehensive environmental efficiency measures for Dutch dairy farms. The environmental efficiency scores were based on the nitrogen surplus, phosphate surplus and the total (direct and indirect) energy use of an unbalanced panel of dairy farms. Boyd and Pang (2000) based on DEA models investigated the role of energy efficiency for two segments of the glass industry, using plant level data from the Census Bureau. After their efforts, many authors have applied data envelopment analysis to measure the energy efficiency of industrial companies, agricultural farms, etc.

Recently, Feng and Wang (2017) have analyzed the total-factor energy efficiency and energy savings potential in China's provincial industrial sectors for the years 2000–2014 based on a meta-frontier data envelopment analysis. Using a dynamic DEA model Guo et al. (2017) have evaluated inter-temporal efficiency for executive efficiency based on fossil-fuel CO_2 emissions in OECD countries and China. Gong et al. (2017), using DEA, have integrated factor analysis with respect to operation classification and proposed a new energy efficiency evaluation method for ethylene production. Using DEA models Li and Tao (2017) have analyzed the main drivers behind energy-related CO_2 emission across agricultural sectors of European countries. Rebolledo-Leiva et al. (2017) have proposed a four-step method for a joint use of carbon footprint assessment and data envelopment analysis to assess the eco-efficiency of five organic blueberry orchards throughout three growing seasons.

2.2 Undesirable data and DEA

Sometimes in addition to use of input resources and the production of desirable outputs, DMUs generate undesirable outputs such as pollution, noise, etc. Fig. 1 shows various methods for considering undesirable data in DEA.

------ [Fig. 1 about here] ------

There are two main methods for considering undesirable data i.e. methods based on weak disposability and methods based on data translation (Fig. 1). The second method has been used in literature more than the first one. See Table 1 for a brief review.

------ [Table 1 about here] ------

2.3 Gaps in the literature

Modern Turnip production methods need significant amount of energy, directly and indirectly. The optimum use of agricultural input resources results in increasing efficiency and decreasing carbon footprint of turnip production. Data envelopment analysis (DEA) is used to evaluate the efficiencies of the turnip farms and calculate the optimal use of resources. As far as we know, there is no published paper having measured the efficiency of turnip farms using DEA models. For this purpose, this paper proposes a new non-radial DEA efficiency model considering undesirable outputs. Many similar models in this subject have two problems: i) a number are sometimes infeasible; ii) a number cannot determine the exact optimal level. This study shows that the proposed model overcomes these problems. Finally, the reduction amount of CO_2 emission for each turnip farm is evaluated.

3. Methodology

3.1 New efficiency measure with undesirable output

This section, first, proposes a scheme where the undesirable outputs are incorporated into DEA models. For this aim, inspired by the generic directional distance model (Chambers et al., 1998), a novel non-oriented model is presented. Assume that there are *n* DMUs that each DMU_j uses *m* inputs x_{ij}, $(i=1,...,m)$ to produce s_1 desirable outputs y_{rj}^{d}, $(r=1,...,s_1)$ and s_2 undesirable outputs y_{tj}^{u}, $(t=1,...,s_2)$. Let us define a modified production possibility set under VRS as follows:

$$PPS = \left\{ (x, y, z) \mid x \geq \sum_{j=1}^{n} \lambda_j x_j, y \leq \sum_{j=1}^{n} \lambda_j y_j^d, z \geq \sum_{j=1}^{n} \lambda_j y_j^u, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0,\ j = 1, \ldots, n \right\}$$

To present our new models, this PPS has been applied.

In order to evaluate the efficiency score of DMU_p under variable returns to scale (VRS), the following direction vector is considered

$$d_p = (-|x_p|, |y_p^d|, -|y_p^u|) = (-|x_{ip}|, i = 1, ..., m; |y_{rp}^d|, r = 1, ..., s_1; -|y_{tp}^u|, t = 1, ..., s_2)$$

This vector is based on the absolute values of data. Note that this direction vector is an extension of the (Allahyar and Rostamy-Malkhalifeh, 2015) direction vector. Our new direction guarantees that the new model always projects the DMUs on the strong efficient frontier. Therefore, initially the following non-radial efficiency model that considers undesirable outputs is presented.

$$\begin{aligned}
&\sigma_p^* = \min\ 1 - \frac{1}{3}\left(\frac{1}{m} \sum_{i=1}^{m} \frac{\theta_i}{\overline{\theta}_p} + \frac{1}{s_1} \sum_{r=1}^{s_1} \frac{\varphi_r}{\overline{\varphi}_p} + \frac{1}{s_2} \sum_{t=1}^{s_2} \frac{\psi_t}{\overline{\psi}_p} \right) \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ip} - \theta_i \left| x_{ip} \right|, \qquad i = 1, ..., m, \\
&\sum_{j=1}^{n} \lambda_j y_{rj}^d \geq y_{rp}^d + \varphi_r \left| y_{rp}^d \right|, \qquad r = 1, ..., s_1, \\
&\sum_{j=1}^{n} \lambda_j y_{tj}^u \leq y_{tp}^u - \psi_t \left| y_{tp}^u \right|, \qquad t = 1, ..., s_2, \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j, \theta_i, \varphi_r, \psi_t \geq 0, \qquad \forall j, i, r, t.
\end{aligned} \tag{2}$$

In the first group of constraints the DMU under evaluation moves towards efficient frontier by decreasing its inputs in direction d_p. The same is true for the third group of constraints. In the second group of constraints the DMU under evaluation moves towards efficient frontier by increasing its desirable outputs in direction d_p. Model (2) measures the relative efficiency of

DMU$_p$ where σ_p^* shows our proposed efficiency score and θ_i shows input contraction. φ_r shows desirable output extension, and also, ψ_t is the undesirable output contraction. λ_j is the intensity amount for DMU$_j$. The following definitions are used in model (2):

$$\bar{\theta}_p = \max_i \left\{ \frac{x_{ip} - x_{iI}}{|x_{ip}|}, x_{ip} \neq 0; \;\; i = 1, \ldots, m \right\}$$

$$\bar{\varphi}_p = \max_r \left\{ \frac{y_{rI}^d - y_{rp}^d}{|y_{rp}^d|}, y_{rp}^d \neq 0; \;\; r = 1, \ldots, s_1 \right\}$$

$$\bar{\psi}_p = \max_r \left\{ \frac{y_{tp}^u - y_{tI}^u}{|y_{tp}^d|}, y_{tp}^u \neq 0; \;\; t = 1, \ldots, s_2 \right\}$$

and

$$x_{iI} = \min_j \{x_{ij}\}; \;\; i = 1, \ldots, m,$$

$$y_{rI}^d = \max_j \{y_{rj}^d\}; \; r = 1, \ldots, s_1,$$

$$y_{tI}^u = \max_j \{y_{tj}^u\}; \; t = 1, \ldots, s_2$$

If $\bar{\theta}_p = 0$, then the statement(s) $\frac{\theta_i}{\bar{\theta}_p}$, $(\forall i)$ will be ignored. The following definition shows the optimal values of each input and output. Actually, this definition shows the projected values.

Definition 1: (Projection Point): For DMU_p, assume that $(\theta_i^*, i = 1, \ldots, m; \varphi_r^*, r = 1, \ldots, s_1; \psi_t^*, t = 1, \ldots, s_2; \lambda_j^*, j = 1, \ldots, n)$ is the optimal solution obtained from model (2). Hence, the projection of DMU_p is defined as follows:

$$(\hat{x}_i = x_{ip} - \theta_i^* \left|x_{ip}\right|, \hat{y}_r^d = y_{rp}^d + \varphi_r^* \left|y_{rp}^d\right|, \hat{y}_t^u = y_{tp}^u - \psi_t^* \left|y_{tp}^u\right|), \;\; \forall i, r, t$$

Note that according to Theorem 4 the above projection point does not need slacks. The projection point is also known as a target value for data. Theorem 1 proves that model (2) is always feasible, and thus, it can be used without extra consideration.

Theorem 1: Model (2) is always feasible.

Proof:

Obviously, the vector $(\tilde{\lambda}_j, \tilde{\theta}_i, \tilde{\varphi}_r, \tilde{\psi}_t), \quad \forall j, i, r, t$, is a feasible solution for model (2). Where

$$\tilde{\lambda}_p = 1; \quad \tilde{\lambda}_j = 0, \quad j \neq p$$
$$\tilde{\theta}_i = 0; \; \tilde{\varphi}_r = 0; \; \tilde{\psi}_t = 0, \quad \forall i, r, t$$

And thus, the proof is completed.

Theorem 2 shows in which situations model (2) gives $\forall i: \; \theta_i = 0$.

Theorem 2: If $\bar{\theta}_p = 0$ then $\forall i: \; \theta_i = 0$.

Proof:

Assume that $\bar{\theta}_p = 0$. Then: $x_{ip} - x_{iI} \leq 0, \quad i = 1, ..., m$. Therefore, the following equality holds:

$$\forall i: \quad x_{ip} = \min_j \{x_{ij}\},$$

Thus, we lead to the following relation:

$$x_{ip} = \min_j \{x_{ij}\} \leq \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ip} - \theta_i \, | \, x_{ip} \, |; \quad i = 1, ..., m,$$

So $x_{ip} \leq x_{ip} - \theta_i \, | \, x_{ip} \, |; \quad i = 1, ..., m,$ and therefore, $\forall i: \; \theta_i = 0$. □

From Theorem 2, the following corollaries can directly be found that their proofs are straightforward.

Corollary 1: If $\bar{\varphi}_p = 0$ then $\forall r: \; \varphi_r = 0$.

Corollary 2: If $\bar{\psi}_p = 0$ then $\forall t: \; \psi_t = 0$.

Theorem 3 guarantees that model (2) presents efficiency score between 0 and 1 for inefficient DMUs.

Theorem 3: $0 \leq \sigma_p^* \leq 1$.

Proof:

Obviously, since $\sum_{j=1}^{n}\lambda_j = 1,\ \lambda_j \geq 0\ (j=1,\dots,n)$, then $\min_i\{x_{ij}\} \leq \sum_{j=1}^{n}\lambda_j x_{ij} \leq \max_r\{x_{ij}\}$. Therefore, from the first constraint of model (2):

$$\min_i\{x_{ij}\} \leq \sum_{j=1}^{n}\lambda_j x_{ij} \leq x_{ip} - \theta_i\left|x_{ip}\right|, \qquad i=1,\dots,m,$$

$$\Rightarrow \quad \theta_i \leq \frac{x_{ip} - \min_i\{x_{ij}\}}{\left|x_{ip}\right|}, \qquad i=1,\dots,m$$

$$\Rightarrow \quad \theta_i \leq \bar{\theta}_p, \qquad i=1,\dots,m$$

Similarly, it can be proved that $\varphi_r \leq \bar{\varphi}_p,\ (r=1,\dots,s_1)$ and $\psi_t \leq \bar{\psi}_p,\ (t=1,\dots,s_2)$. Thus, $0 \leq \sigma_p^* \leq 1$.

Hence, the following two important definitions are obtained. The former is BCC efficiency and the latter is the proposed Model (2) considering undesirable factors.

Definition 2 (Cooper et al., 2002): Assume that $(\theta^*, S^{*-}, S^{*+})$ is an optimal solution of DMU*P*. DMU*P* is strong efficient if both of the following conditions are held simultaneously:

i. $\theta^* = 1$,
ii. $(S^{*-}, S^{*+}) = (0,0)$.

Similarly, DMU*P* in Model)2) is efficient if $\sigma_p^* = 1$.

Theorem 4 proves that the projected point obtained by our proposed model is a strong efficient point, i.e., under VRS technology, inefficient point is projected on strong efficient frontier.

Theorem 4: Model (2) projects each inefficient DMU on the strong efficient frontier.

Proof:

Assume that $(\theta_i^*, i=1,\dots,m; \varphi_r^*, r=1,\dots,s_1; \psi_t^*, t=1,\dots,s_2; \lambda_j^*, j=1,\dots,n)$ is optimal solution obtained from model (2). As definition 2, the projection of DMU_p is

$(\hat{x}_i = x_{ip} - \theta_i^* \left|x_{ip}\right|, \hat{y}_r^d = y_{rp}^d + \varphi_r^* \left|y_{rp}^d\right|, \hat{y}_t^u = y_{tp}^u - \psi_t^* \left|y_{tp}^u\right|), \ \forall i, r, t$. Now, $(\hat{x}, \hat{y})$ is evaluated by BCC model. Assume that $(\hat{\lambda}, \hat{\theta}, \hat{S}^-, \hat{S}^d, \hat{S}^u)$ is optimal solution. Constraints of BCC model for evaluating $(\hat{x}, \hat{y})$ in optimality is as follows:

$$
\begin{aligned}
&\sum_{j=1}^{n} \hat{\lambda}_j x_{ij} + \hat{S}_i^- = \hat{\theta}\hat{x}_i, && i = 1, \ldots, m, \\
&\sum_{j=1}^{n} \hat{\lambda}_j y_{rj}^d - \hat{S}_r^d = \hat{y}_r^d, && r = 1, \ldots, s_1, \\
&\sum_{j=1}^{n} \hat{\lambda}_j y_{tj}^u - \hat{S}_t^u = \hat{y}_t^u, && t = 1, \ldots, s_2, \\
&\sum_{j=1}^{n} \hat{\lambda}_j = 1,
\end{aligned}
$$

By contradiction, assume that $(\hat{x}, \hat{y})$ is not a strong efficient point. Therefore, at least one of the conditions of Definition 1 does not held. Without loss of generality, let $\hat{\theta} < 1$, then, $\exists t$ such that:

$$
\begin{aligned}
&\sum_{j=1}^{n} \hat{\lambda}_j x_{tj} < \hat{x}_t, && (*) \\
&\sum_{j=1}^{n} \hat{\lambda}_j x_{ij} \le \hat{x}_i, && i = 1, \ldots, m; \ i \ne t, \\
&\sum_{j=1}^{n} \hat{\lambda}_j y_{rj}^d \ge \hat{y}_r^d, && r = 1, \ldots, s_1, \\
&\sum_{j=1}^{n} \hat{\lambda}_j y_{tj}^u \le \hat{y}_t^u, && t = 1, \ldots, s_2, \\
&\sum_{j=1}^{n} \hat{\lambda}_j = 1,
\end{aligned}
$$

The constraint (*) can be restated as follows:

$$
\begin{aligned}
&\sum_{j=1}^{n} \hat{\lambda}_j x_{tj} < \hat{x}_t \ \Rightarrow \ \sum_{j=1}^{n} \hat{\lambda}_j x_{tj} < x_{tp} - \theta_t^* \left|x_{tp}\right| \\
&\Rightarrow \ \exists \varepsilon > 1; \quad \sum_{j=1}^{n} \hat{\lambda}_j x_{tj} = x_{tp} - \varepsilon \theta_t^* \left|x_{tp}\right|
\end{aligned}
$$

Therefore, assuming:

$$\begin{aligned}
&\tilde{\lambda}_j = \hat{\lambda}_j, \quad j = 1,\dots,n;\\
&\tilde{\theta}_t = \varepsilon\theta_t^*, \quad (\Rightarrow \quad \tilde{\theta}_t > \theta_t^*)\\
&\tilde{\theta}_i = \theta_i^*, \quad i = 1,\dots,m; \;\; i \neq t,\\
&\tilde{\varphi}_r = \varphi_r^*, \;\; r = 1,\dots,s_1,\\
&\tilde{\psi}_t = \psi_t^*, \;\; t = 1,\dots,s_2.
\end{aligned}$$

Then, it is easy to see that $(\tilde{\lambda},\tilde{\theta},\tilde{S}^-,\tilde{S}^d,\tilde{S}^u)$ is a feasible solution of model (2). Objective function of this feasible solution is $\tilde{\rho}_p$ which is calculated as follows:

$$\tilde{\sigma}_p = 1 - \frac{1}{3}\left(\frac{1}{m}\sum_{i=1}^{m}\frac{\tilde{\theta}_i}{\overline{\theta}_p} + \frac{1}{s_1}\sum_{r=1}^{s_1}\frac{\tilde{\varphi}_r}{\overline{\varphi}_p} + \frac{1}{s_2}\sum_{t=1}^{s_2}\frac{\tilde{\psi}_p}{\overline{\psi}_p}\right) < 1 - \frac{1}{3}\left(\frac{1}{m}\sum_{i=1}^{m}\frac{\theta_i^*}{\overline{\theta}_p} + \frac{1}{s_1}\sum_{r=1}^{s_1}\frac{\varphi_r^*}{\overline{\varphi}_p} + \frac{1}{s_2}\sum_{t=1}^{s_2}\frac{\psi_t^*}{\overline{\psi}_p}\right) = \sigma_p^* \tag{3}$$

Expression (3) shows that a feasible solution that has a better value for the objective function can be found, that is the optimal solution. This contradiction shows $(\hat{x},\hat{y})$ is a strong efficient point. Other cases can be checked in a very similar way, hence, the proof is completed.

3.2 Illustrative example

In the present research, the applicability of the proposed model has been investigated using a numerical example, i.e. seven DMUs with one input and one desirable output and without undesirable output as shown in Table 2. By solving model (2) the efficiency score is calculated as shown in the fourth row of Table 2. Also, the projection point of each DMU appears in the fifth row of Table 2.

------ [Table 2 about here] ------

It is observed that the obtained results confirm the correctness of the Theorems. Fig. 2 illustrates these DMUs. According to Fig. 2, it is clear that there is a difference between the efficiency score of weak and strong efficient DMUs. In addition, the proposed model projects inefficient DMUs on the strong efficient frontier.

------ [Fig. 2 about here] ------

4. A real application: the energy efficiency of turnip production

In this section we investigate the energy efficiency of turnip production in Iran. Turnip production requires large quantity of energy in the form of direct or indirect energy. Managing energy consumption in turnip cultivation is evaluated using non-parametric DEA approach.

4.1. Data collection and energy analysis

The study was carried out in the rural areas of Sepidan, Fars province of Iran, during 2013-2014. Fars province is located in the southern part of Iran. Data were obtained from 30 turnip farms through face to face interviews and responses were gathered in questionnaires. The collected data included hours or the amount of input energy sources such as labor, machinery, diesel fuel, chemical fertilizers, seed and water for irrigation. The output consisted of turnip yield as a desirable output and greenhouse gas emission as an undesirable output.

For energy analysis, a standard procedure was applied to convert each agricultural input to its energy equivalents (Kitani, 1999). The input resources were transformed to energy terms by multiplying the proper coefficient of energy equivalent (Table 3).

------ [Table 3 about here] ------

To determine total energy of farm machinery, the following formula was used (Khoshnevisan et al., 2013):

$$ME = \frac{ELG}{TC_a}$$

where ME is the machinery energy (MJ ha^{-1}), G is the machinery weight (kg), E is the required energy for production of machinery (MJ $kg^{-1}yr^{-1}$), that is presented in Table 3, L is the useful life of machinery (year), T is the economic life time of machinery (h) and C_a is the effective field capacity (h ha^{-1}).

The descriptive statistics of input energy in turnip production are given in Table 4. The wide range of consumption of energy resources among farmers in turnip production indicates the inefficient use of resources in the studied region.

------ [Table 4 about here] ------

Production, storage and distribution of agricultural inputs resulted in the combustion of fossil fuel that emits CO_2 and other greenhouse gases into atmosphere (Khoshroo, 2014). The CO_2 emission of turnip production was determined by multiplying the application rate of inputs by their corresponding CO_2 emission coefficient, presented in Table 5. Average emission of turnip production in the studied area was 580.88 kg CO_{2eq} ha^{-1}. In other studies, emissions of crop production were determined as 1015 kg CO_{2eq} ha^{-1} for watermelon (Nabavi-Pelesaraei et al., 2016a), 1310 kg CO_2 ha^{-1} for kiwifruit (Nabavi-Pelesaraei et al., 2016b), 2442 kg CO_{2eq} ha^{-1} for barley (Bonesmo et al., 2012) and 2483 kg CO_{2eq} ha^{-1} for oat (Bonesmo et al., 2012).

Contribution of different input sources on the total emission is presented in Fig. 3. Results shows that diesel fuel has the highest percentage in total emission followed by nitrogen and phosphate fertilizers.

------ [Table 5 about here] ------

------ [Fig. 3 about here] ------

4.2. Results and discussion

Data were analyzed using the proposed model (2). The efficiency scores for these 30 turnip farms were determined and the results are shown in the Fig. 4. Nine DMUs were recognized as efficient and the others as inefficient. Therefore, thirty percent of all DMUs performed efficiently and the rest performed inefficiently.

------ [Fig. 4 about here] ------

The average value of technical efficiency score of turnip production was 0.746. Technical efficiency varies from 0.396 to 1 with the standard deviation of 0.192. The wide variation in the technical efficiency indicates a substantial inefficiency between the turnip farms in the studied area. The analysis of data shows that for instance, the efficient DMU #28 has the lowest value of inputs labor, machinery, fertilizers and irrigation water. Also, DMU #28 has the lowest value in undesirable output. This shows the correct timing and proper use of input resources for DMU #28.

The results of benchmarking of turnip farms show that nine farms out of 30 farms are efficient (Table 6). These farms are a good example for improving the performance of inefficient farms.

In Table 6, the benchmark DMU for farm 15 is expressed as 20 (0.688), 25 (0.070), 27 (0.721), 28 (0.117), where 20, 25, 27 and 28 are the DMU numbers while the values between parentheses are the intensity vector λ for the respective DMUs. That is, the farms #20, #25, #27 and #28 are recognized as benchmarks for farm #15 and this farm should try to make its inputs and outputs levels much closer to benchmarks ones. The intensity values indicate that what portion should farm #15 receive from each benchmark farm to become an efficient farm. For instance, the target inputs/outputs for farm #15 can be calculated as follows:

Target input/output for farm #15 = 0.688 * (input/output of farm #20) +0.070 * (input/output of farm #25) + 0.721 * (input/output of farm #27)+ 0.117 * (input/output of farm #28).

------ [Table 6 about here] ------

The descriptive statistics of obtained target inputs and target outputs are presented in Table 7. It is important for farmers to know the optimal values of their inputs and outputs. As mentioned before, these optimal values are known as the target values for data. Each farmer needs to know the optimum use of input resources and find the distances between their inputs and outputs and the target values to improve their performance. According to Table 7, the average target (optimum) value for "human labor" is 7239.28 MJ while it was 7422.84 MJ for the observed period. Thus, in average the level of consumption in this factor is slightly high and farmers should try to reduce their consumptions. Result of Table 7 reveals this is true for all other factors.

------ [Table 7 about here] ------

Table 8 demonstrates the present energy use, target energy use and potential energy saving for turnip production. When farmers use the input resources efficiently, labor, machinery, seed, fertilizers and water energies is decreased by 2.47%, 7.86%, 12.08%, 2.55% and 8.3%, respectively, without influencing turnip production level. Clearly, from Table 8, in optimum use of input resources, farmers can reduce seed consumption significantly.

------ [Table 8 about here] ------

The distribution of different sources in the total input energy saving is presented in Fig. 5. Results show that the highest contribution to the total energy saving is from machinery (37.5%) followed by water (29.8 %), labor (17.2%), fertilizers (14.4%) and seed (1.2 %). Based on the energy efficiency viewpoint and from the results, it can be concluded that farmers should pay more attention to management of tractors and farm machinery.

------ [Fig. 4 about here] ------

If each DMU reaches its efficient value (optimal or target value) of input resources, emission reduction is possible. For this purpose, the percentage of emission reduction for efficient use of input resources is illustrated in Fig. 6. Average target CO_2 emission of turnip production in the region is 552.65 kg $CO_{2eq}ha^{-1}$ with standard deviation of 111.48 (Table 7). The average emission reduction of turnip production in the region for inefficient farms is around 7 percent. According to Fig. 6, DMU #6 will have the highest percentage of emission reduction (28.1%), if this DMU becomes efficient and uses the target values of the proposed model. This fact is an interesting result. The farms union should ask DMU #6 to reduce its emission level to make the average CO_2 emission of turnip production in the region much closer to optimum level. Results indicate high potential for reduction of carbon footprint of turnip production in the region through improving energy efficiency. Training programs for farmers should be developed to increase their knowledge of the optimum use of inputs and the environmental consequences of the excessive use of resources in turnip production.

------ [Fig. 5 about here] ------

4.3 Managerial and Environmental Implications

In recent decades, technology has been grown rapidly that it has led to higher energy consumption. The Organization for Economic Co-operation and Development (OECD) warns that, given the current trends, energy-related emissions will increase by 70, percent by 2050. Energy efficiency, means using less energy to provide the same level of product. Therefore, this can be one method to reduce greenhouse gas emissions.

In this study, the results obtained by implementing the DEA model have shown that only nine out of the 30 turnip farms were efficient. This fact provides policy makers with information about farms that need to be actively developed to trigger innovation and growth. It also allows policy makers to identify productive investment and appropriate management activities. From another viewpoint, the efficient DMUs can be selected as a benchmark for other DMUs. Thus, a set of DMUs as benchmarks for each DMU were determined. Also, the optimal values of inputs and outputs were calculated. These values are known as the target values for each DMU and if any inefficient DMU wants to be an efficient one, it should reach its target values. Based on these target values, the amount of energy saving in each input source is calculated.

Results show that "machinery" has the highest contribution in total energy saving. Therefore, farmers should pay special attention to machinery management. Selecting suitable farm machinery considering farm size is the most important factor in machinery energy management. For instance, tractors with proper power and size not only decrease required machinery energy but also reduce the diesel fuel consumption in each farm operation. Furthermore, periodic service and maintenance of tractors and farm machinery help farmers to perform agricultural operation on time and improve energy efficiency.

The second important factor contributing to energy saving is "irrigation water". Management of water consumption in farms that use traditional furrow irrigation is important. Changing traditional irrigation method to a modern irrigation technique will help decrease water consumption. The pattern of fertilizers used in turnip farms shows that inefficient farms should decrease consumption of fertilizers based on suggested values by benchmark farms. Reducing fertilizers consumption decreases greenhouse gas emission, significantly.

Results show there is a great potential for increasing the energy efficiency of turnip production in the region. Farmers should be trained to have enough knowledge about the proper and optimum use of input resources.

Data envelopment analysis is a mathematical programming methodology and widely used to measure energy efficiency. For this purpose, this paper proposed a new non-radial DEA efficiency model considering undesirable outputs. We believe that our newly developed methodology has some unique benefits that can improve the farms quality of evaluation, and as a consequence, the energy efficiency. The first benefit is that the proposed model is always feasible. This shows reasonability of the proposed model and ensures the managerial sector to apply it with no worries. Secondly, the proposed objective function gives a reasonable efficiency score that always lies between zero and one. Furthermore, the proposed model projects each inefficient DMU on the strong efficient frontier. This act is helpful because it gives confidence to find a real strong benchmark. Finally, our methodology can be easily extended to deal with fuzzy and stochastic data. This integration can help managers to make more precise decisions. Using the present methodology will make the results of the evaluation process more acceptable for business unit managers, lead to more improvement actions, and consequently, improved firm performance.

5. Conclusions

Nowadays, energy efficiency policies are becoming a key part of the global energy market. Energy efficiency is a key for ensuring a safe, reliable, affordable and sustainable energy system for the future. The various modern approaches of turnip production consume significant amount of energy, directly and indirectly. The optimum use of agricultural input resources results in increasing efficiency and decreasing carbon footprint of turnip production.

The main aim of this paper is assessing the efficiency of Iranian turnip farms over the period 2013-2014. Other purposes of the current paper are calculating the energy efficiency and optimal use of resources. Data envelopment analysis (DEA) is known as a convenient methodology for measuring efficiencies and assessing the performances of the firms. So, DEA methodology was selected to measure the efficiency of turnip farms.

For this purpose, this paper proposed a new non-radial DEA efficiency model considering undesirable outputs. The proposed DEA model has a number of important properties, as mentioned, making it preferable over other methods. In order to illustrate the proposed model's capabilities, a small numerical example was presented. The results validated the above mentioned properties of the model. In the case study section, the proposed model is applied to evaluate the efficiency of 30 Iranian turnip farms. In order to compare the performances of these farms, five inputs were considered. The collected data included labor, machinery, fertilizers, seed and water for irrigation. The outputs consisted of turnip yield as a desirable output and greenhouse gas emission as an undesirable output. In order to extend the proposed model in the presence of undesirable output, emission output was considered.

The results obtained by implementing the model have shown that the average value of technical efficiency score of turnip production in the studied region is 0.746. The results of benchmarking of turnip farms reveals that nine farms out of 30 farms are efficient. These farms are a good example for improving the performance of inefficient farms. When farmers use input resources efficiently, the target labor, machinery, seed, fertilizers and water energies decreases by 2.47%, 7.86%, 12.08%, 2.55% and 8.3%, respectively, without influencing turnip production level. Average target CO_2 emission of turnip production in the region is 552.65 kg $CO_{2eq}ha^{-1}$ that is 7% less than the present emission. Therefore, training programs for farmers should be developed to increase their knowledge of the optimum use of inputs and the environmental consequences of the excessive use of resources in turnip production.

Our results reveal that the highest contribution to the total energy saving is machinery (37.5%), followed by water (29.8 %), labor (17.2%), fertilizers (14.4%) and seed (1.2 %). Thus, the first priority in the efficient production of turnip is management of machinery energy. Selecting the proper power and size of tractors and farm machinery suitable to the farm size and their periodic service and maintenance are important factors in machinery energy management. The other factors contributing to energy saving of turnip production are management of water consumption and fertilizers. Changing traditional irrigation method to a modern irrigation technique will help decrease water consumption and increase energy efficiency. Also, inefficient farms should decrease consumption of fertilizers based on suggested values by benchmark farms to increase energy efficiency.

Moreover, the obtained results validated the properties stated for the theoretical model. The model could determine the efficiencies of all turnip farms (Theorem 1). All the obtained efficiencies are between 0 and 1 (Theorem 3). Also, the numerical example confirmed that the proposed model projects each inefficient DMU on the strong efficient frontier (Theorem 2):
As for future research, it would be interesting to extend the proposed methodology in other DEA models, such as two stage DEA models and network DEA models. Besides, the proposed model may be extended to cases where fuzzy and stochastic data could be incorporate into the model. We also suggest applying the developed model in this research in measuring the efficiencies in other agricultural farms from the sustainability view point.

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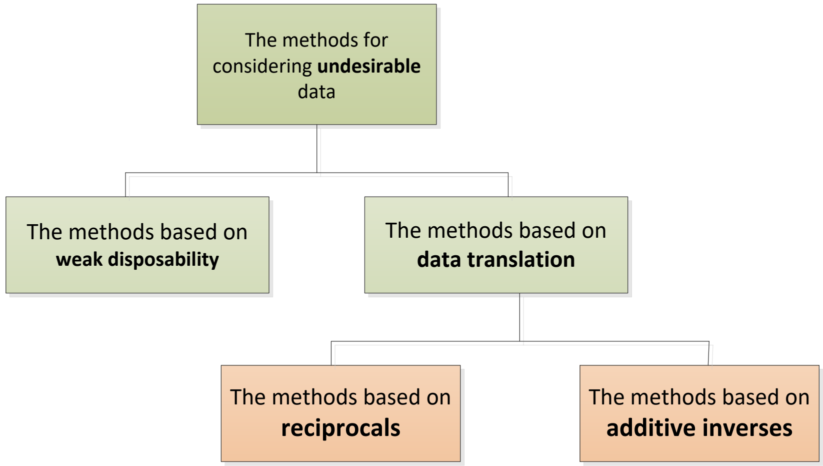

Fig. 1: The various methods of considering undesirable data

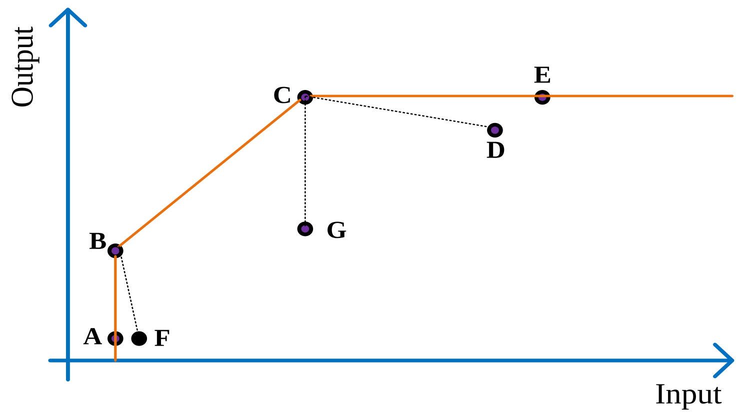

Fig. 2: Obtained target DMUs by our proposed model

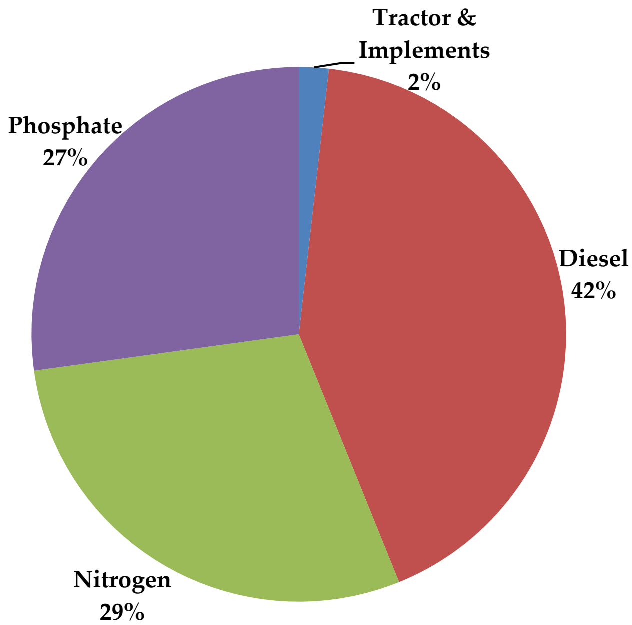

Fig. 3: Contribution of different input sources in the total emission

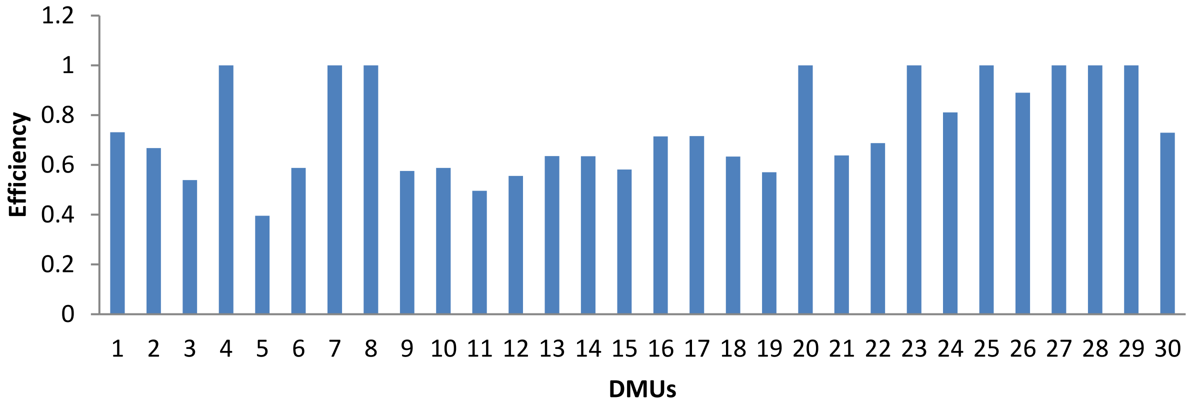

Fig. 4: Distribution of efficiency scores of turnip farms

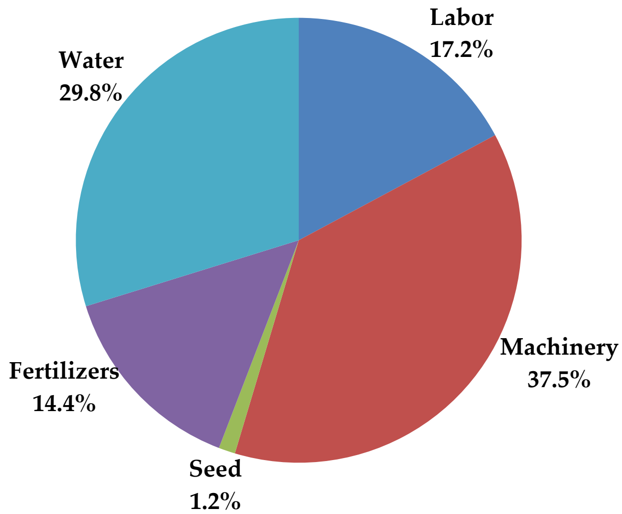

Fig. 5: Distribution of different sources in the total input energy saving

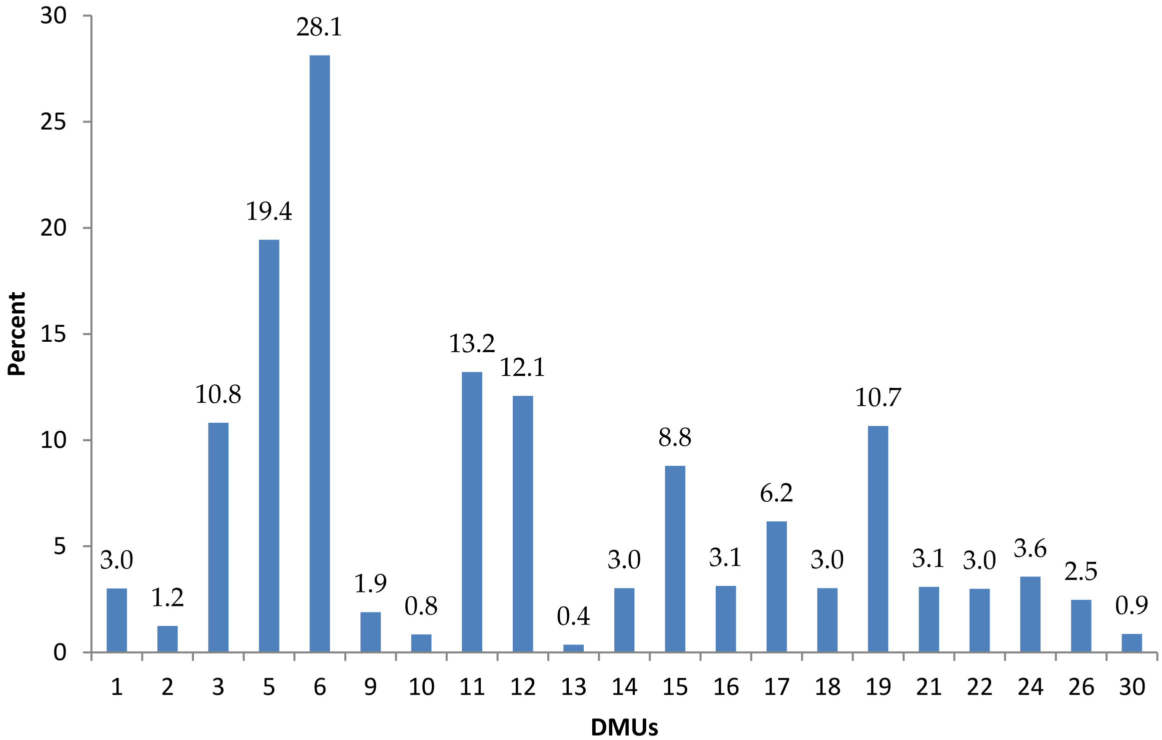

Fig. 6: Percentage of emission reduction in efficient use of input resources

Khoshroo, A., M. Izadikhah, A. Emrouznejad (2018) Improving energy efficiency considering reduction of CO2 emission of turnip production: A novel data envelopment analysis model with undesirable output approach, *Journal of Cleaner Production,* In press, https://doi.org/10.1016/j.jclepro.2018.03.232

Table 1: DEA methods for dealing with undesirable data

Methods		**References**	**Description**
Methods based on weak disposability		(Färe et al., 1993); (Lozano, 2016, Sueyoshi and Goto, 2016);	They treat undesirable outputs in their original forms and assume that these are weakly disposable
Methods based on data translation	Methods based on reciprocal	(Golany and Roll, 1989)	Undesirable outputs are considered in form of their reciprocals
	Methods based on additive inverses	(Scheel, 2001); (Seiford and Zhu, 2002); (Aliakbarpoor and Izadikhah, 2012); (Iftikhar et al., 2016, Liu et al., 2017, Wu et al., 2016);	Undesirable outputs are considered in form of their additive inverses. In these methods, undesirable output is considered as input.

Table 2: Example dataset

DMUs	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Input	2	2	10	18	20	2.5	12
Output	1	5	12	10.5	12	1	6
Efficiency score	0.81818	1.00000	1.00000	0.25004	0.72222	0.31818	0.39996
Projected point	$A' = \begin{pmatrix} 2.00 \\ 5.00 \end{pmatrix}$	$B' = \begin{pmatrix} 2.00 \\ 5.00 \end{pmatrix}$	$C' = \begin{pmatrix} 10.00 \\ 12.00 \end{pmatrix}$	$D' = \begin{pmatrix} 10.00 \\ 12.00 \end{pmatrix}$	$E' = \begin{pmatrix} 10.00 \\ 12.00 \end{pmatrix}$	$F' = \begin{pmatrix} 2.00 \\ 5.00 \end{pmatrix}$	$G' = \begin{pmatrix} 10.00 \\ 12.00 \end{pmatrix}$

Table 3: Energy equivalents for different inputs in agricultural production

Items	**Unit**	**Energy equivalent (MJ Unit^{-1})**	**References**
A. Inputs			
Human labor	h	1.96	(Khoshnevisan et al., 2013)
Machinery	kg		
a. Tractor		9-10	(Kitani, 1999)
b. Implements		6-8	(Kitani, 1999)
Diesel fuel	l	56.31	(Khoshroo et al., 2013)
Seed	kg	14.7	(Ozkan et al., 2004)
Fertilizers	kg		
a. Nitrogen		66.14	(Hatirli et al., 2006)
b. Phosphate		12.44	(Khoshroo and Mulwa, 2014)
Water for irrigation	m^3	1.02	(Khoshroo et al., 2013)

Table 4: Amounts of energy input and output variable for turnip production

Items	Average	Std. Dev.	Min	Max
A. Inputs (MJ ha^{-1})				
Human labor	7422.84	2215.03	3185.98	12727.26
Machinery	5094.63	1124.264	3652.26	9130.65
a. Tractor & Implements	146.09	32.24	104.73	261.83
b. Diesel fuel	4948.54	1092.02	3547.53	8868.83
Seed	106.64	33.98	55.12	158
Fertilizers	6026.65	1586.37	2835.66	10048.05
a. Nitrogen	2693.91	709.11	1267.54	4491.48
b. Phosphate	3332.74	877.26	1568.12	5556.57
Water for irrigation	3838.26	1461.56	1101.6	5728.32
B. Output (kg ha^{-1})				
Turnip	40190	2224.836	35000	43500
Emission	580.88	117.10	335.89	993.90

Table 5: Emission factor for input resources in crop production

Items	**Unit**	**Emission (kg CO_2 eq unit^{-1})**	**References**
Machinery	MJ	0.071	(Dyer and Desjardins, 2006)
Diesel fuel	L	2.762	(Dyer and Desjardins, 2003)
Fertilizers	kg		
a. Nitrogen	MJ	0.05	(Khabbaz, 2010)
b. Phosphate	MJ	0.06	(Khabbaz, 2010)

Table 6: Technical efficiency estimation and benchmarking of turnip production in Iran

DMU	Efficiency Scores	Benchmarks (Intensity Coefficient)				
1	0.732	7 (0.525)	8 (0.472)	25 (0.001)	27 (0.002)	
2	0.668	7 (0.311)	8 (0.516)	25 (0.044)	27 (0.065)	28 (0.064)
3	0.539	7 (1.000)				
4	1.000	4 (1.000)				
5	0.396	27 (0.990)	28 (0.010)			
6	0.588	28 (1.000)				
7	1.000	7 (1.000)				
8	1.000	8 (1.000)				
9	0.576	7 (0.992)	28 (0.008)			
10	0.588	7 (0.969)	25 (0.014)	28 (0.017)		
11	0.496	7 (0.688)	25 (0.077)	27 (0.124)	28 (0.110)	
12	0.556	7 (0.825)	8 (0.157)	25 (0.004)	27 (0.014)	
13	0.636	7 (0.612)	25 (0.105)	27 (0.136)	28 (0.147)	
14	0.635	7 (0.519)	8 (0.480)	25 (0.001)	28 (0.001)	
15	0.581	20 (0.688)	25 (0.070)	27 (0.721)	28 (0.117)	
16	0.715	7 (0.288)	8 (0.576)	25 (0.056)	27 (0.005)	28 (0.075)
17	0.716	20 (0.056)	25 (0.042)	27 (0.808)	28 (0.086)	
18	0.633	7 (0.533)	8 (0.465)	25 (0.001)	28 (0.001)	
19	0.571	7 (0.825)	8 (0.157)	25 (0.004)	27 (0.014)	
20	1.000	20 (1.000)				
21	0.638	25 (0.934)	28 (0.066)			
22	0.688	25 (0.906)	28 (0.094)			
23	1.000	23 (1.000)				
24	0.811	4 (0.908)	25 (0.036)	28 (0.056)		
25	1.000	25 (1.000)				
26	0.890	4 (0.031)	25 (0.897)	28 (0.072)		
27	1.000	27 (1.000)				
28	1.000	28 (1.000)				
29	1.000	29 (1.000)				
30	0.729	7 (0.240)	8 (0.626)	25 (0.033)	27 (0.050)	28 (0.050)

Table 7: Target amounts of energy inputs and outputs in turnip production

Items	Average	Std. Dev.	Min	Max
A. Inputs (MJ ha^{-1})				
Human labor	7239.28	2223.75	3185.98	12727.26
Machinery	4694.07	979.69	3652.26	9130.65
Seed	93.76	28.53	55.12	147
Fertilizers	5872.92	1388.46	2835.66	10048.05
Water for irrigation	3519.67	1573.80	1101.60	5552.06
B. Output (kg ha^{-1})				
Turnip	41821.25	1638.65	37000	43500
Emission	552.65	111.48	335.89	993.90

Table 8: Target energy saving for turnip production

Items	Present use	Target use	Energy saving	Energy saving percentage
Labor	7422.84	7239.27	183.58	2.47
Machinery	5094.63	4694.07	400.55	7.86
Seed	106.64	93.76	12.88	12.08
Fertilizers	6026.65	5872.92	153.73	2.55
Water	3838.26	3519.67	318.59	8.30
Total Input Energy	22489.02	21419.68	1069.34	4.75