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ORIGINAL RESEARCH

Inverse Dynamic Data Envelopment Analysis for Evaluating Faculties of University with Quasi-Fixed Inputs

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Abstract

Like other organizations, universities must evaluate their performance to identify areas for improvement. Although the different aspects of a university are considered for evaluation, the research section is deemed to be the most important and is where the necessity of the performance evaluation is most salient. In this study, the relative efficiency of the sub-units of several faculties of the university has been investigated through dynamic data envelopment analysis (DDEA) and inverse DDEA (IDDEA). The capability of traditional DEA to differentiate between efficient and non-efficient units decreases as the ratio of the number of inputs and outputs to the number of decision-making units increases. To remove this limitation by adding intermediate constraints between stages, a dynamic form of the method was applied in this research. The paper provides distinctions between the faculties as well as sensitivity analysis of the inputs/outputs of each faculty. The proposed IDDEA is implemented to scrutinize the changes in the input and output levels. The proposed approach is output-oriented to account for the homogeneity of faculties and their subordination under a specific unified management policy. A case study of Urmia University is used to demonstrate the proposed approach.

Keywords Inverse data envelopment analysis · Dynamic data envelopment analysis · Quasi-fixed inputs · Dynamic system · University performance · Faculty evaluation

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1 Introduction

Performance evaluation is a process utilized by organizations to determine their purposes and aims and assess whether their goals have been met. Performance evaluation can be done in either a fast, completely systematic manner, or a more specialized manner. Regardless, performance evaluation is necessary for the improvement of performance, because it allows organizations to identify their weaknesses and correct operations before they become big problems. The necessity for performance evaluation of universities is to find an appropriate model. On the other hand, universities as the driving force of science and knowledge in every country are in a high priority to be evaluated because of their crucial importance and unique role in the knowledge-based economy and providing skilled and expert manpower for the job market. As centers for science, universities hold a significant portion of the knowledge production of the country, and performance measurement is vital to such organizations. Therefore, evaluating universities can help allocate an appropriate budget to sub-units, efficient use of resources, and planning to improve the performance of universities.

One of the well-known methodologies for the evaluation of the relative efficiency of a set of units is DEA. DEA is a non-parametric method used to measure the performance of homogeneous decision-making units over a period. This method uses multiple inputs to produce multiple outputs and was first introduced by Charnes et al. (1978) as the Charnes, Cooper, Rhodes (CCR) model, with the assumption that the constant returns to scale. The method was developed further by Banker et al. (1984) as the Banker, Charnes, Cooper (BCC) model, the assumption with the variable returns to scale. Various studies in different areas have used this methodology and are continuously expanding. DEA has been applied in various areas such as energy systems (Meng et al. 2019; Jahangoshai-Rezaee 2015), regional planning (Yu 2019; González et al. 2018), manufacturing systems (Yang et al. 2018a, b; Azadeh et al. 2013), healthcare systems (Avkiran and McCrystal 2014; Karimdadi and Rezaee 2015), supplier selection (Yousefi et al. 2019), transportation systems (Rezaee et al. 2016, Rezaee and Yousefi 2018), portfolio selection and analysis (Mohammadian and Rezaee 2018; Rezaee et al. 2018), financial and banking sectors (Nourani et al. 2018; Naini et al. 2013).

Traditional DEA models measure the efficiency value of the performance of a DMU in a specified period and a static state. However, in the real world, when in a period, the inter-relations between inputs, outputs, and the current situation of the units are dependent on previous periods. As such, traditional DEA models cannot measure the efficiency of a DMU appropriately and the resulting efficiency scores could be misleading. The DDEA model responds to this problem by providing the possibility to evaluate the efficiency of units in several periods and consider the internal relations of inputs and outputs. Sengupta (1994) used an adjustment cost approach to analyze the influence of risk aversion and output fluctuations on the dynamic production frontier. The author entered random price changes into the DEA model and the risk-aversion treatment of DMUs. The efficient frontier was created through the use of the loss function and risk aversion.

Emrouznejad and Thanassoulis (2005) presented a DDEA model which calculated the technical dynamic efficiency measures and evaluated the efficient paths by considering the changes in the capital stock as a particular cause of the inter-temporal dependence of input–output levels. This model was improved further by Jahanshahloo et al. (2006). Tone and Tsutsui (2010) developed a DDEA model in the context of the slack-based model. The proposed model was a non-radial model and could differentiate between efficient and inefficient units. Chen and van Dalen (2010) presented a DDEA model that considered the effects of the middle-term indicators in the calculation of performance. The proposed model was designed to assess the effectiveness of the advertising strategies of several pharmaceutical and locomotive companies in North America. Kao (2013) introduced a relational DDEA model to calculate the radial values of overall and period efficiency as well as revealed the relationship between the efficiency of the entire system in each period because each period has its inputs and outputs in a dynamic system. Also, the proposed DDEA model was implemented for Taiwan's eight forest areas from 1989 to 1991. The efficiency score calculated by the DDEA model was lower than the score calculated by the traditional DEA model because of some extra constraints added to the DDEA model.

More recently, inverse problems have been developed and studied. These models have generally been divided into two categories: Models dealing with resource allocation problems and models dealing with investment analysis problems. The resource allocation problem of DEA is an inverse DEA (IDEA) problem for determining the best possible input for any given output, such that the current efficiency value of the DMU under evaluation (DMU_o) with respect to other DMUs remains unchanged. Another type of IDEA model is an investment analysis problem, which is an IDEA problem for determining the best possible output for the given input, such that the current efficiency value of DMU_o with respect to other DMUs remains unchanged.

Wei et al. (2000) were the first to propose an IDEA model for input and output estimation in response the following question: Among a group of DMUs, how much more output could a DMU produce from a certain input and assume that the DMU maintains its current efficiency value with respect to other DMUs? Or if the outputs are increased to a certain value and the efficiency of the unit remains unchanged, how much more input can be provided to the unit? In the developed IDEA model, the increases in input and output values were assumed to be non-negative values, and the IDEA model was transformed into a multi-objective linear programming (MOLP) problem. Yan et al. (2002) discussed an IDEA problem with preference cone constraints to represent the preferences of decision-makers, which were useful in resource planning. Hadi-Vencheh and Foroughi (2006) discussed an extended IDEA model which takes an increase of some inputs (outputs) and a decrease due to some of the other inputs (outputs) into account at the same time. The method proposed was based on DEA and MOLP, and showed that the solution proposed by Wei et al. (2000) did not guarantee the applicability of the result for input estimation because Wei et al. (2000) considered only the increase of inputs (outputs), although each DMU may subsequently result in the increase of some of the inputs (outputs) and the decrease of the other inputs (outputs) simultaneously.

Evaluating the performance of universities is another important area addressed by DEA. Kao and Hung (2008) applied the assurance-region DEA model for evaluating the relative efficiency of the academic departments at National Cheng Kung University in Taiwan. Four groups of departments have been clustered according to their efficiency scores. Horne and Hu (2008) estimated the cost efficiency of Australian universities for determining the level of utilizing teaching resources. Another application of DEA for measuring performance and quality assessment of the universities has been done by Murias et al. (2008). They proposed a composite indicator for evaluating Spanish universities. In this study, DEA was used to aggregate and weigh the data used to construct the composite indicator. Jahangoshai-Rezaee et al. (2012) proposed a hybrid model based on DEA and game theory for measuring the performance of decision-making units. For this purpose, they divided inputs into two categories including human resources and spatial information. They applied this model for measuring the unified efficiency of health centers under the supervision of the Tehran University of Medical Sciences. Pastor and Serrano (2016) proposed a 5-step methodology for determining the specialization, quality, and inefficiencies of the research output of universities. They concluded that major differences between EU countries are in inefficiency and the difference in resources allocated per researcher is the main source of heterogeneity in scientific outputs.

Rhaiem (2017) reviewed the efficiency of academic researches between 1990 and 2012. The author focused on the studies that applied DEA and stochastic programming. Another research on Italian universities is related to the investigation of the relationship between the pattern of teaching and research performance (Guccio et al. 2016). Sagarra et al. (2017) integrated multidimensional scaling and DEA for defining areas through which Mexico′s universities and their efficiency indicators are clustered. They used statistics for 55 universities during the period 2007–2012 and 12 ratios and estimated 21 DEA models under different conditions.

The inefficiency of Chinese research universities has been evaluated by Yang et al. (2018a, b) based on a two-stage network DEA model. They applied the modified Luenberger productivity indicator to measure the productivity changes of universities. The effects of the economic crisis on university efficiency have been investigated by Lehmann et al. (2018). They compared 133 public universities in the Italia and Germany over the period 2006–2011. Universities have been evaluated for determining the influence of public funding into the multiple outputs of a university, such as graduating students, publishing research, and patenting activity. They concluded the Italian universities have better performance during the crisis than their German counterparts. Berbegal-Mirabent (2018) investigated regulatory framework reformation of research and knowledge transfer activities at Spanish universities. For this purpose, the efficiency of public universities and the effects of evolution in their performance were evaluated during the period 2006–2010. An integrated approach based on the DEA-based Malmquist index and truncated regression were applied. Guironnet and Peypoch (2018) evaluated and ranked both educational diffusion and research productivity from higher education. They considered two different aspects for this evaluation including rural versus urban as well as public and private universities. In this paper, the authors used conventional DEA models.

As mentioned before, Dynamic DEA and Inverse DEA are two separate concepts in performance evaluation methodology by DEA. The dynamical model of DEA implies that units are evaluated over time. On the other hand, the inverse DEA model is used to optimize the input/output values to achieve a specified level of efficiency. In this paper, as a contribution, the combination of dynamic DEA and inverse DEA has been employed. In other words, this paper integrates DDEA and IDEA to build a hybrid model to evaluate the performance of the faculties at Urmia University. The aggregation of IDEA and DDEA is the first to be used to estimate the input/output values of a system. Also, with regard to the structure of universities, inputs are treated as outputs in the system with different time delays, so considering these real conditions is another contribution in this paper. The proposed model can be used to calculate not only the overall efficiency but also the efficiency of units for each specified period. The model can also be applied to estimate inputs/outputs of optimal value and perform sensitivity analysis.

The rest of the paper is organized as follows: Sect. 2 provides the methodologies used including dynamic DEA and inverse DEA. The proposed approach is discussed in Sect. 3. In Sect. 4, the case study is provided. The results and sensitivity analysis are given in Sect. 5. Finally, in Sect. 6, the conclusion will be presented.

2 Methodological Background

DEA is a non-parametric method for evaluating the performance of comparable DMUs. DEA evaluates the relative efficiency of a set of homogeneous DMUs by using a ratio of the weighted sum of outputs to the weighted sum of inputs. The output-oriented model for measuring the efficiency of $\mathrm{DMU_o}$, under the assumption of constant returns-to-scale by considering one period (static system), can be formulated as follows (Charnes et al. 1978):

$$
\begin{aligned}
& 1/\mathrm{E_o} = \mathrm{Min Z_o} = \sum_{i=1}^{m} \nu_i x_{io} \\
& \text{s.t.} \quad \sum_{r=1}^{s} u_r y_{ro} = 1 \\
& \qquad \sum_{i=1}^{m} \nu_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \quad j = 1, \ldots, n \\
& \qquad r = 1, 2, \ldots, s; \quad u_r \geq \varepsilon, \nu_i \geq \varepsilon \\
& \qquad i = 1, 2, \ldots, m
\end{aligned}
\tag{1}
$$

where u_r and v_i are virtual multipliers and ε is a small non-Archimedean number imposed to avoid ignoring any factor in calculating efficiency. The envelopment form of output-oriented CCR model is formulated as follows:

$$
\begin{aligned}
& \varphi_o = \max \varphi \\
& \text{s.t.} \quad \sum_{j=1}^{n} \lambda_j X_j \leq X_o \\
& \qquad \sum_{j=1}^{n} \lambda_j Y_j \geq \varphi Y_o \\
& \qquad \lambda_j \geq 0, \quad j = 1, \ldots, n \\
& \qquad \varphi \text{ is free}
\end{aligned}
\tag{2}
$$

2.1 Dynamic DEA

In measuring the relative efficiency of a set of n DMUs which use m inputs to produce s outputs during p periods, the total quantities over all periods are generally used. Let $X_{ij}^{(t)}$ and $Y_{rj}^{(t)}$ denote the ith input and rth output respectively for jth DMU in period t. Furthermore, denote $X_{ij} = \sum_{t=1}^{P} X_{ij}^{(t)}$ and $Y_{rj} = \sum_{t=1}^{P} Y_{rj}^{(t)}$ as the sum of ith input and rth output during p periods, respectively.

The dynamic system considered in this paper is a sequence of periods linked by flows Z_{fj}^{t} as depicted in Fig. 1. The concept of the flow used in this paper is very generic. It can be a quasi-fixed input when in a specific period, a portion of the output produced is reserved for the production of the current one. Also, these non-discretionary intermediate measures can

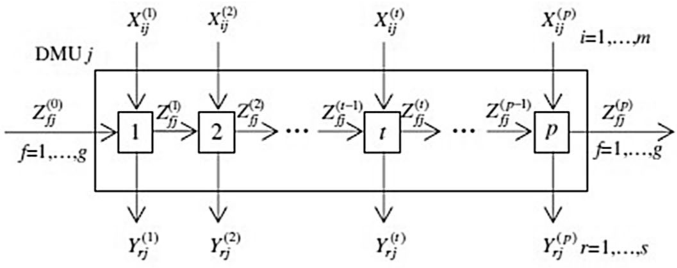

Fig. 1 Dynamic system with flows connecting two consecutive periods

be completely used in the next period (Jaenicke 2000). Without any problem, if all or a portion of the flows of a period is used as an input for the next one, the structure of the dynamic system is the same. The portion used for production in the next period is presented by Z^t_{fj}, and the portion as an output of the current period is presented by Y^t_{rj}. The model is first developed to evaluate the efficiency of a dynamic system, in which two consecutive periods are linked by any kind of flows. This model is presented by Kao (2013) and it is formulated as follows:

$$
\begin{aligned}
&1/\mathrm{E}_{\mathrm{o}}^{\mathrm{R}} = \mathrm{Min}\mathrm{Z}_{\mathrm{o}} = \sum_{\mathrm{i}=1}^{\mathrm{m}} v_{\mathrm{i}}\mathrm{x}_{\mathrm{io}} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}\mathrm{z}_{\mathrm{fo}}^{(0)} \\
&\text{s.t.} \qquad \sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u}_{\mathrm{r}}\mathrm{y}_{\mathrm{ro}} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}\mathrm{z}_{\mathrm{fo}}^{(\mathrm{P})} = 1 \\
&\qquad \left(\sum_{\mathrm{i}=1}^{\mathrm{m}} v_{\mathrm{i}}\mathrm{x}_{\mathrm{ij}} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}\mathrm{z}_{\mathrm{fj}}^{(0)}\right) - \left(\sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u}_{\mathrm{r}}\mathrm{y}_{\mathrm{rj}} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}\mathrm{z}_{\mathrm{fj}}^{(\mathrm{P})}\right) \geq 0 \quad j = 1, \ldots, n \\
&\qquad \left(\sum_{\mathrm{i}=1}^{\mathrm{m}} v_{\mathrm{i}}\mathrm{x}_{\mathrm{ij}}^{(\mathrm{t})} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}\mathrm{z}_{\mathrm{fj}}^{(\mathrm{t}-1)}\right) - \left(\sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u}_{\mathrm{r}}\mathrm{y}_{\mathrm{rj}}^{(\mathrm{t})} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}\mathrm{z}_{\mathrm{fj}}^{(\mathrm{t})}\right) \geq 0 \\
&\qquad \mathrm{j} = 1, 2, \ldots, \mathrm{n};\ t = 1, \ldots, \mathrm{P} \quad \mathrm{u}_{\mathrm{r}} \geq \varepsilon, v_{\mathrm{i}} \geq \varepsilon, \mathrm{w}_{\mathrm{f}} \geq \varepsilon \\
&\qquad \mathrm{i} = 1, 2, \ldots, \mathrm{m} \quad \mathrm{f} = 1, \ldots, \mathrm{g}
\end{aligned}
\tag{3}
$$

The third set of constraints are equal to the constraint associated with the system, and the second set of constraints are equal to the constraint associated for each DMU. Once an optimal solution ($\mathrm{u}_{\mathrm{r}}^*$, $\mathrm{v}_{\mathrm{i}}^*$, $\mathrm{w}_{\mathrm{f}}^*$) is obtained, the efficiencies of the whole system, $\mathrm{E}_{\mathrm{o}}^{(\mathrm{S})}$, and period t, $\mathrm{E}_{\mathrm{o}}^{(\mathrm{T})}$, t=1 … P, for $\mathrm{DMU}_{\mathrm{o}}$, can be calculated as:

$$
\mathrm{E}_{\mathrm{o}}^{(\mathrm{S})} = \frac{\sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u}_{\mathrm{r}}^*\mathrm{Y}_{\mathrm{ro}} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}^*\mathrm{Z}_{\mathrm{fo}}^{(\mathrm{P})}}{\sum_{\mathrm{i}=1}^{\mathrm{m}} v_{\mathrm{i}}^*\mathrm{X}_{\mathrm{io}} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}^*\mathrm{Z}_{\mathrm{fo}}^{(0)}} \tag{4}
$$

$$
\mathrm{E}_{\mathrm{o}}^{(\mathrm{T})} = \frac{\sum_{\mathrm{r}=1}^{\mathrm{s}} \mathrm{u}_{\mathrm{r}}^*\mathrm{Y}_{\mathrm{ro}}^{(\mathrm{t})} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}^*\mathrm{Z}_{\mathrm{fo}}^{(\mathrm{t})}}{\sum_{\mathrm{i}=1}^{\mathrm{m}} v_{\mathrm{i}}^*\mathrm{X}_{\mathrm{io}}^{(\mathrm{t})} + \sum_{\mathrm{f}=1}^{\mathrm{g}} \mathrm{w}_{\mathrm{f}}^*\mathrm{Z}_{\mathrm{fo}}^{(\mathrm{t-1})}} \tag{5}
$$

The envelopment form of the model, which is the dual of Model (3) is formulated as:

$$
\begin{aligned}
& 1/E_o^R = \max\varphi \\
& \text{s.t.} \quad \sum_{t=1}^{P}\sum_{j=1}^{n}\lambda_j^{(t)}X_{ij}^{(t)} + \sum_{j=1}^{n}\lambda_j X_{ij} \le X_{io} \quad i = 1, \ldots, m \\
& \sum_{t=1}^{P}\sum_{j=1}^{n}\lambda_j^{(t)}Y_{rj}^{(t)} + \sum_{j=1}^{n}\lambda_j Y_{rj} \le \varphi Y_{ro} \quad r = 1, \ldots, s \\
& \sum_{t=1}^{P}\sum_{j=1}^{n}\lambda_j^{(t)}\left(Z_{fj}^{(t)} - Z_{fj}^{(t-1)}\right) + \sum_{j=1}^{n}\lambda_j\left(Z_{fj}^{(P)} - Z_{fj}^{(0)}\right) + Z_{fo}^{(0)} \le \varphi Z_{fo}^{(P)} \quad f = 1, \ldots, g \\
& \lambda_j^{(t)},\ \lambda_j \ge 0 \quad j = 1, \ldots, n \quad t = 1, \ldots, P \\
& \varphi \text{ is free}
\end{aligned} \tag{6}
$$

2.2 Inverse DEA

Inverse DEA was first introduced by Wei et al. (2000). They proposed this model in response to the following this Question: "If the efficiency index φ_o remains unchanged, but the inputs increase, how much should the outputs of DMU_o increase?".

Suppose that the inputs of DMU_o are increased from X_o to $\alpha_o = X_o + \Delta X_o$, where $\Delta X_O \ge 0$ and $\Delta X \ne 0$. The aim of the problem is estimating the output vector β_o^* provided that the efficiency of DMU_o is still φ_o. $\beta_o^* = (\beta_{1o}^*, \beta_{2o}^*, \ldots, \beta_{mo}^*)^t = Y_o + \Delta Y_o\ ,\ \Delta Y_o \ge 0$. Suppose DMU_{n+1} represents DMU_o after changing the inputs and outputs. The following model measures the efficiency score of DMU_{n+1}:

$$
\begin{aligned}
& \varphi_{n+1} = \max\varphi \\
& \text{s.t.} \quad \sum_{j=1}^{n}\lambda_j X_j + \lambda_{n+1}\alpha_o \le \alpha_o \\
& \sum_{j=1}^{n}\lambda_j Y_j + \lambda_{n+1}\beta_o^* \ge \varphi Y_o \\
& \lambda_j \ge 0, \quad j = 1, \ldots, n, n+1
\end{aligned} \tag{7}
$$

If the optimal values of Models (2) and (8) are equal, we say that the efficiency is unchanged, i.e., $\varphi(\alpha_o,\ \beta_o^*) = \varphi(X_o,\ Y_o)$. To response Question 1, Wei et al. (2000) proposed the following multiple-objective linear programming (MOLP) problem.

$$
\begin{aligned}
& \max(\beta_{1o},\ \beta_{2o}, \ldots, \beta_{so}) \\
& \text{s.t.} \quad \sum_{j=1}^{n}\lambda_j X_j \le \alpha_o \\
& \sum_{j=1}^{n}\lambda_j Y_j \ge \varphi_o Y_o \\
& \beta_o \ge Y_o \\
& \lambda_j \ge 0, \quad j = 1, \ldots, n
\end{aligned} \tag{8}
$$

In the above model, $(\lambda, \beta_o) \in R$ are the variable vector. In this model, φ_o is the optimal value of Model (2). The following theorem contains some of the main results of Wei et al. (2000). This theorem answers Question1 when DMU_o is output-oriented inefficient (i.e., $\varphi_o > 1$).

Theorem 1 (Wei et al. 2000) *Suppose that $\varphi_o > 1$ and the inputs for DMU_o are going to increase from X to $X + \Delta X_O$, where $\Delta X_O \geq 0$ and $\Delta X \neq 0$.*

(a) *Let (λ^*, β_o^*) be a weak Pareto solution of MOLP (Model 8). Then, when the outputs of DMU_o are increased to β_o^* we have $\varphi(\alpha_o, \beta_o^*) = \varphi(X_o, Y_o)$*
(b) *Conversely, let (λ^*, β_o^*) be a feasible solution of MOLP (Model 8). If $\varphi(\alpha_o, \beta_o^*) = \varphi(X_o, Y_o)$ then (λ^*, β_o^*) is a Weak Pareto solution to MOLP (Model 8).*

For the case $\theta_o = 1$ Wei et al. (2000) used a linear programming problem as follows:

$$\begin{aligned} \varphi_o &= \max \varphi \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j X_j \leq \alpha_o \\ & \sum_{j=1}^{n} \lambda_j Y_j \geq \varphi_o Y_o \\ & \lambda_j \geq 0, \quad j = 1, \ldots, n \end{aligned} \tag{9}$$

In the above model $(\lambda, \varphi) \in R$ is the decision variables. The following theorem responses Question 1 when DMU_o is output-oriented efficient.

Theorem 2 (Wei et al. 2000) *Suppose that $\varphi_o = 1$ and the inputs for DMU_o are going to increase from X to $X + \Delta X_O$, where $\Delta X_O \geq 0$ and $\Delta X \neq 0$. Then $\varphi(\alpha_o, \varphi_o Y_o) = \varphi(X_o, Y_o)$, where φ_o is the optimal value of Model (9).*

3 Proposed Approach

In this paper inverse dynamic DEA (IDDEA) model is proposed to measure changes input/output index by taking into account in the dynamic DEA model. For this purpose, two different models according to inputs or outputs estimation are expressed in the following.

3.1 Output Estimation in Inverse Dynamic CCR Model

In this section, the inverse dynamic CCR model is extended and responded to the question provided by Wei et al. (2000), in dynamic DEA model. Suppose DMU_{n+1} represents the unit obtained after changing the inputs and outputs of DMU_o. Models (2) and (8) measure the (output-oriented) efficiency scores of DMU_o and DMU_{n+1}, respectively. Similarly, Model (10) is presented for output estimation in IDDEA model:

$$
\begin{aligned}
&1/\mathrm{E}^{ID} = \max\ \beta_{ro} \\
&\quad \text{s.t.} \quad \sum_{t=1}^{P}\sum_{j=1}^{n}\lambda_j^{(t)}X_{ij}^{(t)} + \sum_{j=1}^{n}\lambda_j X_{ij} \le \alpha_{io} \quad i = 1,\dots,m \\
&\quad \sum_{t=1}^{P}\sum_{j=1}^{n}\lambda_j^{(t)}Y_{rj}^{(t)} + \sum_{j=1}^{n}\lambda_j Y_{rj} \ge \varphi_o\beta_{ro} \quad r = 1,\dots,s \\
&\quad \sum_{t=1}^{P}\sum_{j=1}^{n}\lambda_j^{(t)}\left(Z_{fj}^{(t)} - Z_{fj}^{(t-1)}\right) + \sum_{j=1}^{n}\lambda_j\left(Z_{fj}^{(P)} - Z_{fj}^{(0)}\right) + Z_{fo}^{(0)} \ge \varphi_o Z_{fo}^{(P)} \quad f = 1,\dots,g \\
&\quad \beta_{ro} \ge Y_{ro} \\
&\quad \lambda_j^{(t)},\ \lambda_j \ge 0 \quad j = 1,\dots,n \quad t = 1,\dots,P
\end{aligned} \tag{10}
$$

In the above model, (β_{ro} , λ_j , $\lambda_j^{(t)}$) are the variables. In this model, φ_o is the optimal value of Model (7) and (α_{io}, β_{ro}) are the sum of inputs and outputs for the specific period, respectively.

3.2 Input Estimation in Inverse Dynamic CCR Model

Similarly the above models, input-oriented IDDEA model formulated as Model (11). Therefore Model (11) is presented for input estimation in IDDEA model:

$$
\begin{aligned}
&1/\mathrm{E}^{IID} = \max \alpha_{io} \\
&\quad \text{s.t.} \quad \sum_{t=1}^{P}\sum_{j=1}^{n}\mu_j^{(t)}X_{ij}^{(t)} + \sum_{j=1}^{n}\mu_j X_{ij} \le \theta_o\alpha_{io} \quad i = 1,\dots,m \\
&\quad \sum_{t=1}^{P}\sum_{j=1}^{n}\mu_j^{(t)}Y_{rj}^{(t)} + \sum_{j=1}^{n}\mu_j Y_{rj} \ge \beta_{ro} \quad r = 1,\dots,s \\
&\quad \sum_{t=1}^{P}\sum_{j=1}^{n}\mu_j^{(t)}\left(Z_{fj}^{(t-1)} - Z_{fj}^{(t)}\right) + \sum_{j=1}^{n}\mu_j\left(Z_{fj}^{(0)} - Z_{fj}^{(P)}\right) + Z_{fo}^{(P)} \le \theta_o Z_{fo}^{(0)} \quad f = 1,\dots,g \\
&\quad \alpha_{io} \ge X_{io} \\
&\quad \mu_j^{(t)}, \mu_j \ge 0 \quad j = 1,\dots,n \quad t = 1,\dots,P
\end{aligned} \tag{11}
$$

In the above model, (μ_j , μ_j^t , α_{io}) are the variables. In this model, θ_o is the reverse of φ_o so that $\theta_o = 1/\varphi_o$.

Table 1 Statistical description of data

Faculty	Number of academic staff (X_1)				Number of postgraduate students (Z1)				Research funds (Z2)			
	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
Veterinary	49	59	55.25	4.5	446	561	495	46.244	990,816.6	2,095,690.61	1,406,343.442	421,024.508
Agriculture	77	92	85	7.165	425	797	591.6	155.022	158,788.1	3,783,159.33	2,024,849.486	1,339,824.58
Engineering	57	67	60.5	4.726	438	860	623.6	169.783	750,000	1,652,432.16	1,186,610.972	370,533.544
Basic Sciences	71	82	76	4.69	697	984	817.2	105.241	873,246	2,488,294.36	1,453,496.072	648,092.2183
Literature and Humanities	52	66	59.25	6.076	288	679	473.2	164.831	147,752.428	769,330	548,343.886	249,160.399
Physical Education and Sports Science	12	12	12	0	81	221	141.6	60.678	55,151.869	22,260,608	4,656,591.974	9,841,783.611
Economics and Management	20	26	23	2.944	78	280	163.8	85.048	152,000	542,797.195	296,639.439	157,166.688
Natural Resources	11	19	16	3.464	38	173	97.4	54.215	181,770	653,865.649	367,612.31	198,731.719
Arts	9	15	12	2.944	0	25	8	10.512	0	41,200	17,440	17,625.777
Faculty	Number of published papers in the Scientific database (Y_1)				Income of research projects (Y_2)				Number of citations to the articles published in the Scientific database (Y_3)			
	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
Veterinary	80,000	425,000	250,875	141,131.366	20	60	34.75	17.462	46	229	121.75	88.232
Agriculture	85,000	2,388,500	1,595,888.75	1,044,496.946	52	84	66.75	14.175	130	324	191	89.748
Engineering	747,200	3,140,000	1,784,976.191	997,322.236	80	101	90.25	9.179	238	544	399.25	125.293
Basic Sciences	885,500	4,933,140	2,104,660	1,911,509.495	67	89	75.75	9.57	216	365	274.25	66.143
Literature and Humanities	0	245,000	128,750	104,273.279	5	28	12	10.739	1	41	12.25	19.242
Physical Education and Sports Science	0	563,788	268,447	275,742.477	2	9	4.25	3.304	4	53	22	22.73
Economics and Management	120,000	691,250	306,562.5	259,826.414	1	7	4	2.582	0	6	1.75	2.872
Natural Resources	0	1,550,000	912,897.5	674,498.912	1	6	4	2.449	0	32	11.5	14.434
Arts	0	2,248,500	869,977.5	1,049,776.566	0	0	0	0	0	0	0	0

4 Case Study: Urmia University

Urmia University, as a large university in Iran, continuously evaluates the efficiency whole faculties so knowing it is better at allocating resources to facilities. For this purpose, dynamic DEA in four periods from 2011 to 2014 is used. Nine faculties as decision-making units are considered. Afterward, efficient and inefficient faculties in different areas are determined and then an inverse DDEA is proposed for the analysis results and estimated outputs (inputs) with an increase in the inputs (outputs) with no change in efficiency. Finally, sensitivity analysis is performed according to specific scenarios. In the case study, one input including the number of academic staff (X_1) and three outputs including the number of published papers in the scientific journals (Y_1), income of research projects (Y_2) and the number of citations to the articles published in the scientific journals (Y_3) as well as the finally two quasi-fixed inputs (intermediate measures) including the number of graduate students (Z_1) and research funds (Z_2) are used. Table 1 shows the statistical description of the data used.

5 Results and Sensitivity Analysis

First, the dynamic efficiencies of nine faculties from Urmia University from 2011 to 2014 are calculated (see Table 2). Because of used output-oriented model, the objective function values is a greater one. For this reason, the inverse of efficiency values is reported. As can be seen in Table 2, the Faculty of Engineering is the most efficient and the Faculty of Arts is the most inefficient one. The variance of efficiency scores is much higher than expected, which indicates that the difference in inputs and outputs between the best faculty and the worst faculty is significant. The results and analyses are divided into three parts including results of DDEA, sensitivity analysis of DDEA model, estimating inputs or outputs using IDDEA.

5.1 Results of Dynamic DEA Model

To demonstrate the ability of DDEA model, the results of the static DEA and DDEA are compared. As shown in Table 3, the presence of additional constraints on the results of DDEA is more logical and more realistic than the static one. The efficiency value of static DEA for the nine faculties is greater than dynamic DEA scores, and this result shows that dynamic DEA model can make more distinct between faculties. In Table 3, values of period efficiencies for the nine faculties are shown. As seen the faculty of Arts in 2011 is efficient and its efficiency score is almost 1. In 2012 the faculties Engineering and Natural resources are efficient. In the year of 2013, the faculties of Physical Education & Sports Science and Engineering are efficient and the end, in 2014 the faculty of Natural resources score reaches to 0.986. Faculty of Art for the years 2012, 2013 and 2014 is inefficient and these results show that the faculty of Art is generally inefficient. Table 3 shows when the efficiency value for even a year is less than one, overall efficiency cannot be one. It also presents that dynamic models can provide more discrimination between faculties' efficiency.

Figure 2 shows the period efficiencies of different faculties. It is observed the efficiency of the faculty of Engineering during the four periods is almost the highest level. According to Fig. 2, the faculty of Art efficiency scores for 2012, 2013 and 2014 is at the lowest level.

Figure 3 shows the comparison of the dynamic DEA model and static DEA model. As shown in Fig. 3, the curve of static DEA for the nine faculties is above the curve of dynamic DEA, and these results show that the static DEA provides the optimistic efficiencies. Also,

Table 2 Results of DDEA model

Faculty	E_o (%)	Rank
Literature and Humanities	50.6	8
Physical Education and Sports Science	73.70	4
Veterinary	59.31	7
Basic Sciences	75.07	3
Engineering	95.96	1
Agriculture	61.28	6
Natural Resources	77.36	2
Arts	38.82	9
Economics and Management	65.13	5

Table 3 Comparison between the results of dynamic DEA and static DEA models

Faculty	Efficiency of Static-DEA	Efficiency of Dynamic-DEA				
		Overall efficiency	2011	2012	2013	2014
Literature and Humanities	0.732	0.506	0.719	0.739	0.851	0.727
Physical Education and Sports Science	1	0.7370	0.756	0.963	1	0.850
Veterinary	0.914	0.593	0.750	0.820	0.793	0.875
Basic Sciences	0.991	0.750	0.793	0.801	0.885	0.941
Engineering	1	0.959	0.933	1	1	0.976
Agriculture	0.734	0.612	0.679	0.789	0.769	0.807
Natural Resources	1	0.773	0.707	1	0.818	0.983
Arts	1	0.388	0.999	0.137	0.463	0.270
Economics and Management	0.938	0.651	0.934	0.654	0.999	0.912

the results of dynamic DEA model prove the claim about better discrimination between faculties.

5.2 Sensitivity Analysis of Dynamic DEA Model

For further analysis, the sensitivity analysis has been done for each faculty. The efficiency of each faculty to get the best performance should be one. Since the change in the input values and the policies of the Ministry of Science, Research and Technology are dynamic and are often determined outside of universities, it is not rational that sensitivity analysis is done based on the inputs. For this reason, inputs are considered constant and analysis is provided on outputs. Defined scenarios for all faculties are percentage increase except for faculties of Natural resources, Art and Economics and Management that their scenarios are additive. Note that the rank of each faculty is calculated for the current efficiency value of other faculties. In the next figures, new ranks of faculties in each scenario are presented in parentheses.

Figure 4 shows when the outputs are increased, the rank of the faculty of Literature and Humanities increases one degree and it is observed that efficiency value changes little. Also, the efficiency scores by applying scenario increase but this increase very little and the rank of this faculty changes from 8 to 7. It indicates that this faculty is not sensitive to the increase in output values. In other words, to enhance the performance of this faculty, its outputs must increase much higher than the current one. But in the faculty of Basic Sciences, this performance improvement is more significant (see Fig. 5). With increasing 80% output values, it can upgrade own rank. The scores of faculty's efficiency by increasing in outputs show the faculty can have better performance. Also, this trend can be seen at the faculty of Physical Education and Sports Science. The related figure of this faculty, the curve slope is almost steep. In other words, if the outputs are increased, the efficiency scores increase tangibly.

Figure 6 shows that by increasing the outputs of the Natural faculty, in half of the cases, the rank and efficiency was almost is constant. But in other cases, it achieves to efficiency 1. This result shows that if the Natural faculty can bring "the number of published papers in the scientific database" and "the number of citations to the articles published in the scientific database" from the initial value 16 to 28, it will have the best performance. The 12 units include the sum of the "the number of published papers in the scientific database" and "the number of citations to the articles published in the scientific database" in the 4 years. The second index that "income of research projects" with 12 units increasing is constant for this reason just the first and the third index increased until the efficiency score reaches to 1.

For other faculties, the related figures have been presented in "Appendix". According to the results, the faculty of Art needs much enhancement to reach efficiency 1. Art faculty's efficiency changes slightly through even great rises in output values, and it holds the ninth and last order among all the faculties. But the curve slope almost fixed for the faculty of Economic. By increasing four units in the output values, the rank of economic faculty is upgraded from 7 to 5 and is unchanged this rank after this increasing. Efficiency value with attended little increase and these results show that this faculty has input surplus, for this reason, it needs output value increase mostly. The similar analysis may be provided for other faculties that the related figures have been presented in "Appendix".

5.3 Estimated Input/Output Values Using IDDEA

Table 4 shows the results of Model (10) when the input level increase 1% and the value of the dynamic index are fixed. In the table, the increase in the value of the second input is shown. Similar analyses for other faculties with the different increase in input level (3%

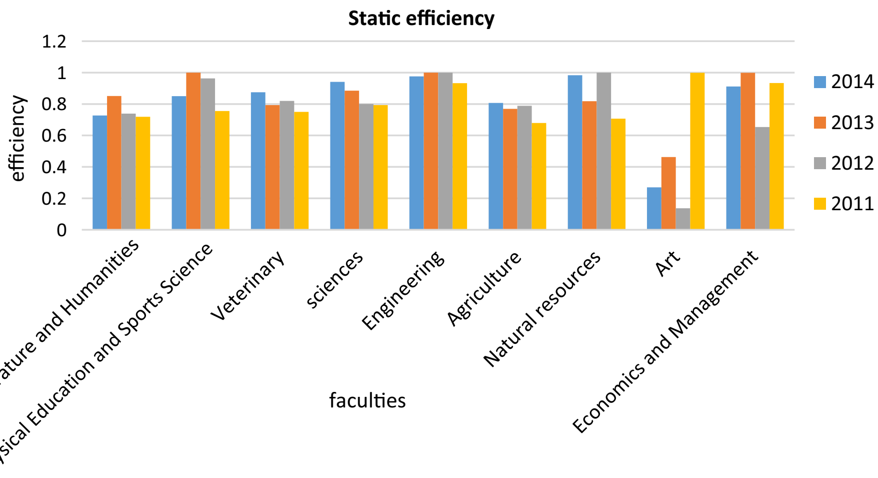

Fig. 2 Static efficiency for four periods separately

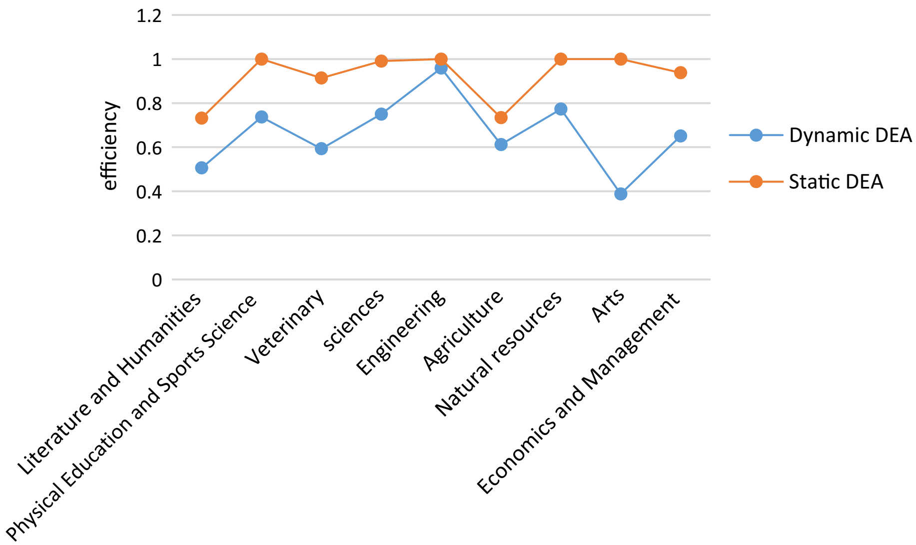

Fig. 3 Comparison between dynamic DEA and static DEA

and 5%) have been provided in "Appendix". As can be seen in Table 4, if faculty of engineering wants to increase 1% of its academic staff and fixe its efficiency value, it will be must increase "the number of citations to the articles published in the scientific database" and "income of research projects" from 1597 and 71,399.04762 to 1819 and 77,198.93 respectively, and fix "the number of published papers in the scientific database". These interpretations may be provided for other faculties and variations. Most changes have taken place for the faculties of Literature & Humanities and Economics & Management. On the other hand, the faculty of Physical Education and Sports Science has the slightest changes.

According to Table 4 and related tables in "Appendix", the value of the change for the output index are caused little change and the second index is noticeable so that this change for the second index is rather much. Each faculty to get the best performance should be reached the value of efficiency to 1. Hence, in this section, output values are estimated

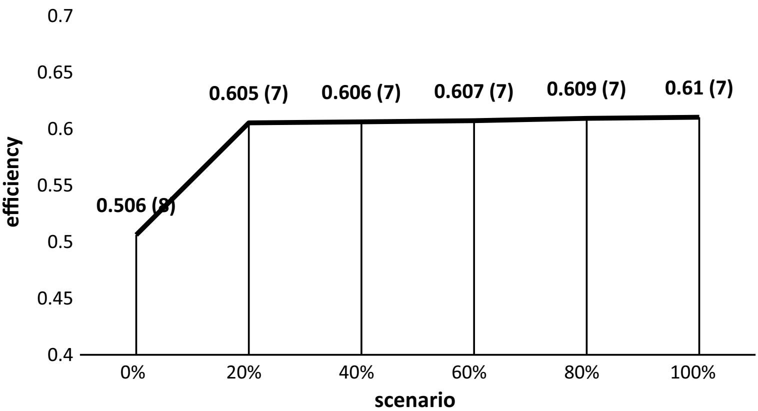

Fig. 4 Efficiency changes of Literature and Humanities faculty with increase in outputs

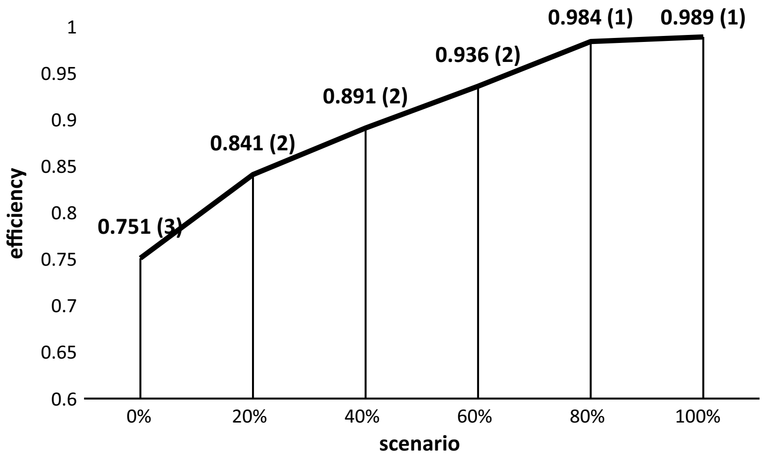

Fig. 5 Efficiency changes of Basic Sciences faculty with increase in outputs

when the values of input and dynamic index are fixed and the value of efficiency is considered 1 for each faculty. Estimate the output values are done in two cases, in the first case, by limiting the output values so that the estimated output values should be greater than their current values and in the second case, they do not have any limitation. Table 5 shows the value of each output when the efficiency factor is equal to 1. In this situation, the change in output values does not have any limitation. As we can see, the second output has significant change and two others have not any sensible changes.

Table 6 shows the results of Model (11) when the outputs are changed according to an increase of 10%, 5%, and 10% respectively, while the dynamic measure value is fixed. Similar analyses for other faculties with the different increase in outputs level [(15%, 10%, and 15%) and (20%, 15%, and 20%)] have been provided in "Appendix". As specified in the table, just for the Engineering faculty, the input value is changed, since the Engineering faculty is efficient. It means for producing outputs, there is not surplus input so that by increasing the output values, the input value increases too. But for the other faculties, since the value of efficiency is less than 1, by increasing the outputs, the input value is not changed, because first, the surplus input must be offset. The range of input change according to outputs changes for Engineering Faculty is presented in Tables 7, 8, 9 and 10.

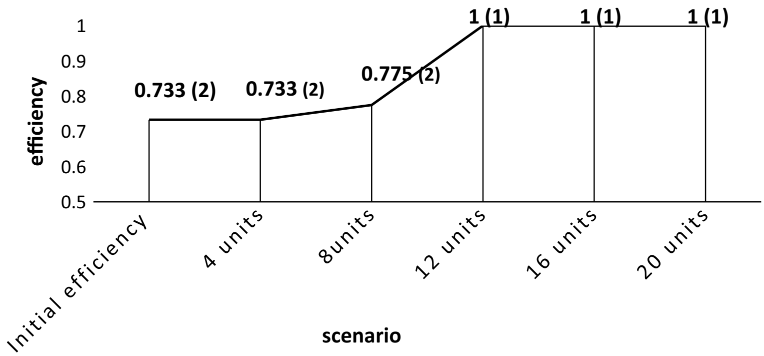

Fig. 6 Efficiency changes of Natural Resources faculty with increase in outputs

Table 4 Output estimation with increasing 1% in the input value and without the change in the dynamic measure

Faculty	Number of published papers in the Scientific database		Income of research projects (10^6)		The number of citations to the articles published in the Scientific database	
	Initial value	Changed value	Initial value	Changed value	Initial value	Changed value
Literature and Humanities	48	48	5150	33,927.12	49	168
Physical Education and Sports Science	17	20	10,737.88	12,712.15	88	88
Veterinary	139	139	10,035	39,735.98	487	561
Basic Sciences	303	303	84,186.40	89,995.26	1097	1109
Engineering	361	361	71,399.05	77,198.93	1597	1819
Agriculture	267	268	63,835.66	69,032.85	764	1273
Natural Resources	16	19	36,515.90	45,039.72	46	93
Art	0	3	34,799.10	35,274.10	0	10
Economics and Management	16	18	12,262.50	17,089.84	7	40

Table 5 Output estimation with having efficiency score 1 for faculties

Faculty	Number of published papers in the Scientific database		Income of research projects (10^6)		The number of citations to the articles published in the Scientific database	
	Initial value	Changed value	Initial value	Changed value	Initial value	Changed value
Literature and Humanities	48	48	5150	385,657.90	49	211
Physical Education and Sports Science	17	19	10,737.88	53,458.37	88	88
Veterinary	139	139	10,035	321,844.61	487	583
Basic Sciences	303	303	84,186.40	323,612.51	1097	1157
Engineering	361	361	71,399.04762	102,623.22	1597	1826
Agriculture	267	268	63835.66	457,132.15	764	1345
Natural Resources	16	17	36,515.90	84,701.75	46	88
Art	0	737	34,799.10	95,299	0	79
Economics and Management	16	17	12,262.50	134,782.43	7	84

Table 6 Input estimation with increasing (10%, 5%, and 10%) in the output value without the change in dynamic measure

Faculty	Number of academic staff		Changed percent
	Initial value	Changed value	
Literature and Humanities	237	237	Unchanged
Physical Education and Sports Science	48	48	Unchanged
Veterinary	221	221	Unchanged
Basic Sciences	304	304	Unchanged
Engineering	242	249	2.9% increased
Agriculture	340	340	Unchanged
Natural Resources	64	64	Unchanged
Art	48	48	Unchanged
Economics and Management	92	92	Unchanged

6 Conclusion

The necessity for performance evaluation of universities and their sub-units is to find an appropriate and effective model. On the other hand, universities are in a high priority to be evaluated because of their crucial importance and unique role in the knowledge-based economy and providing skilled and expert manpower for the job market. DEA as the well-known, most powerful and most used evaluation methodology in various areas including industrial, service, agricultural, etc. can be suitable for universities. Since the performance of some units in the real world should be analyzed along the time, the dynamic DEA would be more appropriate. In this study, both the Static DEA and Dynamic DEA have been applied to evaluate the performance of Urmia University's faculties, and their results have been compared. According to these results, DDEA provides more discrimination than static DEA and the results are close to reality because of the nature of DDEA model. As evidence, most of the faculties were wrongly showed efficient by static DEA. However, according to DDEA, Engineering and Natural Resources faculties were turned out as the most efficient ones with 0.9596 and 0.7736 efficiencies, respectively. Moreover, Art faculty with 0.3883 and Economics and Management faculty with 0.6513 were known as the most inefficient faculties among all nine university faculties. Then, the sensitivity analysis was done on faculties using a set of scenarios by increasing outputs. Finally, IDDEA has been developed to determine the changes in inputs and outputs in the form of certain increases. This information contributes to the understanding of the changes required of outputs (inputs) to hold the faculties' current efficiency level, and the potential effects of certain increases in their inputs (outputs). Regarding the different nature and difference of activities of each faculty, and not considering these differences is one of the limitations of the model that may be considered in future research. Also, evaluating and comparing universities by considering departments or facilities as internal components of each university may be considered for future endeavors.

Appendix: Tables and Figures Generated for Sensitivity Analysis and Input/Output Estimation

See Figs. 7, 8, 9, 10, 11, 12 and Tables 7, 8, 9 and 10.

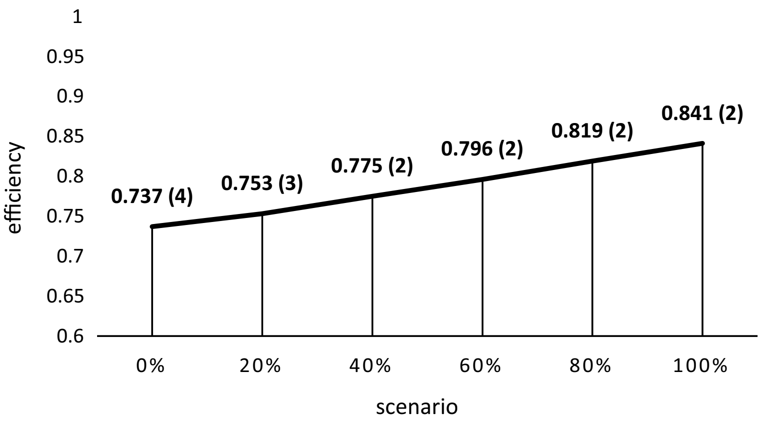

Fig. 7 Efficiency changes of Physical Education and Sports Science faculty with the increase in outputs

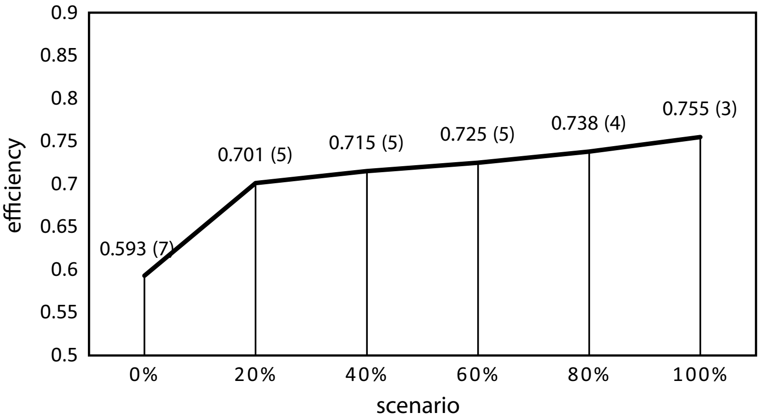

Fig. 8 Efficiency changes of Veterinary faculty with the increase in outputs

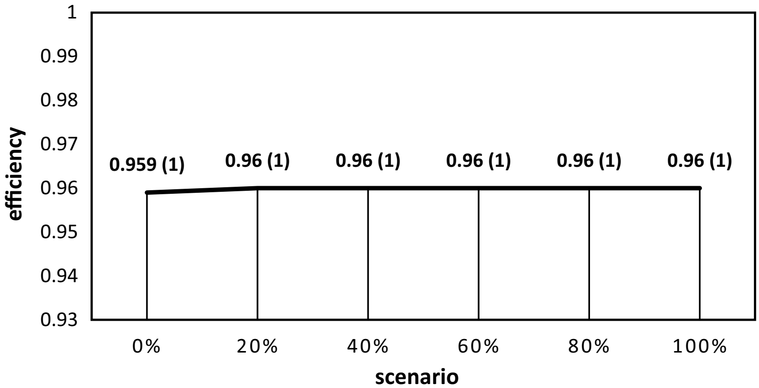

Fig. 9 Efficiency changes of Engineering faculty with the increase in outputs

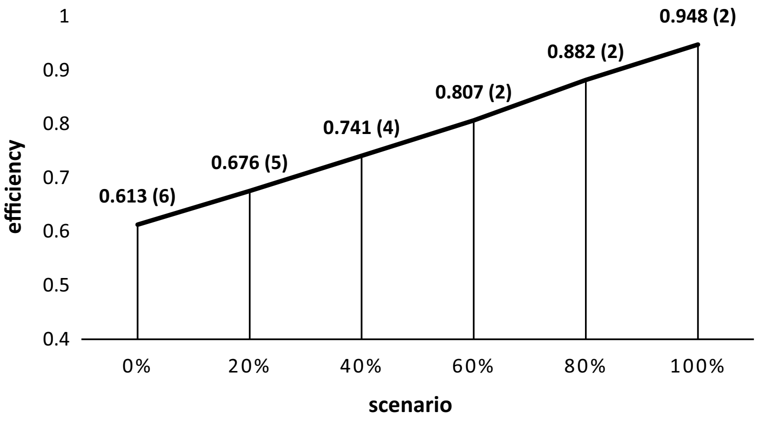

Fig. 10 Efficiency changes of Agriculture faculty with the increase in outputs

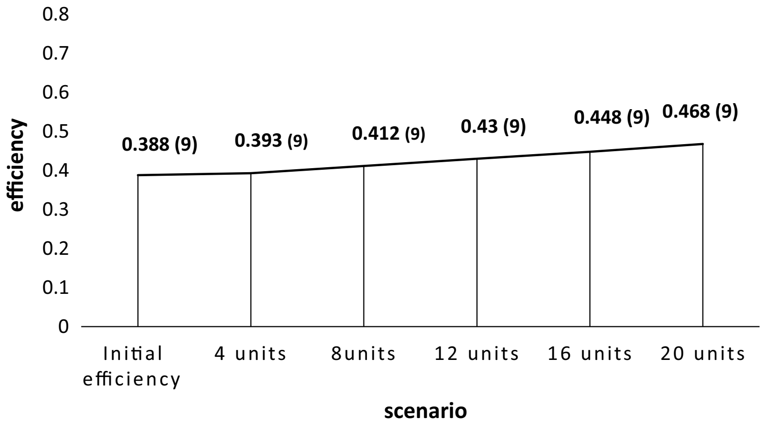

Fig. 11 Efficiency changes of Arts faculty with the increase in outputs

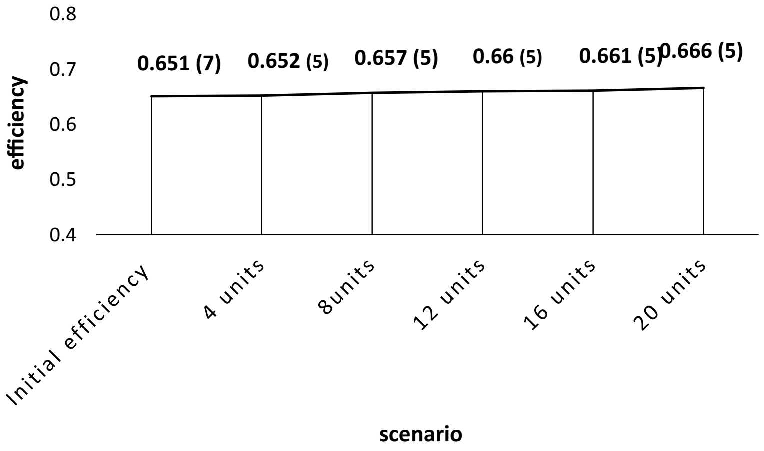

Fig. 12 Efficiency changes of Economics and Management faculty with the increase in outputs

Table 7 Output estimation with increasing 3% in the input value and without the change in the dynamic measure

Faculty	Number of published papers in the Scientific database		The income of research projects (10^6)		The number of citations to the articles published in the Scientific database	
	Initial value	Changed value	Initial value	Changed value	Initial value	Changed value
Literature and Humanities	48	48	5150	56,320.70	49	200
Physical Education and Sports Science	17	20	10,737.88	14,648.43	88	88
Veterinary	139	139	10,035	51,263.52	487	488
Basic Sciences	303	303	84,186.40	101,446.61	1097	1109
Engineering	361	361	71,399.05	88,816.65	1597	1819
Agriculture	267	268	63,835.66	79,471.96	764	1273
Natural Resources	16	19	36,515.90	47,481.13	46	93
Arts	0	3	34,799.10	36,200.15	0	10
Economics and Management	16	19	12,262.50	26,771.27	7	58

Table 8 Output estimation with increasing 5% in the input value and without the change in the dynamic measure

Faculty	Output estimation with increasing 5% in the input value					
	Number of published papers in the Scientific database		Income of research projects (10^6)		The number of citations to the articles published in the Scientific database	
	Initial value	Changed value	Initial value	Changed value	Initial value	Changed value
Literature and Humanities	48	48	5150	71,305.88	49	222
Physical Education and Sports Science	17	19	10,737.88	16,584.72	88	88
Veterinary	139	139	10,035	57,836.05	487	488
Basic Sciences	303	303	84,186.40	112,809.78	1097	1109
Engineering	361	361	71,399.05	100,434.37	1597	1819
Agriculture	267	268	63,835.66	89,826.89	764	1273
Natural Resources	16	19	36,515.90	49,922.54	46	93
Arts	0	3	34,799.10	37,126.20	0	10
Economics and Management	16	20	12,262.50	36,536.90	7	76

Table 9 Input estimation with increasing (15%, 10%, and 15%) in the output value without the change in the dynamic measure

Faculty	Number of academic staff		Changed percent
	Initial value	Changed value	
Literature and Humanities	237	237	Unchanged
Physical Education and Sports Science	48	48	Unchanged
Veterinary	221	221	Unchanged
Basic Sciences	304	304	Unchanged
Engineering	242	261	7.85% increased
Agriculture	340	340	Unchanged
Natural Resources	64	64	Unchanged
Art	48	48	Unchanged
Economics and Management	92	92	Unchanged

Table 10 Input estimation with increasing (20%, 15%, and 20%) in the output value and without the change in the dynamic measure

Faculty	Number of academic staff		Changed percent
	Initial value	Changed value	
Literature and Humanities	237	237	Unchanged
Physical Education and Sports Science	48	48	Unchanged
Veterinary	221	221	Unchanged
Basic Sciences	304	304	Unchanged
Engineering	242	272	12.39% increased
Agriculture	340	340	Unchanged
Natural Resources	64	64	Unchanged
Art	48	48	Unchanged
Economics and Management	92	92	Unchanged

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