International Journal of Industrial Engineering & Production Research

September 2015, Volume 26, Number 4
pp. 255 - 268

pISSN: 2008-4889

http://IJIEPR.iust.ac.ir/

An Integrated Approach for Measuring Performance of Network Structure: Case Study on Power Plants

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KEYWORDS

Thermal Power plant, Data envelopment analysis,
Game theory,
Balanced scorecard,
Competitive environment.

ABSTRACT

Data envelopment analysis (DEA) and balanced scorecard (BSC) are two well-known approaches for measuring performance of decision making units (DMUs). BSC is especially applied with quality measures, whereas, when the quantity measures are used to evaluate, DEA is more appropriate. In the real-world, DMUs usually have complex structures such as network structures. One of the well-known network structures is two-stage processes with intermediate measures. In this structure, there are two stages and each stage uses inputs to produce outputs separately where the first stage outputs are inputs for the second stage. This paper deals with integrated DEA and game theory approaches for evaluating two-stage processes. In addition, it is an extension of DEA model based on BSC perspectives. BSC is used to categorize the efficiency measures under two-stage process. Furthermore, we propose a two-stage DEA model with considering leader-follower structure and including multiple sub stages in the follower stage. To determine importance of each category of measures in a competitive environment, cooperative and non-cooperative game approaches are used. A case study for measuring performance of power plants in Iran is presented to show the abilities of the proposed approach.

1. Introduction

This paper proposes and develops an approach aimed at evaluating power plants by integrating data envelopment analysis (DEA), balanced scorecard (BSC) and game theory. Conventional DEA models are based on linear programming for evaluating relative efficiencies of decision making units (DMUs). DEA is introduced by Charnes et al. [1] and is extended by Banker et al. [2]. With using DEA, the relative efficiency of DMUs that produce multiple outputs by using multiple inputs, is calculated by assigning 1 for efficient DMUs and less than 1 for inefficient DMUs [1].

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Since DEA was introduced in 1978, there have been various applications in many different areas such as healthcare systems, university departments, criminal courts, military operations, information system projects, human resources, bank branches, power plants, mining operations, manufacturing productivity and transportation evaluation [3-10].

On the other hand, balanced scorecard is one of the most popular approaches for measuring performance of DMUs. Balanced scorecard was suggested by Kaplan and Norton [11]. The BSC allows managers to control and evaluate their organizations from four important perspectives including the learning and growth, financial, customer and internal process perspectives. Applications of the BSC approach have been increased in various scientific and business research fields such as SCM, R&D projects, financial analysis, strategic planning, e-commerce and e-business projects [12-15].

The BSC is usually applied for measuring performance of an organization at the firm level. Also, it is embedded extensively in other methodologies such as DEA. When the quantity measures are used to evaluate, DEA is more appropriate. This is because DEA models can integrate unlike inputs and outputs to make simultaneous comparisons of DMUs [16]. However, when the quality measures are applied, BSC is a better approach than others. Additional information for integrating DEA and BSC can be found in [17-20].

One of the points that must be considered in usage of DEA is relationship between the number of DMUs and the number of inputs/outputs. Managers wish to apply a large set of indicators as well as classify them in order to present a relatively comprehensive evaluation. However, if all indicators are considered, the existing models may be failed. With decreasing in the number of DMUs, the error of the production frontier estimation increases, and the possibility of domination for each DMU decreases by others. Therefore, the numbers of efficient DMUs increase. In practice, a finite number of units are used for evaluating. There are sufficient units in some cases such as bank branches or schools whereas; there is no access to a large number of units in many other cases such as power plants. In other words, there are many inputs and outputs that decision makers are interested in using them in evaluation, but the number of DMUs is not sufficient. On the other hand, it is important for managers that their considered measures are used in evaluation, but it is not impossible in conventional DEA models. In this research, measures classifications have been divided into four categories according to BSC framework which can be used for more realistic evaluation of power plants. This paper is aimed to overcome the standard models limitations and to discriminate among DMUs. In addition, DMUs do be compared by four different categories of measures in the competitive environment. For this purpose, bargaining game as a cooperative game model and the conventional DEA models are combined.

In the following, some basic researches as well as the backgrounds of evaluation of power plants are briefly reviewed. One of the first papers for evaluating power plants with using DEA was published by Golany et al. [21] in 1994. They measured and evaluated the operating efficiency of power plants in the Israeli Electric Corporation. Emphasis is placed on the process of screening the list of potential input and output factors and determining the most relevant ones.

Cook et al. [22] proposed an approach based on DEA to evaluate DMUs in different hierarchies and groups. They used two different types of aggregation methods. The first involves hierarchical evaluation and the second evaluates DMUs in groups. Korhonen and Luptacik [23] proposed two different approaches based on DEA for ecological analysis. In the first approach, they measured technical and ecological efficiencies. In the second approach, they considered pollutants as inputs when increasing desirable outputs and decreasing pollutants. Their proposed approaches were applied for measuring efficiency of 24 power plants in a European country. Another approach for evaluating power plants can be found in [24]. It has proposed an approach based on the additive DEA to evaluate economic and environmental efficiency of district heating plants.

Cook and Zhu [25] considered a state that power plants have been divided into groups. Each group must be evaluated under its own assumptions. They used DEA and goal programming for obtaining common-multiplier set. For this purpose, they minimized the maximum discrepancy among the within-group scores from their ideal levels. They applied this approach for evaluating a set of power generating units, where each power generating unit contains a set of units under a common plant management.

Sarica and Or [26] used DEA to analyze and compare the performance of electricity power plants in Turkey. They considered 65 thermal, hydro and wind power plants from private and public sectors. In their study, the results for public versus private sector plants and natural gas plants versus coal and oil fired plants have been discussed. Barros and Peypoch [27] used a two-stage procedure to analyze the technical efficiency of Portuguese thermoelectric power generating units. In the first stage, they estimated the relative technical efficiency by using DEA to determine which power plants are efficient. In the second stage, bootstrapped procedure is applied to estimate the efficiency derivers. Also, Sozen et al. [28] applied DEA for measuring efficiency of power plants in Turkey by using two basic DEA models (CCR and BCC) to compare and analyze results to offer suggestions to reveal the redundancies in the input variables for the reduction in the environmental effects. Azadeh et al. [29] proposed a flexible and dynamic algorithm for assessing, ranking, and optimizing of utility sectors. Input-oriented CRS, input-oriented VRS, COLS, and SFA models are applied for estimating the efficiency scores of utility sectors. They applied the proposed algorithm on two real case studies. One of the case studies was about the Iranian electricity distribution sectors. They claimed their proposed algorithm provides comprehensive solutions for policy making process through integrating various ranking methods.

Sueyoshi and Goto [30] proposed an approach based on non-radial DEA for evaluating power plants with considering operational, environmental and both-unified efficiency measures of US coal-fired power plants. They applied non-radial DEA to measure operational efficiency on desirable outputs and environmental efficiency on undesirable outputs. Also, Sueyoshi and Goto [31] applied the new type of unified measures. They divided inputs classification into energy and non-energy inputs. It is important for managers to incorporate two separations inputs (desirable and undesirable outputs as well as energy and non-energy inputs). In their research, both of inputs and outputs classification have been divided into two categories which can be used for more realistic evaluation of power plants. The related discussion on integrating DEA and game theory is found in the recent paper of Jahangoshai-Rezaee et al. [32].

The CRS model assumes that the DMUs are operating at an optimal scale. Also, it has been used for evaluations when all DMUs operate in similar conditions and environments. This model permits a measure of global technical efficiency to be obtained without variations in returns to scale. In the real world, however, this optimal behavior is often precluded by some factors such as imperfect competition. Banker, Charnes and Cooper [3] have extended DEA to the case of variable returns to scale (VRS). This model distinguishes between pure technical efficiency and scale efficiency (SE), identifying if increasing, decreasing or constant returns to scale are present. We use CRS model in this research, because all power plants are in Iran and they operate under similar conditions. Although we can use VRS model, but the contribution of this paper is not comparison of CRS and VRS models.

This paper is organized as follows: The performance measures under two-stage process are defined based on BSC perspectives in Section 2. The DEA-game theory evaluation model is given in Section 3. Section 4 presents a case study of power plants to show the abilities of the proposed approach. Finally, summary and conclusion are given in Section 5.

2. Definition of Measures Based on BSC Perspectives

Kaplan and Norton [11] defined four perspectives including the financial, customer, internal process, as well as learning and growth perspectives. The structure of measures (inputs and outputs) according to BSC perspectives is defined in this section. Based on this framework, the structure of performance evaluation is proposed as Fig. 1.

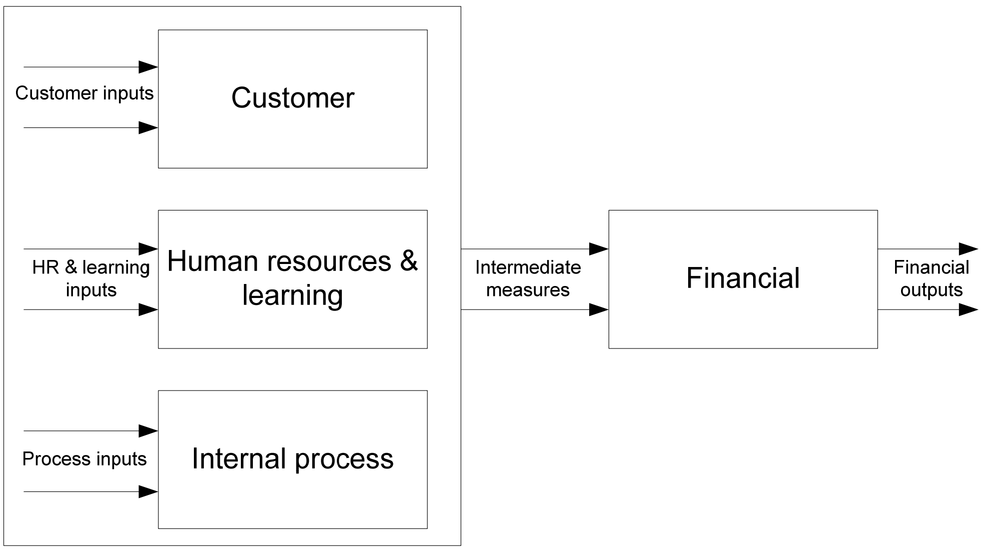

Fig 1. Structure of power plants performance evaluation

The perspectives are divided into two stages. The second stage includes financial perspective. It is considered as the leader stage, because the goals of each company should satisfy the stockholders. The measurements from financial perspective indicate “whether the company’s strategy, implementation, and execution are contribution to bottom-line improvement” [11]. For this stage, we define total revenue (TR) (billions of monetary unit) as desirable output and also CO_2 emission (1000 ton) as undesirable output. We consider CO_2 emission as financial output because power plants pay heavy fines proportional to the amount of pollution. The first stage (follower stage) consists of three parallel sub stages. According to BSC perspectives, these sub stages include: customer, process and human resources and learning perspectives. Each sub stage includes separate inputs and common outputs. Common outputs as intermediated measures are the second stage inputs. The total amount of electricity generated (EG) (MWh) and total hours of operation (THO) per period are considered as intermediate measures. The first sub stage in the follower stage is the customer perspective. This perspective can force the companies to view their performance through customers’ eyes. Customer perspective inputs include: ratio of planned outage count and unplanned or forced outage count to total properly operated hours (%). Outages count (planned and forced) is very important for power distribution companies as the costumers of power plants. Less outages count provides more stable services of power distribution companies for final customers. The human resources and learning inputs include: total cost of training (TCT) (billions of monetary unit), number of operational employees (OE) and number of non-operational employees (NOE). Generation capacity (GC) (MW), amount of fuel consumption (FC) (terajoule) and internal consuming (IC) (MWh) are defined as process perspective measures.

- The hypotheses on interrelationships among four perspectives of these measures are as follows: The factors of customer, process and human resources and learning perspectives are significantly related to the factors of financial perspective.
- The interrelationship among the customers, process and learning and human resources perspectives are unknown and determined by game models in competitive structure.
- The main goal of power plants policy is satisfaction of stockholders. Therefore, the second stage is considered as the leader and the first stage is considered as the follower.

3. DEA-Game Theory Evaluation Model Based on BSC Perspectives

In this section, we propose the combined DEA and game model to evaluate DMUs. The concepts of non-cooperative and cooperative games are used to develop conventional DEA models for measuring performance. The proposed approach optimizes the leader's efficiency score and then maximizes the follower's efficiency score while the efficiency of the leader must be unchanged. We firstly use non-cooperative game (leader-follower) between two stages and secondly, the cooperative game is used between sub stages in stage 1. According to Fig. 1, for notational purposes, we define:

n	No. DMUs
m_c	No. inputs for customer perspective
m_h	No. inputs for human resources and learning perspective
m_p	No. inputs for process perspective
D	No. intermediate measures
s	No. outputs for financial perspective
v^1	Inputs weight vector for customer perspective
v^2	Inputs weight vector for human resources and learning perspective
v^3	Inputs weight vector for process perspective
w	weight vector for Intermediate measures
u	Outputs weight vector for financial perspective
x_{ij}^{c}	ith input for DMU$_j$ in customer perspective
x_{kj}^{h}	kth input for DMU$_j$ in human resources and learning perspective
x_{qj}^{p}	qth input for DMU$_j$ in process perspective
z_{dj}	dth intermediate measure
y_{rj}	rth output for DMU$_j$ in financial perspective

3-1. Leader-Follower Formulation

As mentioned, stage 2 (financial perspective) is more important than stage 1. Firstly, we must calculate the efficiency of stage 2. When the efficiency of stage 2 is kept constant, we evaluate stage 1 by using follower model when the sub stages in stage 1 bargain with each other.

3-2. Bargaining Game for Follower Sub Stages

The proposed efficiency models for evaluation of two stages are presented separately in this section. As mentioned, there is no priority among substages in the follower stage. In other words, the parallel stages must be evaluated simultaneously and the efficiencies should be kept constant relative to each other. For this purpose, we apply bargaining game model (Model 1) to obtain substages and unified efficiencies.

On the other hand, the goal of bargaining game is dividing the benefits between two players. In bargaining game model [33], it is assumed that the individual payoff is greater than the individual breakdown payoff. Breakdown payoffs are the starting point for bargaining which represent the possible payoff pairs obtained if one player decides not to bargain with other players. If u_i is the utility function for player i $(i=1,\dots,n)$, then it maximizes $\prod_{i=1}^{n}\left|u_i(x)-u_i(d)\right|$, where $u_i(d)$ is the utility obtained if one decides not to bargain with other players. Therefore, the DEA-bargaining game model for follower stage can be expressed as:

$$
\begin{aligned}
\max\ & \left(\frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{i=1}^{m_c} v_i^c x_{io}^c}-\theta_o^c\right)\left(\frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{k=1}^{m_h} v_k^h x_{ko}^h}-\theta_o^h\right)\left(\frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{q=1}^{m_p} v_q^p x_{qo}^p}-\theta_o^p\right)\\
\text{s.t.}\ & \frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{i=1}^{m_c} v_i^c x_{io}^c}\ge\theta_o^c\\
& \frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{k=1}^{m_h} v_k^h x_{ko}^h}\ge\theta_o^h\\
& \frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{q=1}^{m_p} v_q^p x_{qo}^p}\ge\theta_o^p \qquad\qquad (1)\\
& \frac{\sum_{d=1}^{D} w_d z_{dj}}{\sum_{i=1}^{m_c} v_i^c x_{ij}^c}\le 1,\quad j=1,\dots,n\\
& \frac{\sum_{d=1}^{D} w_d z_{dj}}{\sum_{k=1}^{m_h} v_k^h x_{kj}^h}\le 1,\quad j=1,\dots,n\\
& \frac{\sum_{d=1}^{D} w_d z_{dj}}{\sum_{q=1}^{m_p} v_q^p x_{qj}^p}\le 1,\quad j=1,\dots,n\\
& \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{d=1}^{D} w_d z_{do}}=\theta_o^{2*}\\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} w_d z_{dj}}\le 1,\quad j=1,\dots,n\\
& u_r, w_d>0,\quad r=1,\dots,s,\ d=1,\dots,D\\
& v_i^c, v_k^h, v_q^p>0,\quad i=1,\dots,m_c,\ k=1,\dots,m_h,\ q=1,\dots,m_p
\end{aligned}
$$

We suppose $t_c = \left(\sum_{i=1}^{m_c} v_i^c x_{io}^c\right)^{-1}$, $t_h = \left(\sum_{k=1}^{m_h} v_k^h x_{ko}^h\right)^{-1}$, $t_p = \left(\sum_{q=1}^{m_p} v_q^p x_{qo}^p\right)^{-1}$, $t_f = (\sum_{d=1}^{D} w_d z_{do})^{-1}$, $\omega_d^f = t_f w_d$, $\omega_d^c = t_c w_d$, $\omega_d^h = t_h w_d$, $\omega_d^p = t_p w_d$, $\mu_r = t_f u_r$, $\upsilon_i^c = t_c v_i^c$, $\upsilon_k^h = t_h v_k^h$ and $\upsilon_q^p = t_p v_q^p$. On the other hand, we have following equations:

$$\begin{cases} \omega_d^c = \dfrac{t_c}{t_f}\omega_d^f \\ \omega_d^h = \dfrac{t_h}{t_f}\omega_d^f \\ \omega_d^p = \dfrac{t_p}{t_f}\omega_d^f \end{cases} \tag{2}$$

By denoting $\alpha_1 = \frac{t_c}{t_f}$, $\alpha_2 = \frac{t_h}{t_f}$ and $\alpha_3 = \frac{t_p}{t_f}$, the objective function is converted to $(\alpha_1\sum_{d=1}^{D}\omega_d^f z_{do} - \theta_o^c)(\alpha_2\sum_{d=1}^{D}\omega_d^f z_{do} - \theta_o^h)(\alpha_3\sum_{d=1}^{D}\omega_d^f z_{do} - \theta_o^p)$.

On the other hand, we have $\sum_{d=1}^{D} w_d z_{do} = 1$. Therefore, Model 1 can be expressed as follows:

$$\begin{aligned}
& max\ (\alpha_1 - \theta_o^c)(\alpha_2 - \theta_o^h)(\alpha_3 - \theta_o^p) \\
& \text{s.t. } \alpha_1 \ge \theta_o^c \\
& \alpha_2 \ge \theta_o^h \\
& \alpha_3 \ge \theta_o^p \\
& \alpha_1 \sum_{d=1}^{D} \omega_d^f z_{dj} - \sum_{i=1}^{m_c} v_i^c x_{ij}^c \le 0, \quad j = 1,\dots,n \\
& \alpha_2 \sum_{d=1}^{D} \omega_d^f z_{dj} - \sum_{k=1}^{m_h} v_k^h x_{kj}^h \le 0, \quad j = 1,\dots,n \\
& \alpha_3 \sum_{d=1}^{D} \omega_d^f z_{dj} - \sum_{q=1}^{m_p} v_q^p x_{qj}^p \le 0, \quad j = 1,\dots,n \\
& \sum_{i=1}^{m_c} v_i^c x_{io}^c = 1 \\
& \sum_{k=1}^{m_h} v_k^h x_{ko}^h = 1 \\
& \sum_{q=1}^{m_p} v_q^p x_{qo}^p = 1 \\
& \sum_{d=1}^{D} \omega_d^f z_{do} = 1 \\
& \sum_{r=1}^{s} \mu_r y_{ro} = \theta_o^{2*} \\
& \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{d=1}^{D} \omega_d^f z_{dj} \le 0, \quad j = 1,\dots,n \\
& \mu_r, \omega_d^f > 0, \quad r = 1,\dots,s, d = 1,\dots,D \\
& v_i^c, v_k^h, v_q^p > 0, \quad i = 1,\dots,m_c, k = 1,\dots,m_h, q = 1,\dots,m_p
\end{aligned} \tag{3}$$

where, θ_o^{2*} is the leader efficiency score. Also, θ_o^c, θ_o^h and θ_o^p are breakdown points for three substages. $\frac{\alpha_i}{\alpha_j}$ $(i, j = 1, 2, 3$ and $i \neq j)$ can be the factors for determining value of each perspective in comparison with other perspectives. In other words, $\frac{\alpha_1}{\alpha_2}$ and $\frac{\alpha_1}{\alpha_3}$ are the ratio of sum of weighted inputs for the human resources and learning and the process perspectives to sum of weighted inputs for the customer perspective, respectively. Also, $\frac{\alpha_2}{\alpha_3}$ is the ratio of sum of weighted inputs for the process perspective to sum of weighted inputs for the human resources and learning perspective. It shows ratio of the weighted value for each category of inputs to the weighted value of another category. In fact, it depicts each power plant in which category of measures has a better performance than other power plants.

3-3. Breakdown Points

To use Model 3 for measuring performance, we need to calculate the breakdown points for each sub stage in the follower stage. Breakdown points are the efficiency scores for DMUs under pessimistic conditions when each DMU plays its own strategy versus other DMUs optimal strategies. In this paper, we propose the cross-efficiency approach to determine the breakdown points.

The cross-efficiency score of a DMU by using conventional DEA model is obtained by the set of optimal weights $v_{1d}^*, \ldots, v_{md}^*, u_{1d}^*, \ldots, u_{sd}^*$. Then cross-efficiency of the specified DMU by using the weights of other DMUs is defined as:

$$E_{qj} = \frac{\sum_{r=1}^{s} u_{rq}^* z_{rj}}{\sum_{i=1}^{m} v_{iq}^* x_{ij}}, \quad q, j = 1, \ldots, n \tag{4}$$

The average of all E_{qj} $(q=1,\ldots,n)$ are the cross-efficiency of DMU$_j$ $(j=1,\ldots,n)$.

$$\bar{E}_j = \frac{1}{n}\sum_{q=1}^{n} E_{qj} \tag{5}$$

where, $\bar{E}_j$ is cross-efficiency score for DMU$_j$.

We use cross-efficiency approach to determine breakdown points that are applied in bargaining game model. Equation 6 is proposed to be used to determine the breakdown points.

$$\theta_j = \inf_q (E_{qj}) \tag{6}$$

Our suggested approach to obtain the breakdown points is closer to reality. According to this approach, the breakdown points are calculated for three categories of measures. We denote θ_j^c, θ_j^h and θ_j^p as breakdown points in Model 3 for each category of measures.

4. The Case Study and Analysis

In this section, we apply the data set to show abilities of the approach for evaluating power plants as well as some findings and outcomes. The data have been collected for 20 Iranian power plants in 2003 and has been displayed in Table 1. The details of case study are presented in Fig. 1. In the case study, two stages behave as leader-follower game. Also, each sub stage competes with other sub stages to maximize its own efficiency when using bargaining game. In other words, power plants bargain to reach a level of agreement among sub stages. The model does not make distinguish between parallel sub stages. It is caused that three parallel sub stages modify their own efficiency until efficiency scores reach to enough satisfaction level for parallel sub stages. Therefore, they have motivation to accept the scores because the bargaining solution is a Pareto solution.

The data have been run with Model 3 and the results have been analyzed to show abilities of the approach. We first run the standard DEA for three sub stages in the follower stage and obtain the efficiency scores for each category. Secondly, Model 3 is applied to evaluate the efficiencies of power plants in the unified framework. Also, the breakdown points for each category of measures are calculated by Equation 6. Table 2 summarizes the results of four perspectives in two-stage structure and the relationships between perspectives. The second column of Table 2 presents the efficiency of power plants for the leader stage. The results of efficiency scores for three sub stages in the follower stage are shown in three next columns of Table 2. Furthermore, in three last columns of Table 2, the relationships between perspectives in the follower stage are given. It is also shown which categories of measures are more effective in the performance of each power plant.

Another finding in Table 2 is that there are differences among the efficiency scores for four perspectives when bargaining game model is applied. With using the bargaining game model, most of the efficiency scores are less than unity because the power plants would lose their own efficiency scores in a competitive environment. Fig. 2 compares three categories of perspectives by the efficiency scores for each power plant. In fact, it shows power plants in which perspectives have high efficiency and in which perspective have low efficiency. In addition, except PP12 and PP15, the efficiency of customer perspective for other power plants has the less variance and is closer to each other than others. Afterwards, the process, HR and learning and financial perspectives are in the next order of ranks respectively. According to Fig. 2, the efficiencies of PPs in the customer and the financial perspectives are sort of smaller and greater than others respectively.

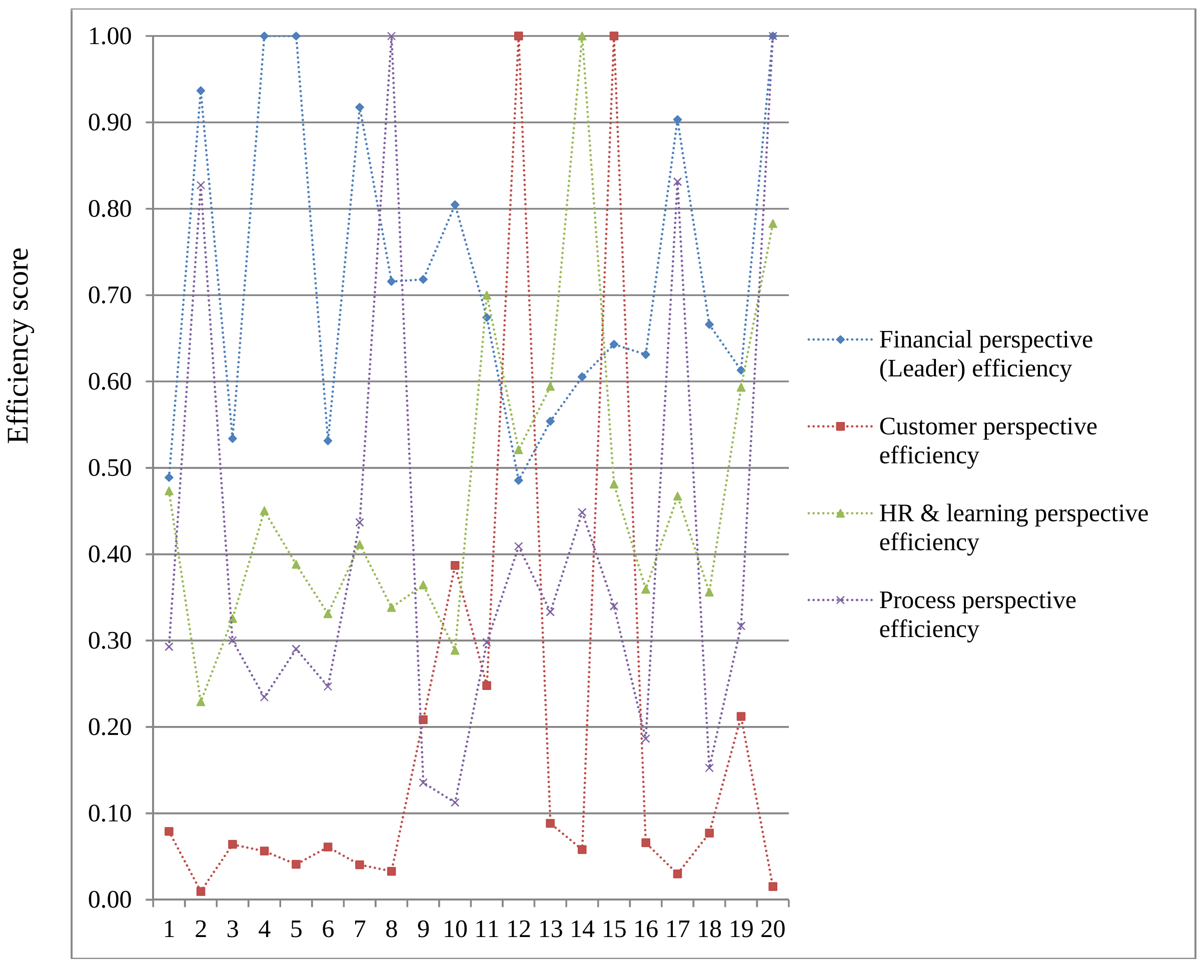

Fig 2. Shift of efficiency scores for four perspectives

Figs. 3, 4 and 5 depict other findings of the research. They show how much each power plant loses its own efficiency in each perspective in the follower stage. Fig. 3 shows that with applying Model 3, PP_{12}, PP_{15} and PP_{20} have not any changes in efficiencies, whereas PP_{10} has the greatest decrease in performance in the customer perspective. Also, PP_{14} has no change and PP_{10} has the greatest decrease in efficiency in the human resources and learning perspective (see Fig. 4). Furthermore, according to Fig. 5, the standard efficiency score of PP_8, PP_{17} and PP_{20} are equal to the score of the game model and PP_{11} has the greatest decrease in efficiency in the process perspective with using Model 3.

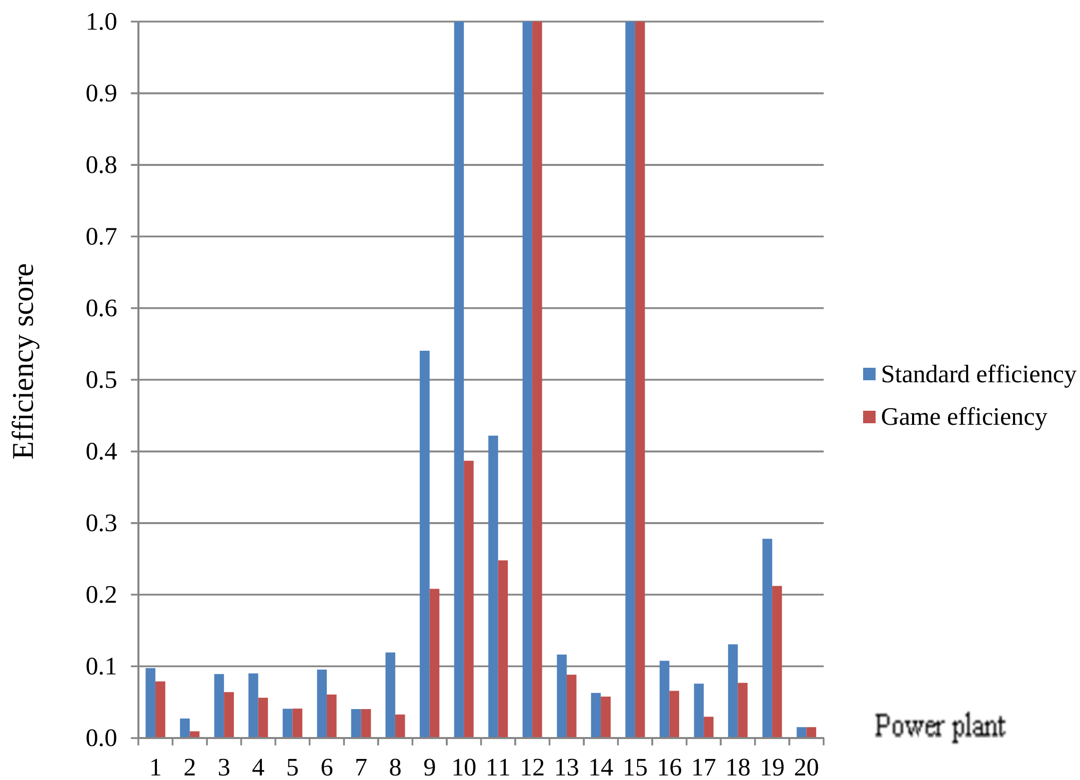

Fig 3. Comparison of standard DEA and model 3 scores for customer perspective

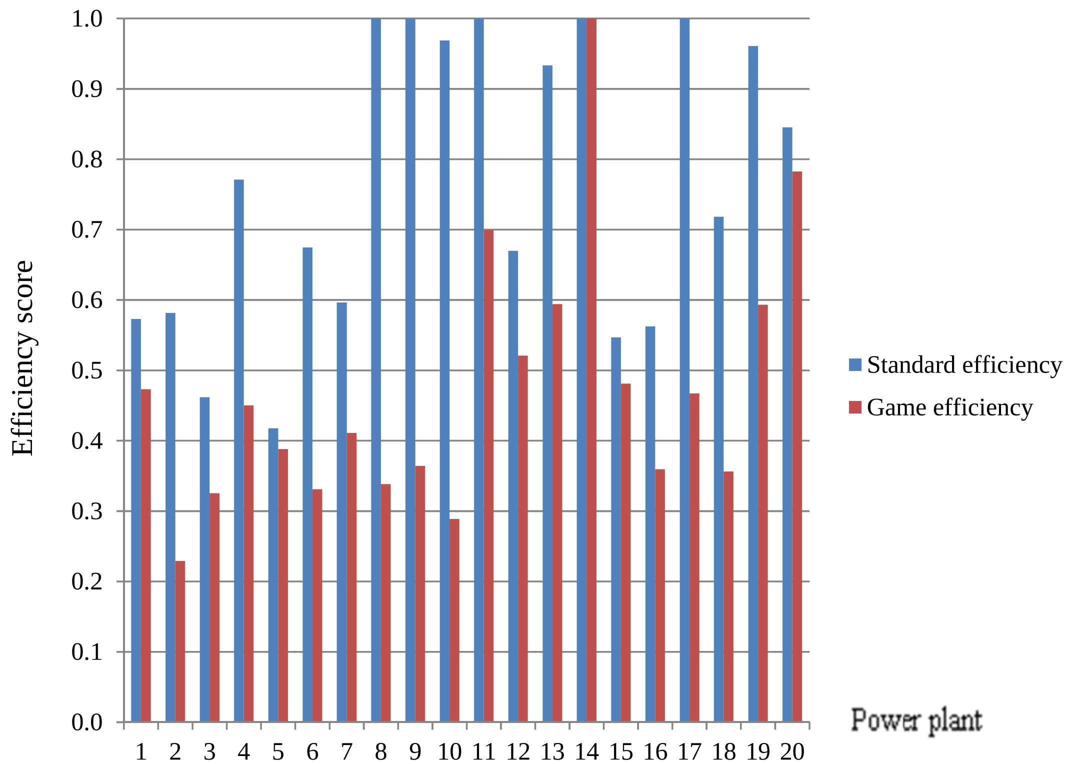

Fig 4. Comparison of standard DEA and model 3 scores for human resources and learning perspective

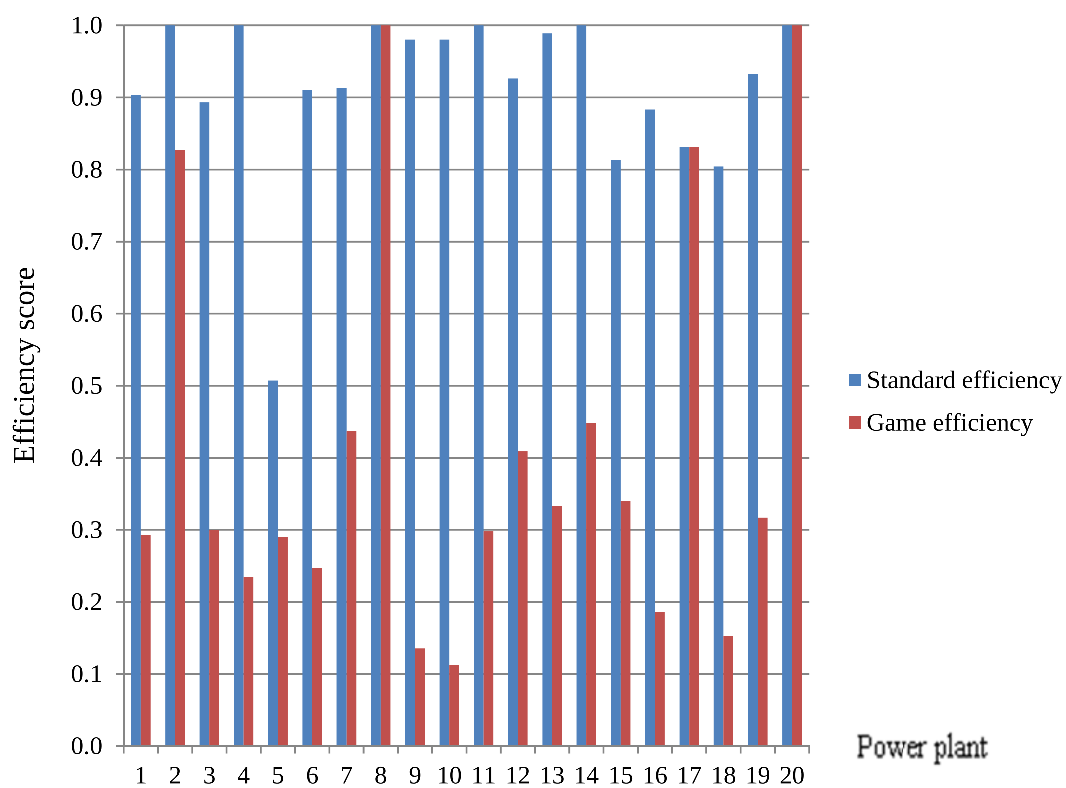

Fig 5. Comparison of standard DEA and model 3 scores for process perspective

Fig. 6 compares three categories of perspectives by the value of α_i for each power plant. In fact, it shows each power plant in which perspective has better performance compared to others. On the other hand, it shows a ratio of the weighted value of the *i*th perspective inputs to the weighted value of *j*th perspective inputs. For this case study, the value of $\frac{\alpha_1}{\alpha_2}$ and $\frac{\alpha_1}{\alpha_3}$ for most PPs are less than 1. It shows the importance of customer perspective is more than the importance of HR and learning and process perspectives in the follower stage. But for PP_9, PP_{10}, PP_{12} and PP_{15}, customer perspective uses fewer inputs than HR and learning perspective. Also, this condition satisfies between customer and process perspectives for PP_{10}, PP_{12} and PP_{15}. Whereas, $\frac{\alpha_2}{\alpha_3}$ for most PPs are greater than 1. It shows that process perspectives uses more inputs than HR and learning perspective. In other words, the HR and learning perspective is more important than process perspective for evaluating of PPs.

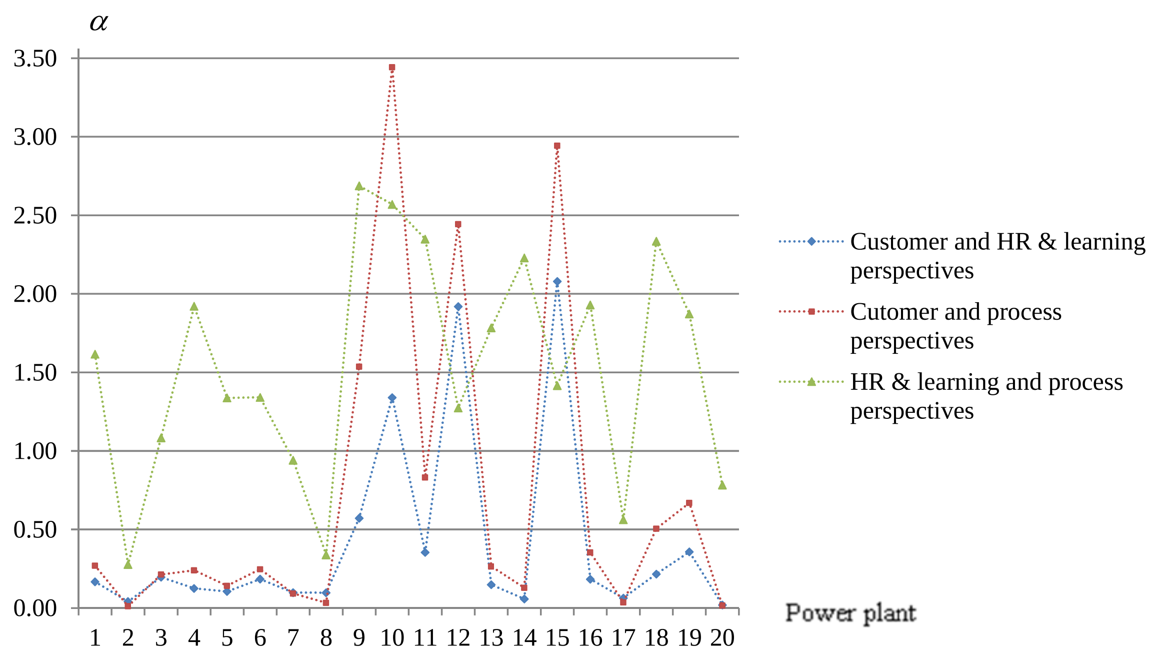

Fig 6. Visual description for effect of each perspective in comparison with the other perspectives

5. Summary and conclusion

This paper has presented an integrated DEA-BSC-game theory approach to evaluate decision making units. The measures are categorized into two-stage structure. The second stage has been considered as the leader and includes financial perspective. The model has been proposed according to these assumptions and developed as an extended DEA model. Both of the cooperative and non-cooperative games have been used in the model. The case study of Iranian power plants presented to show the abilities of the proposed approach. This model can discriminate among power plants more effectively. In addition, power plants can be compared by different categories of measures in two-stage leader-follower structure. Moreover, we can determine that each power plant in which category has better performance compared to other categories. In addition, the results of the case study give more practical and managerial views to managers and policy makers.

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