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ORIGINAL RESEARCH

Integrated data envelopment analysis and cooperative game for evaluating energy efficiency of transportation sector: a case of Iran

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Abstract Transportation sector with the consumption of 25% of energy play a major role in Iranian economy. This sector produces 27% of total undesirable greenhouse gases in Iran which has directly harmful effects on the environment. Hence, performance assessment of energy efficiency of transportation sector is one of the most important issues for policy makers. In this paper, energy efficiency of transportation sector of 20 provinces in Iran is evaluated based on data envelopment analysis (DEA)—cooperative game approach. First, selected inputs and outputs are categorized into energy and non-energy inputs and desirable and undesirable outputs. Then, classical DEA model is applied to evaluate and rank the provinces. Since, the classical DEA model can't distinguish between efficient provinces, so, this paper ranks the provinces based on combination of cross-efficiency DEA and cooperative game approaches. In the cooperative game theory, each province is considered as a player and the suitable characteristic function is defined for players. Finally, by calculating the Shapley value for each player, the final ranks of transportation sectors in provinces are concluded. The results indicate that some smaller provinces have better energy efficiency in transportation sector in comparison with big provinces.

Keywords DEA · Cross-efficiency DEA · Cooperative game · Transportation sector · Energy efficiency

1 Introduction

In real competitive world, energy is considered as one of the most important inputs for economy. Lack of access to affordable and sustainable energy has led to the poor or even negative economic and social growth in developed and developing countries. With increasing grows in population, economic and energy consumption, energy demand has recently

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been increased (www.eia.gov). Hence, supply and consumption of energy is one of the most critical topics which has effects on the economic progress of countries. In the energy field, there are two different topics namely supplying energy and creating revenue for the country. Transportation as an energy-intensive sector plays a vital role in enabling all people access to economic and social opportunities (Zhang et al. 2011). In fact, transportation system has substantial impacts over economic, social and individual development and public welfare. In Iran, transportation sector consumes about 25% of total energy consumption which is equivalent to consuming 309.2 million barrels crude oil each year (www.mop.ir). So, investigating and analyzing energy efficiency in transportation sector of Iran is very important for policy makers. On the other hand, transportation sector can lead to harmful consequences on environment if it is carefully not planned. Indeed, transportation is a producer of greenhouse gases which disperses into atmosphere and causes environment to become acidic. As a result, it is considered as one of the critical environmental problems. In other words, energy and environment are interconnected parts of transportation sectors and use of energy although leads to improvement of the transportation, however could be considered as a threat to the environment. Therefore, in the evaluation of energy efficiency, environmental consequences should be addressed so that in addition to achieve higher efficiency, the cost of environmental degradation should be minimized. Hence, this study calculates the efficiency of transportation system in provinces of Iran by using some energy and environmental indicators.

Despite of the significant effects of energy in transportation sector and consequently countries' economic, a few numbers of studies have focused on energy efficiency of transportation systems. For instance, Saidur et al. (2007) evaluated energy and exergy efficiency in Malaysia from 1995 to 2003 in transportation sector. Their results showed that the road sub-system was the most efficient than other sub-systems. Jaber et al. (2008) discussed energy analysis and exergy utilization in the transportation sector of Jordan. The results indicated that the energy and exergy efficiencies of the Jordanian transport sector are lower than Turkey and higher than Malaysia, Saudi Arabia and Norway. Zhang et al. (2011) analyzed energy and exergy efficiencies in the Chinese transportation sector from 1980 to 2009 and concluded that highways transport was the biggest energy consumer, which consumed 82.0% of total transport energy consumption in 2009. Lipscy and Schipper (2013) examined energy efficiency in the Japanese transportation sector since 1970. They illustrated that Japan in comparison with the United States and other developed economies primarily stands out due to low activity levels and modal structure rather than modal energy intensity.

This paper measures energy efficiency of transportation system in provinces of Iran using data envelopment analysis (DEA) model which is the most popular model for evaluation and performances assessment. DEA is a non-parametric model which was introduced to measure the relative efficiency of decision making units (DMU) with multiple inputs and multiple outputs. DEA was first proposed by Charnes et al. (1978) and later extended by Banker et al. (1984). The DEA model is classified to constant return to scale (CRS) and variable return to scale (VRS). It has been used for efficiency estimating in many real world applications. Also, in transportation systems, DEA have been applied by several researchers. Ramanathan (2000) used DEA model for evaluating efficiency of rail and road transportation in India. Wu et al. (2016a, b) divided transportation system into two sub-systems: passenger transportation and freight transportation. They considered the sub-system as a parallel and extended a parallel DEA model to evaluate the efficiency of each sub-system. The results showed that 30 provinces of China in three large areas had a low efficiency in transportation sector and the East area had highest efficiency in compared with central and west areas. Chu et al. (2016) applied a slacks-based measure DEA (SBM-DEA) model for evaluating environmental efficiency of transportation systems in China's provinces. They introduced two algorithms to face the problem of existing big data in DEA model.

To estimate the energy efficiency of transportation sector, there are some undesirable factors such as greenhouse emissions. According to the U.S. environmental protection agency (EPA) report,[1] transportation sector produces 27% of global greenhouse gases emissions. Therefore, improving energy efficiency of transportation sector without considering the harmful effects of greenhouse gases on environment, health and welfare would be lead to unreliable and unreasonable results. So, greenhouse gases emissions should be considered as undesirable variables in the DEA model. Unfortunately, traditional DEA models can't handle the undesirable factors and they need to be developed. In order to deal with this problem, some researchers have developed DEA models with undesirable inputs and outputs. Seiford and Zhu (2002) proposed a DEA model based on undesirable outputs in the traditional DEA framework. They introduced a novel DEA model by transferring data of undesirable outputs to desirable ones. Liu et al. (2010) studied several classes of DEA models with undesirable inputs and outputs. They focused on DEA models without transferring undesirable data. Chang et al. (2013) evaluated efficiency of 30 provinces of China using a non-radial DEA model with slacked based measure. They showed that the most provinces in China were not eco-efficiency and transportation system of provinces could reduce CO2 emissions and energy consumption to perform better. Cui and Li (2014) analyzed energy efficiency of transportation sector in 30 provinces of China from 2003 to 2012 based on three-stage virtual frontier DEA model with desirable and undesirable factors. They concluded that their proposed model is more logical than super efficiency DEA models. Zhou et al. (2014) used DEA model with undesirable outputs for evaluating energy efficiency of 30 administrative regions of China in the period 2003–2009. They indicated that except some years such as 2008, in other years the eastern area of China performed better than the central and western area. Li et al. (2016a, b, c) applied super slacked based measure DEA model with undesirable output for evaluating energy efficiency of 29 provinces of China in three regions. They proved that the efficiency score of the most provinces are lower than 50% in the period 1995–2012. Bi et al. (2014) presented a non-radial DEA model and multidirectional efficiency analysis (MEA) for measuring the energy and environmental efficiency of transportation sector. The inputs were labor, capital and energy and the outputs were value-added and CO_2 emissions. They investigated energy saving and CO_2 reducing for 30 provinces of China in three region during 2006–2010. Song et al. (2016) combined a super efficiency slack based measure model with undesirable outputs to calculate the environmental efficiencies of highway transportation in region of China. They also calculated the consumption redundancy of gasoline and diesel and excess emissions of nitrogen oxides and particular matter. Meng et al (2017) proposed an integrated framework includes of material flow analysis (MFA), cumulative energy demand (CED), exergy analysis (EXA) and emergy assessment (EMA) to examine the energy efficiency of high speed urban bus transportation system compare with conventional bus transportation systems in the city of Xiamen in China. Liu et al. (2017a, b) proposed a parallel slack based measure DEA model for evaluating the overall efficiency of land transportation sector and individual efficiencies of the railway transportation and highway transportation subsectors at the same time considering CO_2 emissions. Llorca and Jamasb (2017) in their research analyzed the energy efficiency and rebounded effects for road freight transport in 15 European countries during the 1992–2012 period and they obtained, on average, a fuel efficiency of 89% and a rebound effect of 4%.

[1] www.epa.gov.

In DEA model, inefficient DMUs are properly rating, but the scores of all efficient DMUs are equal to unit. In the other words, classical DEA model proposed by Charnes et al (1978) is unable to fully rank the efficient DMUs. Several researchers introduced different approaches such as super efficiency, virtual frontier DEA (VFDEA) and cross-efficiency for ranking efficient DMUs. One of the most DEA models for fully ranking of efficient DMUs was introduced by Andersen and Petersen (1993). They proposed a super efficiency DEA model in order to rank of all DMUs, completely. The proposed super efficiency DEA model has been widely applied in many real world applications such as evaluating efficiency of China's banks by Avkiran (2011), investigating performance assessment of Iranian provincial gas companies by Sadjadi et al. (2011), allocating fixed cost by Li et al. (2009) and etc. However, in super efficiency DEA model proposed by Andersen and Petersen (1993), a new frontier for each efficient DMU under consideration is constructed. In other words, efficient DMUs are evaluated based on multi frontiers which is not fair. Actually, it produces multiple new frontiers and the efficient DMUs are compared by the different frontiers.

Virtual frontier DEA was first introduced by Bian and Xu (2013) and developed by Cui and Li (2015), Li et al. (2015, 2016a, b, c) and Cui et al. (2016). In this model, a virtual frontier as a new optimal frontier is constructed. In VFDEA models, the reference DMU set and the evaluated DMU set are two different sets which offers the possibility of differentiating between the efficient DMUs in the traditional DEA model. During the evaluating process, the reference DMU set remains unchanged (Cui and Li 2014). Wanke and Barros (2016) applied virtual frontier dynamic range adjusted model—data envelopment analysis (VDRAM-DEA) to assess Latin American airlines efficiencies. Also, Barros et al. (2017) used VDRAM-DEA to evaluate Angolan hydro-electric power stations which cause higher efficiency score discrimination.

To increase distinguish power between DMUs and make weights more flexible, cross-efficiency DEA model was originally proposed by Sexton et al. (1986). In this model, DMUs are evaluated peer instead of self-evaluated. Cross-efficiency DEA models have been applied in several real world applications. Yu et al. (2010) used cross-efficiency DEA model to design different information-sharing scenarios to analyze the supply chain performance. Ruiz (2013) extended the cross-efficiency evaluation for use with directional distance function. Lim et al. (2014) proposed a new use of cross-efficiency DEA model to stock portfolio selection in the Korean stock market. Mashayekhi and Omrani (2016) combined Markowitz and cross-efficiency DEA model for portfolio selection of firms listed in stock exchange market of Iran. Liu et al. (2017a, b) applied cross-efficiency DEA model considering undesirable outputs for evaluating eco-efficiency analysis of coal-fired power plants in China. Hatami-Marbini et al (2017) developed a flexible cross-efficiency evaluation methodology based on DEA for identifying suppliers' performances in supply chain management sourcing problem. Wu et al (2016a, b) proposed a cross-efficiency evaluation approach based on Pareto improvement to generate Pareto-optimal cross efficiencies for DMUs. Oral et al. (2015) used a cross-efficiency DEA method which deals with multiple solution cases within the context of cross-efficiency models. Also, in order to enhance discriminate power of the 15 baseball players, Oukil and Amin (2015) developed a methodology that combines cross-efficiency, preference voting and ordered weighted averaging. Dotoli et al (2015) presented a novel cross-efficiency fuzzy DEA technique to evaluate the performance of DMUs under uncertainty and applied the proposed technique to performance evaluation of healthcare systems in an Italian region. Roboredo et al. (2015) applied cross-efficiency DEA Game to rank the Brazilian football teams in season 2014. Their model was suitable when there is no cooperation among DMUs and enhances the efficiencies discrimination.

Unfortunately, Sexton et al. (1986) approach has some drawbacks. For instance, it produces the weights which may not acceptable for all DMUs. To overcome this problem and produce the acceptable and fair weights, different models have been introduced by researchers. Ramón et al. (2010) focused on the choice of the weights profiles to be used in the calculation of the cross-efficiency scores. Their approach allows the inefficient DMUs to make a choice of weights that prevent them from using unrealistic weighting schemes. Lam (2010) developed a novel methodology based on applying discriminant analysis, super-efficiency DEA model and mixed-integer linear programming to choose suitable weight sets to be used in computing cross-evaluation. Wu et al. (2011) reviewed the cross-efficiency DEA models and eliminated the assumption of average cross-efficiency scores. They utilized the Shannon entropy to determine the weights for ultimate cross-efficiency scores.

One of the powerful technique for producing a set of fair weights is game theory approach. In recent years, DEA and game theory approach have been combined in order to rank DMUs, fairly and completely. Nakabayashi and Tone (2006) introduced a model based on DEA and game theory approach of consensus-making between organizations. Wu et al. (2009) combined Nakabayashi and Tone (2006) approach with cross-efficiency DEA and found out the weights for ranking DMUs, fairly. Liang et al. (2008) presented a new method based on cross-efficiency and non-cooperative game. Wu and Liang (2012) proposed a game cross-efficiency DEA model in which each DMU was viewed as a player who seeks to maximize its own score under the condition that the cross-evaluation scores of each of other DMUs does not deteriorate. The obtained game cross-evaluation scores were unique and constituted a Nash equilibrium point. Based on DEA and bargaining game approach, Rezaee et al. (2012) combined multi-objective DEA model and Shapley value to solve the problem of many numbers of inputs and outputs and small number of DMUs. To increase the distinguish power of DEA model in presence of many inputs and outputs, Omrani et al. (2015) used principal component analysis (PCA)—DEA model with cooperative game for performance assessment of Iranian electricity distribution companies. In another study, Rezaee et al. (2016) proposed a DEA model with bargaining game to performance evaluation of bus lines from both managerial and geographic perspective in California with two category of inputs (operational and spatial). The model could discriminate among bus lines when the number of inputs/outputs enhanced. Li et al. (2016a, b, c) combined DEA and cooperative game theory to rank efficient DMUs with a common platform. In their study, each efficient DMU is regarded as a player, each possible subset of efficient DMUs is regarded as a coalition. They defined a characteristic function for the coalition and proved that the characteristic function satisfies super additivity. Then, they used a Shapley value as a solution to the cooperative game and to rank DMUs.

This paper modifies the DEA-Game proposed by Nakabayashi and Tone (2006) and applies the modified model for energy efficiency estimation of transportation sector in provinces of Iran. We have enhanced the evaluation of energy efficiency and revised the results. So, the main contribution of this paper is two issues: (1) modification of proposed DEA-game model by Nakabayashi and Tone (2006) (2) Application of the modified model for a real world problem.

In this paper, energy efficiency of transportation sector in 20 provinces of Iran is investigated. First, a DEA model is performed with energy and non-energy inputs and desirable and undesirable outputs. In classical DEA model, some provinces get efficiency score equal to one and in order to fully rank of them, the cross-efficiency DEA model is applied. In cross-efficiency DEA model, the score of jth DMU is calculated using the average of other DMUs' scores. As mentioned before, there are several studies for finding a suitable set of scores' weights in cross-efficiency DEA models. In this paper, instead of simple average of DMUs' scores, a set of acceptable and fair weights are produced based on the cooperative game theory approach which can be used for calculating efficiency score of DMUs. For this purpose, each province is considered as a player. Then, a new characteristic function is introduced for dividing pay-offs among the players in coalitions. Finally, by using a linear programming model, the fair weights are produced and the efficiency scores of provinces are calculated. The rest of this paper is organized as follows: In Sect. 2, the cross-efficiency DEA—cooperative game is described. In Sect. 3 a numerical example has been investigated. Sect. 4 discusses the input and output variables and the related data. In Sect. 5, the proposed approach is applied by using some actual data from transportation sector in the provinces of Iran and results have been presented. Finally, the summarization of the paper is discussed in the conclusion.

2 Methodology

The methodology of this paper is based on combining cross-efficiency DEA model and cooperative game theory approach. In this study, there are desirable and undesirable outputs, so, the DEA model is re-expressed with them. Also, inputs are categorized into two sections: energy and non-energy factors. Assume that there are K non-energy and L energy inputs. Also, assume there are M desirable and H undesirable outputs. The represented model according to DEA technology under variable returns to scale (VRS) is as follows:

$$P = \left\{(x^n, x^e, y^d, y^u)|(x^n, x^e) \text{ can produce } (y^d, y^u)\right\} \tag{1}$$

DMU_d is the unit under evaluation and n is the number of DMUs. For the jth DMU, ${x_{kj}}^n(k = 1, \ldots, K)$ represents kth non-energy input and ${x_{lj}}^e(l = 1, \ldots, L)$denotes lth energy input. Also, ${y_{mj}}^d(m = 1, \ldots, M)$ and ${y_{hj}}^u(h = 1, \ldots, H)$ denote mth desirable output and hth undesirable output, respectively. To confront with undesirable outputs in DEA model, we change them to desirable outputs by data transformation function. According to Seiford and Zhu (2002) approach, hth undesirable output of DMU$_j$ is subtracted from a positive number w_h as ${y_{hj}}^{newd} = w_h - {y_{hj}}^u$. The new output is desirable and can be used as ordinary output in DEA model. In this paper, the value of w_h is determined as $w_h = \max_{j=1\ldots n}\{{y_{hj}}^u\} + min_{j=1\ldots n}\{{y_{hj}}^u\}$. Finally, the envelopment form of DEA-VRS model can be shown as follows:

$$\begin{aligned}
&P_d = \min\theta \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{kj}^n \le x_{kd}^n \quad k = 1, \ldots, K \\
&\sum_{j=1}^{n} \lambda_j x_{lj}^e \le \theta x_{ld}^e \quad l = 1, \ldots, L \\
&\sum_{j=1}^{n} \lambda_j y_{mj}^d \ge y_{md}^d \quad m = 1, \ldots, M \\
&\sum_{j=1}^{n} \lambda_j y_{hj}^{newd} \ge y_{hd}^{newd} \quad h = 1, \ldots, H \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0 \quad j = 1, \ldots, n
\end{aligned} \tag{2}$$

As mentioned before, in this paper, the cross-efficiency DEA model is used. In cross-efficiency DEA model, the weights of inputs and outputs should be calculated. To find out the weights of inputs and outputs, multiplier form of DEA-VRS model (2) is written as model (3):

$$
\begin{aligned}
&eff_d = \max\left[\sum_{m=1}^{M}\mu_m y_{md}^{d} + \sum_{h=1}^{H}\mu_h' y_{hd}^{newd} - \mu_0 - \sum_{k=1}^{K} w_k x_{kd}^{n}\right]\\
&s.t.\\
&\sum_{m=1}^{M}\mu_m y_{mj}^{d} + \sum_{h=1}^{H}\mu_h' y_{hj}^{newd} - \mu_0 - \sum_{k=1}^{K} w_k x_{kj}^{n} - \sum_{l=1}^{L} w_l' x_{lj}^{e} \le 0 \quad j = 1, \ldots, n\\
&\sum_{l=1}^{L} w_l' x_{ld}^{e} = 1\\
&\mu_m, \mu_h', w_k, w_l' \ge 0 \quad m = 1, \ldots, M, \quad h = 1, \ldots, H, \quad k = 1, \ldots, K, \quad l = 1, \ldots L\\
&\mu_0 free
\end{aligned} \tag{3}
$$

where$(\mu_m, \mu'_h, w_k, w'_l)$ represents the weights of $({y_{mj}}^{d}, {y_{hj}}^{newd}, {x_{kj}}^{n}, {x_{lj}}^{e})$.

The DEA-VRS model (3) does not lead to completely ranking of DMUs. Usually, there are some DMUs with efficiency score equal to one and it is necessary to introduce an approach to rank them. One of the important models for fully rating of DMUs is the cross-efficiency DEA. Hence, in this section, the cross-efficiency DEA model is described. The cross-efficiency DEA uses peer-evaluation instead of a self-evaluation. For each $DMU_d(d = 1 \ldots n)$ under evaluation, a set of optimal weights for inputs and outputs are gained as $({\mu_{md}}^{*} \ldots {\mu'_{hd}}^{*}, {w_{kd}}^{*}, {w'_{ld}}^{*})$. Then, the cross-efficiency of $DMU_j\,(j = 1 \ldots n)$ can be calculated by weights of model (3) as follows:

$$
E_{dj} = \left(\sum_{m=1}^{M}\mu_{md} y_{mj}^{d} + \sum_{h=1}^{H}\mu'_{hd} y_{hj}^{newd} - \mu_0\right)\Bigg/\left(\sum_{k=1}^{K} w_{kd} x_{kj}^{n} + \sum_{k=1}^{K} w'_{kd} x_{kj}^{e}\right) \quad d, j = 1, \ldots, n \tag{4}
$$

The cross-efficiency matrix $E = (E_{dj})\, \epsilon\, {R_+}^{n\times n}$ is shown in Table 1. As shown, d and j are the row and column of the matrix and each element E_{dj} is the efficiency of DMU_j by using the weights of DMU_d.

For $DMU_j(j = 1\ldots n)$, the average of all $E_{dj}(d = 1\ldots n)$, namely $\bar{E}_j = \frac{1}{n}\sum_{d=1}^{n} E_{dj}(j = 1\ldots n)$ is the cross-efficiency score. Although this average can be used for fully ranking of

Table 1 The cross-efficiency DEA matrix

DMUs	DMUs				
	1	2	3	…	n
1	E_{11}	E_{12}	E_{13}	…	E_{1n}
2	E_{21}	E_{22}	E_{23}	…	E_{2n}
3	E_{31}	E_{32}	E_{33}	…	E_{3n}
…	…	…	…	…	…
n	E_{n1}	E_{n2}	E_{n3}	…	E_{nn}
Mean	$\overline{E_1}$	$\overline{E_2}$	$\overline{E_3}$	…	$\overline{E_n}$

efficient DMUs, but it is not acceptable for all DMUs. In other words, the weights generated for calculating cross-efficiency may not admit by all DMUs. As mentioned before, the researchers proposed different approaches to overcome the problems of weights in literature (Wu et al. 2009, 2011; Ramón et al. 2010; Lam 2010). In this paper, the game theory approach is applied to produce a set of suitable weights for calculating cross-efficiency scores, equitably. Before using the game theory approach, the cross-efficiency matrix should be row-wise normalized. The cross-efficiency matrix is normalized by dividing each value in a row by the sum of all values $\sum_{j=1}{}^{n} E_{dj} (d = 1, \ldots, n)$. Each element of dth row after row-wise normalizing is shown as $(E'_{d1}, \ldots, E'_{dn})$ which $\sum_{j=1}{}^{n} E'_{dj} = 1\ (d = 1, \ldots, n)$.

The DEA-Game model was introduced by Nakabayashi and Tone (2006). They used the cooperative game so that the players organized a coalition with each other. The pay-off gained by each coalition is calculated by a function which called characteristic function. The characteristic function is used in Shapley value formula to calculate the value of each player. Therefore, first, the characteristic function C(S) for the coalition $S\ (S \subset N)$, $N = 1, \ldots, n$ should be introduced (N is the number of players). Let the coalition S be a subset of the N. The scalar $e'_d(S)$ is calculated as Eq. (5):

$$e'_d(S) = \sum_{j \in S} E'_{dj}(S)\ (d = 1 \ldots n) \tag{5}$$

There values of $e'_d(S)(d = 1 \ldots n)$ are shown in a n $\times$ 1 column vector as $K'(S) = \left[e'_1(S)\ e'_2(S) \ldots e'_n(S) \right]^T$. It is clear that the vector $K'(S)$ has n elements which are represented as $e'_d(S)(d = 1 \ldots n)$. For example, let there are n DMUs and the DMUs (players) 1, 2 and 3 be in a coalition and $S = \{1, 2, 3\}$. By using row-wise normalized of Table 1, we have $e'_1(1, 2, 3) = E'_{11} + E'_{12} + E'_{13}$, $e'_2(1, 2, 3) = E'_{21} + E'_{22} + E'_{23}, \ldots, e'_n(1, 2, 3) = E'_{n1} + E'_{n2} + E'_{n3}$. Indeed, $K'(1, 2, 3) = \left[e'_1(1, 2, 3)\ e'_2(1, 2, 3) \ldots e'_n(1, 2, 3) \right]^T$ is a n $\times$ 1 column vector. Since, there are $2^n - 1$ coalitions, so, we have $2^n - 1$ vectors $K'(S)$, too.

The characteristic function can be expressed as follows:

$$C(S) = \min\ K'(S) = \min_{d=1 \ldots n} \left\{ e'_d(S) \right\} \tag{6}$$

$C(S)$ is the minimum value of vector $K'(S)$. To prove the Eq. (6), the approach proposed by Nakabayashi and Tone (2006) is considered. According to Nakabayashi and Tone (2006), assume there is a game by (N, D) where N is the number of players and D is the characteristic function for this game. The proposed characteristic function (7) was introduced by Nakabayashi and Tone (2006) as follows:

$$\begin{aligned} & D(j) = \max \sum_{d=1}^{n} w_d^j E'_{dj} \\ & s.t. \sum_{d=1}^{n} w_d^j = 1 \\ & w_d^j \geq 0 \quad d = 1, \ldots, n \end{aligned} \tag{7}$$

The objective function of model (7) maximizes cross-efficiency of jth DMU. Indeed, DMUj wants to find optimal weights for maximizing its' cross-efficiency score. Also, the characteristic function of coalition S can be expressed as follows (Nakabayashi and Tone 2006):

$$
\begin{aligned}
& D(S) = \max \sum_{d=1}^{n} w_d e'_d(S) \\
& s.t. \sum_{d=1}^{n} w_d = 1 \\
& w_d \geq 0 \quad d = 1, \ldots, n
\end{aligned} \tag{8}
$$

where $e'_d(S)(d = 1 \ldots n)$ was defined in Eq. (5). Model (8) tries to maximize the efficiencies of all DMUs in coalition by finding an optimal set of weights. Thus, we have a game in coalition form with transferable utility, as represented by (N, D). It is notable that the objective function of model (7) is cross-efficiency of DMU j. When the DMU j joins to coalition S, the efficiency score of all coalition members is calculated using the model (8). Model (8) maximizes the cross-efficiency of coalition by finding an optimal set of weights. Since the characteristic function D is a sub-additive, Nakabayashi and Tone (2006) considered the opposite side of the game (N, D) as follows:

$$
\begin{aligned}
& C(j) = \min \sum_{d=1}^{n} w_d^j E'_{dj} \\
& s.t. \sum_{d=1}^{n} w_d^j = 1 \\
& w_d^j \geq 0 \quad d = 1, \ldots, n
\end{aligned} \tag{9}
$$

The optimal value $C(j)$ is the minimum division that player j can expect from the game. For the coalition $S \subset N$, the characteristic function C(S) is defined as follows:

$$
\begin{aligned}
& C(S) = min \sum_{d=1}^{n} w_d e'_d(S) \\
& s.t. \sum_{d=1}^{n} w_d = 1 \\
& w_d \geq 0 \quad d = 1, \ldots, n
\end{aligned} \tag{10}
$$

Nakabayashi and Tone (2006) proved that the game (N, C) in model (7) is super-additive, $C(S \cup T) \geq C(S) + C(T)$ for any $S \subset N$ and $T \subset N$ with $S \cap T = \phi$. Also, $C(S) + D(N \backslash S) = 1$ and the games (D, N) and (C, N) are dual games. As mentioned, the game (N, C) is supper-additive and it is possible to divide among DMUs the extra efficiency obtained by coalition. In other words, the transferable utility in this game is the extra efficiency obtained by players (DMUs) in the coalition S. In order to prove the Eq. (6), the dual program of model (10) is expressed in (11).

$$
\begin{aligned}
& C(S) = \max y \\
& s.t: \\
& y \leq e'_d(S) \quad d = 1, \ldots, n \\
& y \ is \ free
\end{aligned} \tag{11}
$$

The model (11) has one decision variable y and it is clear that the optimal solution of y is as Eq. (6). According to Nakabayashi and Tone (2006) and Wu et al. (2009), the Shapley value of player ith in the game (N, C) is defined as follows:

$$\varphi_i(D) = \frac{(s-1)!\,(n-s)!}{n!}\{C(S) - C(S-i)\} \tag{12}$$

where s is the number of members of coalition. The phrase $\{C(S) - C(S-i)\}$ means that if player ith joint to the coalition, how much the value can increase.

To calculate the final cross DEA-Game efficiency, based on Nakabayashi and Tone (2006) approach, Wu et al. (2009) suggested the model (13). In the model (13), the weights $w = (w_1 \ldots w_n) \in R^n$ associates with the imputations $\varphi = (\varphi_1 \ldots \varphi_n) \in R^n$. The imputations are obtained from the Shapley value formula (12).

$$\begin{aligned}
&\min p\\
&s.t: wE'_j + s_j^+ - s_j^- = \varphi_j \quad (j = 1, \ldots, n)\\
&w_1 + \cdots + w_n = 1\\
&s_j^+ \le p, s_j^- \le p \quad (j = 1, \ldots, n)\\
&w_i \ge 0 \quad (i = 1, \ldots, n)\\
&s_j^+ \ge 0, s_j^- \ge 0 \quad (j = 1, \ldots, n)
\end{aligned} \tag{13}$$

where E'_j is the jth column of matrix E' (the normalized cross-efficiency matrix). In the model (10), $s_j{}^+$, $s_j{}^-$, p and w_i are decision variables. It is clear that the left-hand side of the first constraint is normalized cross-efficiency and the right-hand side is the Shapley value of DMU j. Model (13) tries to set $p = 0$ which means $s_j{}^+ = s_j{}^- = 0$. Also, one can use Core or Nucleolus instead of Shapley value. The imputation vector in Shapley value, Core or Nucleolus may not be the same. Therefore, the right-hand side of the first constraint in the model (13) changes and generated weights can change too. Hence, the final cross-efficiency DEA scores will change. By solving the model (13), optimal weights $w_d{}^*$ are obtained. Therefore, the final cross-efficiency DEA-Game scores are calculated as follows:

$$E_j^{\text{DEA-Game}} = \sum_{d=1}^{n} w_d^* E_{dj}, \quad j = 1, \ldots, n \tag{14}$$

3 Numerical example

In this section, a numerical example is solved to illustrate the capability of the cross-efficiency DEA-Game model. The example was reported in Wu and Liang (2012). There are six DMUs with four attribute and the data for DMUs are shown in Table 2.

Table 3 shows the cross-efficiency and normalized cross-efficiency DEA for the numerical example. Also, the pay-off for each coalition of DMUs are shown in Table 4. For example, the pay-offs for A and B are 0.0976 and 0.1686, respectively. If A and B form a coalition, the pay-off of coalition (A, B) is 0.3094. In this case, the extra value 0.0432 $(= 0.3094 - 0.0976 - 0.1686)$ is divided between players A and B.

Based on the pay-offs reported in Table 4, the Shapley values for all DMUs are calculated by using the Eq. (12). Also, Table 5 shows the weights generated by linear programming model (13).

Table 2 The data for numerical example

	x	y1	y2	y3	y4
A	1	3	1	2	3
B	1	4	5	5	2
C	1	6	9	6	2
D	1	3	2	2	1
E	1	2	2	3	2
F	1	1	4	3	3

The results of DEA-CCR, arbitrary cross-efficiency DEA (traditional cross-efficiency DEA), aggressive cross-efficiency DEA (proposed by Sexton et al. 1986), cross-efficiency DEA-Game (proposed by Wu and Liang 2012) and cross-efficiency DEA-Game (this paper) are shown in Table 6.

The results show that the ranks generated by cross-efficiency DEA-Game model is similar to the arbitrary and aggressive cross-efficiency DEA models. Indeed, the results of the three mentioned models lead to the same ranks. The Spearman correlation between proposed cross-efficiency DEA-Game and DEA-Game proposed by Wu and Liang (2012) is 0.829 which is significant at the 0.05 level.

4 Data

Transportation section has a particular significance especially in developing countries. Iran is a developing country which has a different planning for economic sectors such as transportation. Iran has 31 provinces that consists small provinces with simple transportation system such as Ilam, Mazandaran, and Semnan and big provinces with high population and complicated transportation system such as Tehran, Isfahan, and Khorasan Razavi. This paper analyzes the energy efficiency of transportation systems in 20 provinces of Iran. It is notable that the data of some provinces are emerged together. For example, the data of North Khorasan, South Khorasan and Khorasan Razavi are presented in Khorasan Razavi. Also, the data of Tehran and Alborz provinces, which known before as Tehran province, are reported as Tehran-Alborz. Unfortunately, for rest provinces like Ardebil, Kohgiluye and Boyer ahmad, Lorestan and Hormozgan data is not available. Due to unavailability data, some provinces are removed from analyzing. Transportation policies are suitable tools for improving energy efficiency. The population of centers of big provinces such as Tehran and Tabriz are increasing which cause irreparable damages such as irregular energy consumption and environment pollution.

In this paper, the transportation system of provinces in Iran is compared focusing on energy and environmental efficiency. One of the most important steps in efficiency estimation studies is the selection suitable inputs and outputs. The inputs and outputs in this paper are selected based on previous studies. Zhou et al. (2014) considered the amount of labor as non-energy input and consumption of coal, gasoline, kerosene, diesel oil, and electricity as energy inputs. Also, passenger kilometers (PKM) and tone kilometers (TKM) as desirable outputs and emissions of CO_2 gas as undesirable output were considered. Cui and Li (2014) considered three variables for inputs: non-energy inputs were the number of staff that working in transportation system and transportation fixed assets investment. The energy input was energy consumption volume, too. The desirable outputs were the freight turnover volume and

Table 3 The results of cross-efficiency DEA and normalized cross-efficiency DEA for numerical example

	Cross-efficiency DEA						Normalized cross-efficiency DEA					
	A	B	C	D	E	F	A	B	C	D	E	F
A	1.000	0.810	0.917	0.435	0.694	0.950	0.208	0.169	0.191	0.090	0.144	0.198
B	0.917	0.917	1.000	0.417	0.750	1.000	0.183	0.183	0.200	0.083	0.150	0.200
C	0.288	0.625	1.000	0.316	0.305	0.417	0.098	0.212	0.339	0.107	0.103	0.141
D	0.595	0.698	1.000	0.500	0.397	0.294	0.171	0.200	0.287	0.144	0.114	0.084
E	0.923	0.915	1.000	0.419	0.750	1.000	0.184	0.183	0.200	0.084	0.150	0.200
F	0.943	0.856	0.971	0.413	0.714	1.000	0.193	0.175	0.198	0.084	0.146	0.204
Mean	0.778	0.804	0.981	0.417	0.662	0.777						

Table 4 Pay-off for each coalition for the numerical example

S	C(S)	S	C(S)	S	C(S)	S	C(S)
{A}	0.0976	{C, E}	0.3353	{B, C, E}	0.5039	{A, C, D, F}	0.6667
{B}	0.1686	{C, F}	0.3713	{B, C, F}	0.5571	{A, C, E, F}	0.6560
{C}	0.1909	{D, E}	0.2105	{B, D, E}	0.4034	{A, D, E, F}	0.4495
{D}	0.0833	{D, F}	0.2278	{B, D, F}	0.4282	{B, C, D, E}	0.5943
{E}	0.1034	{E, F}	0.1982	{B, E, F}	0.3986	{B, C, D, F}	0.6475
{F}	0.0843	{A, B, C}	0.5658	{C, D, E}	0.4257	{B, C, E, F}	0.6856
{A,B}	0.3094	{A, B, D}	0.4166	{C, D, F}	0.4789	{B, D, E, F}	0.5421
{A,C}	0.3833	{A, B, E}	0.4128	{C, E, F}	0.4852	{C, D, E, F}	0.6234
{A,D}	0.2048	{A, B, F}	0.4507	{D, E, F}	0.3417	{A, B, C, D, E}	0.7958
{A,E}	0.2010	{A, C, D}	0.4667	{A, B, C, D}	0.6500	{A, B, C, D, F}	0.8500
{A,F}	0.2389	{A, C, E}	0.5333	{A, B, C, E}	0.7115	{A, B, C, E, F}	0.8565
{B,C}	0.3594	{A, C, F}	0.5421	{A, B, C, F}	0.7426	{A, B, D, E, F}	0.6613
{B,D}	0.2590	{A, D, E}	0.3082	{A, B, D, E}	0.5200	{A, C, D, E, F}	0.7882
{B,E}	0.3130	{A, D, F}	0.3461	{A, B, D, F}	0.5579	{B, C, D, E, F}	0.7919
{B,F}	0.2847	{A, E, F}	0.3424	{A, B, E, F}	0.5542	{A, B, C, D, E, F}	1.0000
{C,D}	0.2813	{B, C, D}	0.4498	{A, C, D, E}	0.6167		

Table 5 The Shapley values and weights for the numerical example

	Shapley value	Weight
A	0.156414	0.20986
B	0.191538	0.065763
C	0.26511	0.328507
D	0.109442	0.250603
E	0.125768	0.066177
F	0.151729	0.079091

passenger turnover volume. Li et al. (2016a, b, c) divided inputs to non-resource inputs such as labor and capital and resource input such as energy consumption in transportation sector. Also, outputs were GDP and turnover as desirable and CO_2 emission as undesirable. Chang et al. (2013) considered labor and capital as non-energy inputs and energy consumption as energy input. The value-added and CO_2 emissions were chosen as desirable and undesirable outputs, respectively.

According to previous studies, this research selects energy and non-energy inputs and desirable and undesirable outputs. Five factors are selected as the inputs and four factors as outputs. The non-energy inputs are: number of vehicles as capital of each province in the transportation system and the number of employees (labor). The consumption volume of gasoline, oil gas and nature gas is considered as energy inputs. In the case of outputs, GDP based on current prices in the transportation system is selected as desirable output. In addition, passenger kilometers (PKM) and tone kilometers (TKM) are selected as other desirable outputs. Finally, the emission of greenhouse gases is considered as undesirable output. The greenhouse gases is sum of eight different gases consist of NO_x, SO_2, SO_3, CO, SPM, CO_2, CH_4 and NO_2. The inputs and outputs are shown in Table 7.

Table 6 The data for numerical example

	DEA		Arbitrary cross-efficiency DEA (traditional)		Aggressive cross-efficiency DEA		Cross-efficiency DEA-Game (Wu and Liang 2012)		Cross-efficiency DEA-Game (this paper)	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
A	1	1	0.778	3	0.714	3	0.995	2	0.650	3
B	0.917	4	0.804	2	0.729	2	0.906	4	0.739	2
C	1	1	0.981	1	0.889	1	1	1	0.980	1
D	0.500	6	0.417	6	0.370	6	0.474	6	0.408	6
E	0.750	5	0.602	5	0.559	5	0.743	5	0.501	5
F	1	1	0.777	4	0.694	4	0.986	3	0.621	4

Table 7 Selected inputs and outputs for transportation sector

	Variable
Inputs	
Non-energy	Number of vehicles
	Labor
Energy	Gasoline (*1000 Liter)
	Gas oil (*1000 Liter)
	Nature gas (Million Cubic meter)
Outputs	
Desirable	GDP (Billion Rials)
	Passenger kilometers (PKM) (Million)
	Ton kilometers (TKM) (Million)
Undesirable	Greenhouse gas emission (*1000 Ton)

The actual data is extracted from statistical yearbook of Iran. The raw data are gathered for 20 provinces of Iran in year 2012 and shown in Table 8. It is notable that the emission of greenhouse gases is an undesirable output and it is changed to desirable output in the last columns of Table 8.

5 Results

In this section, the proposed approach is applied for performance assessment of energy efficiency in transportation sectors of 20 provinces in Iran. First, DEA-VRS model is applied to measure the relative efficiency scores of provinces. Then, for fully ranking the DMUs, cross-efficiency DEA is used. Finally, the proposed DEA-Game model is applied to re-calculate the cross-efficiency of all provinces. In the following the results of DEA-VRS, cross-efficiency DEA and cross-efficiency DEA-Game model are discussed, separately.

5.1 DEA-VRS results

In this section, in order to calculate the energy efficiency of transportation sector of 20 provinces of Iran, DEA-VRS model is used. The results are provided in Table 1 and Fig. 1. According to the results, nine provinces including Ilam, Gilan, Khorasan Razavi, Kurdistan, Markazi, Semnan, Sistan and Baluchestan, Tehran-Alborz and Yazd are located in the efficient frontier and they are technically efficient. In other words, these provinces have best performance in converting two non-energy and three energy inputs to three desirable and one undesirable outputs than the other non-efficient provinces. As it observed in the results, some efficient provinces are less developed provinces like Sistan and Baluchestan, Kurdistan, Ilam and some of them have small population and simple transportation system like Semnan and Yazd. Only four provinces including Tehran-Alborz, Khorasan Razavi, Markazi and Gilan which are relatively large and developed efficient provinces. In contrast, Qazvin with the efficiency score of 0.632 has the weakest performance in producing outputs by using inputs. The efficiency scores of other provinces are distributed in interval 0.636 (Kermanshah) and 0.975 (Golestan). Also, the mean of energy efficiency scores for all provinces is 0.8851 which shows that the energy performance of transportation sector in Iran is generally acceptable. According to the DEA-VRS model (2), except the efficient units, other provinces should reduce energy inputs (gasoline, gas oil and natural gas) and consequently reduce their

Table 8 Raw data for provinces of Iran in year 2012

	Number of vehicles	Labor	Gasoline	Gas oil	Natural gas	GDP	PKM	TKM	Greenhouse gas emission	Greenhouse gas as desirable output
East Azarbaijan	30′612	84′052	978′082	836′995	520	17′886	1′608	6′674	25′167.64	102′174
West Azarbaijan	28′064	65′350	771′002	499′029	406	14′181	1′444	4′207	16′440.26	110′901.4
Esfahan	84′331	114′606	1′808′298	2′181′745	449	31′095	3′754	19′684	45′862.06	81′479.58
Ilam	5′103	9′980	156′614	128′304	31	2′045	955	890	2′515.47	124′826.2
Tehran-Alborz	345′096	402′336	5′819′004	2′074′054	1004	260′990	10′367	15′603	12′5221.9	2′119.708
Khorasan Razavi	61′020	138′884	1′749′539	1′342′922	612	31′656	5′927	15′556	38′610.84	88′730.8
Zanjan	9′877	17′284	301′729	275′426	123	3′414	382	1′792	6′453.993	120′887.6
Semnan	7′770	13′301	267′992	429′493	110	5′907	419	4′142	5′027.249	122′314.4
Sistan and Baluchestan	27′268	52′341	786′106	547′249	0	6′750	1′946	3′044	11′765.21	115′576.4
Fars	95′548	146′827	1′646′629	1′312′197	412	18′968	3′491	10′970	39′441.6	87′900.04
Qazvin	10′203	35′700	429′489	542′987	182	6′738	423	2′534	11′960.76	115′380.9
Kurdistan	8′603	30′868	388′983	209′094	146	3′433	778	2′065	8′124.21	119′217.4
Kerman	33′760	48′412	1′052′847	1′112′364	137	11′938	1′319	8′831	16′417.67	110′924
Kermanshah	14′540	52′023	467′177	510′624	187	6′913	1′122	2′495	11′775.43	115′566.2
Golestan	22′396	51′250	406′388	233′742	203	5′853	942	2′162	12′272.4	115′069.2
Gilan	19′308	67′302	907′062	306′755	256	13′353	1′139	2′649	19′548.7	107′792.9
Mazandaran	30′929	83′442	1′321′034	569′648	367	22′105	1′034	4′379	22′806.4	104′535.2
Markazi	12′472	28′394	445′321	595′976	146	6′721	603	6′151	13′826.87	113′514.8
Hamedan	16′137	88′985	438′469	396′941	137	7′098	1′137	3′496	14′812.96	112′528.7
Yazd	28′410	25′230	452′453	900′556	96	7′661	634	10′728	10′491.15	116′850.5

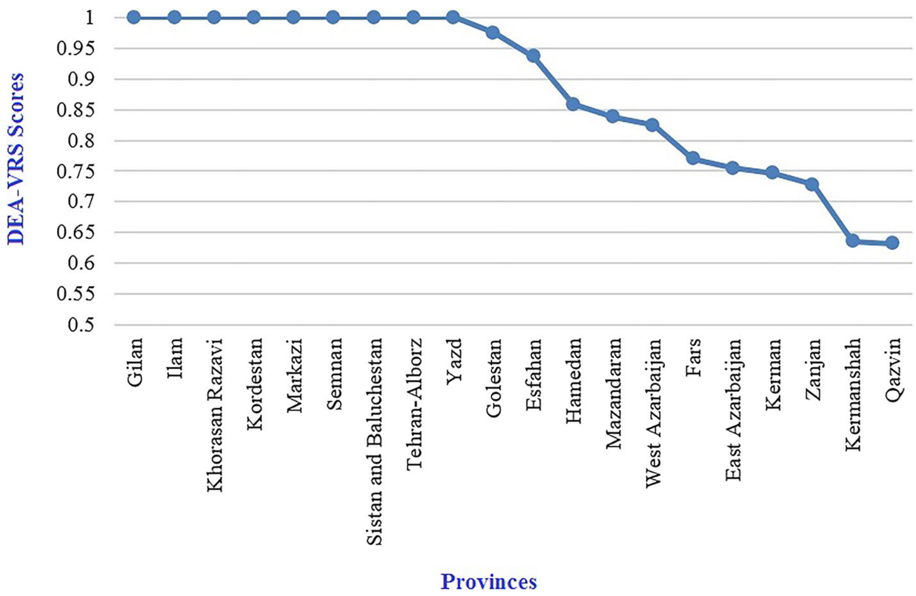

Fig. 1 Efficiency scores of DEA-VRS model

greenhouse gases emissions. For instance, Qazvin has located in the route of transit of goods and passengers from the west to east and vise-versa and has relatively high GDP, TKM and PKM outputs. In addition, high density of vehicles to move passengers and goods alongside of heavy industries cause to produce a relatively considerable amount of greenhouse gases. These factors lead to weakest performance of Qazvin in energy efficiency. In order to improve energy efficiency, Qazvin, Kermanshah and Zanjan should reduce energy inputs about 37, 36 and 27%, respectively.

As it can be seen, DEA-VRS is unable to completely rank the provinces and results are somehow difficult to interpret. For example, various provinces in terms of population, development and geographical position are considered as efficient DMUs. Hence, this paper proposes a novel cross-efficiency DEA-Game model to increase the distinguish power of the DEA-VRS and to cover the disadvantage of conventional cross-efficiency DEA in assigning appropriate weights for DMUs, simultaneously.

5.2 Cross-efficiency DEA model

As shown, the efficiency score for nine provinces is one and the DEA-VRS model unable to distinguish among them. Hence, in this section, cross-efficiency DEA model is applied for fully ranking of all provinces. The cross-efficiency DEA model is used to increase distinguish power between DMUs and make weights more flexible. The results of the cross-efficiency DEA model are presented in Table 12 and Fig. 4. According to the results reported in Table 12, Ilam with the efficiency scores of 0.917 has the best performance in energy efficiency. Yazd and Khorasan Razavi with efficiency scores of 0.899 and 0.876 are the second and third best energy performance, respectively. As mentioned before, completely ranking of provinces help us to provide more interpretations about energy efficiency of provinces. Although Ilam is the smallest province of Iran in terms of population, however in converting inputs to outputs performs better than metropolises like Tehran-Alborz and Khorasan Razavi. Since Ilam has the simple and small transportation system, it uses the lowest energy inputs and meanwhile produces the lowest undesirable greenhouse gases. Based on the cross-efficiency DEA-VRS results, Qazvin with efficiency score of 0.366 is at the bottom of the ranking again. As mentioned in Sect. 5.1, in order to increase energy efficiency, Qazvin should reduce energy inputs and increase environmental-friendly vehicles, which produce less greenhouse gases. Also, as it observed in the Table 12, the efficiency scores of all efficient provinces have changed. Indeed, the cross-efficiency DEA model is capable in completely ranking of DMUs. It can be also seen that the efficiency scores of all provinces have decreased in new ranking, thereby the mean of efficiency scores in cross-efficiency model is 0.656 which is lower than DEA-VRS model. In cross-efficiency DEA, the score of each DMU is obtained by using a simple average of DMUs' scores. As mentioned before, the cross-efficiency score of jth province is calculated by Eq. $\bar{E}_j = \frac{1}{n}\sum_{d=1}^{n} E_{dj} \quad (j = 1 \ldots n)$. It is clear that the weights of efficiency scores of all provinces are equal to $\frac{1}{n}$. Although cross-efficiency DEA can fully rank all DMUs, this model can't generate acceptable weights for reliable and fair ranking. However in comparison with DEA-VRS, this method can completely change the efficiency scores of the efficient DMUs and consequently can change ranks.

5.3 Cross-efficiency DEA-game model

As mentioned before, there are several studies for producing acceptable and fair weights in literature which was mentioned in introduction section. The generated weights are used to evaluate and rank the DMUs. Here, the final weights are generated by using cross-efficiency DEA-cooperative game model. First, the weights generated by multiplier DEA model (3) is considered and cross-efficiency for all efficient provinces are calculated based on Eq. (4). The cross-efficiency scores are shown in Table 9.

Table 9 should be normalized. Table 10 shows row-wise normalized of cross-efficiency matrix.

In this section, the pay-off for each coalition is calculated by using the characteristic function Eq. (6). There are $2^{20} - 1 = 1{,}048{,}575$ coalitions and we need to calculate 1,048,575 pay-off for all coalitions. Based on the pay-offs, the Shapley value of each province is calculated by using the Eq. (12). Table 11 and Fig. 2 show the Shapley value for all efficient provinces.

After calculating the Shapley values for each province, the fair weights are generated by the model (13). The weights are shown in Table 11. Based on the weights reported in Table 11, the DEA-Game efficiency scores for all provinces are generated by using the Eq. (14). The results are shown in Table 12 and Fig. 3.

As shown in Table 12, Ilam is top ranked and it is followed by Sistan and Baluchestan and Yazd. Also, Qazvin and Zanjan have the worst performance among the provinces respectively. The performance of Qazvin was the worst in all DEA, cross-efficiency DEA and DEA-Game models which implies that the transportation system in Qazvin should be revised and re-planed. Generally, the big provinces due to more population and complex transportation sector have more fuel consumption and consequently high emissions of greenhouse gases. In contrast, small provinces with less population has simpler transport system that causes less dangerous effect on the environment and low energy consumption. So, small provinces such as Ilam, Sistan and Baluchestan, Yazd and Semnan have better scores in comparison with big provinces such as Qazvin, Khorasan Razavi and Fars. As it can be seen in Table 12, some smaller provinces in term of population such as Sistan and Baluchestan and Ilam which have smaller transportation sectors are top ranked in the first and second position. The data reported in Table 8 shows that Ilam has minimum values of gasoline and gas oil as two energy inputs. Also, Ilam has minimum value of greenhouse emission as an undesirable output. In

Table 9 The cross-efficiency DEA matrix for the provinces

	East Azarbaijan	West Azarbaijan	Esfahan	Ilam	Tehran-Alborz	Khorasan Razavi	Zanjan	Semnan	Sistan and Baluchestan	Fars
East Azarbaijan	0.80	0.84	0.78	0.96	1.00	1.00	0.73	1.00	0.54	0.64
West Azarbaijan	0.74	0.83	0.76	1.00	1.00	1.00	0.71	0.90	0.56	0.72
Esfahan	0.41	0.38	0.94	0.64	1.00	1.00	0.00	0.34	1.00	0.73
Ilam	0.03	0.07	0.09	1.00	0.12	0.23	0.08	0.10	1.00	0.12
Tehran-Alborz	0.07	0.13	0.26	1.00	1.00	0.26	0.14	0.61	1.00	0.00
Khorasan Razavi	0.34	0.33	0.77	1.00	0.45	1.00	0.11	0.58	1.00	0.59
Zanjan	0.73	0.82	0.75	1.00	1.00	0.97	0.73	0.92	0.54	0.70
Semnan	0.43	0.51	0.56	1.00	0.44	0.72	0.55	1.00	0.33	0.33
Sistan and Baluchestan	0.34	0.39	0.57	1.00	1.00	1.00	0.00	0.12	1.00	0.67
Fars	0.50	0.50	0.83	1.00	1.00	1.00	0.37	0.67	1.00	0.77
Qazvin	0.56	0.58	0.52	1.00	1.00	0.53	0.64	1.00	0.35	0.37
Kurdistan	0.68	0.71	0.72	0.94	0.41	0.91	0.70	0.93	0.50	0.61
Kerman	0.50	0.50	0.83	1.00	1.00	1.00	0.38	0.67	1.00	0.77
Kermanshah	0.66	0.65	0.84	1.00	1.00	1.00	0.37	0.81	0.55	0.65
Golestan	0.74	0.83	0.76	1.00	1.00	1.00	0.71	0.90	0.56	0.72
Gilan	0.78	0.81	0.68	1.00	1.00	0.90	0.72	1.00	0.50	0.51
Mazandaran	0.80	0.84	0.77	0.93	1.00	1.00	0.72	1.00	0.53	0.61
Markazi	0.76	0.75	0.77	0.87	0.65	1.00	0.65	1.00	0.52	0.59
Hamedan	0.74	0.83	0.76	1.00	1.00	1.00	0.71	0.90	0.56	0.72
Yazd	0.63	0.61	0.79	0.00	0.66	1.00	0.30	0.69	0.36	0.70

Table 9 continued

	Qazvin	Kurdistan	Kerman	Kermanshah	Golestan	Gilan	Mazandaran	Markazi	Hamedan	Yazd
East Azarbaijan	0.57	1.00	0.71	0.57	0.82	0.95	0.85	0.98	0.87	1.00
West Azarbaijan	0.49	1.00	0.68	0.53	0.97	0.89	0.76	0.91	0.86	1.00
Esfahan	0.12	0.22	0.66	0.39	0.29	0.31	0.29	0.48	0.56	1.00
Ilam	0.00	0.15	0.10	0.12	0.10	0.04	0.00	0.02	0.13	0.06
Tehran-Alborz	0.04	0.08	0.49	0.09	0.00	0.01	0.14	0.20	0.03	1.00
Khorasan Razavi	0.07	0.34	0.71	0.30	0.22	0.18	0.19	0.57	0.48	1.00
Zanjan	0.51	1.00	0.68	0.53	0.97	0.88	0.76	0.91	0.85	1.00
Semnan	0.29	0.68	0.60	0.30	0.35	0.23	0.40	0.76	0.45	1.00
Sistan and Baluchestan	0.04	0.33	0.38	0.35	0.38	0.39	0.25	0.23	0.51	0.30
Fars	0.31	0.58	0.75	0.45	0.53	0.55	0.48	0.75	0.74	1.00
Qazvin	0.63	0.51	0.42	0.59	0.61	0.46	0.47	0.68	0.66	0.80
Kurdistan	0.49	1.00	0.68	0.50	0.77	0.77	0.65	0.94	0.80	1.00
Kerman	0.31	0.58	0.75	0.45	0.53	0.55	0.48	0.75	0.74	1.00
Kermanshah	0.44	0.47	0.54	0.64	0.60	0.44	0.42	0.70	0.75	1.00
Golestan	0.49	1.00	0.68	0.53	0.97	0.89	0.76	0.91	0.86	1.00
Gilan	0.63	0.97	0.65	0.60	0.69	1.00	0.90	0.92	0.82	0.84
Mazandaran	0.58	1.00	0.71	0.57	0.77	0.99	0.89	0.98	0.86	0.97
Markazi	0.54	0.95	0.72	0.55	0.67	0.83	0.74	1.00	0.82	1.00
Hamedan	0.49	1.00	0.68	0.53	0.97	0.89	0.76	0.91	0.86	1.00
Yazd	0.28	0.51	0.65	0.29	0.50	0.53	0.56	0.81	0.60	1.00

Table 10 The normalized cross-efficiency DEA matrix

	East Azarbaijan	West Azarbaijan	Esfahan	Ilam	Tehran-Alborz	Khorasan Razavi	Zanjan	Semnan	Sistan and Baluchestan	Fars
East Azarbaijan	0.05	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.03	0.04
West Azarbaijan	0.05	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.03	0.04
Esfahan	0.04	0.04	0.09	0.06	0.09	0.09	0.00	0.03	0.09	0.07
Ilam	0.01	0.02	0.02	0.28	0.03	0.06	0.02	0.03	0.28	0.03
Tehran-Alborz	0.01	0.02	0.04	0.15	0.15	0.04	0.02	0.09	0.16	0.00
Khorasan Razavi	0.03	0.03	0.07	0.10	0.04	0.10	0.01	0.06	0.10	0.06
Zanjan	0.05	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.03	0.04
Semnan	0.04	0.05	0.05	0.09	0.04	0.07	0.05	0.09	0.03	0.03
Sistan and Baluchestan	0.04	0.04	0.06	0.11	0.11	0.11	0.00	0.01	0.11	0.07
Fars	0.04	0.04	0.06	0.07	0.07	0.07	0.03	0.05	0.07	0.06
Qazvin	0.05	0.05	0.04	0.08	0.08	0.04	0.05	0.08	0.03	0.03
Kurdistan	0.05	0.05	0.05	0.06	0.03	0.06	0.05	0.06	0.03	0.04
Kerman	0.04	0.04	0.06	0.07	0.07	0.07	0.03	0.05	0.07	0.06
Kermanshah	0.05	0.05	0.06	0.07	0.07	0.07	0.03	0.06	0.04	0.05
Golestan	0.05	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.03	0.04
Gilan	0.05	0.05	0.04	0.06	0.06	0.06	0.05	0.06	0.03	0.03
Mazandaran	0.05	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.03	0.04
Markazi	0.05	0.05	0.05	0.06	0.04	0.07	0.04	0.07	0.03	0.04
Hamedan	0.05	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.03	0.04
Yazd	0.06	0.05	0.07	0.00	0.06	0.09	0.03	0.06	0.03	0.06

Table 10 continued

	Qazvin	Kurdistan	Kerman	Kermanshah	Golestan	Gilan	Mazandaran	Markazi	Hamedan	Yazd
East Azarbaijan	0.03	0.06	0.04	0.03	0.05	0.06	0.05	0.06	0.05	0.06
West Azarbaijan	0.03	0.06	0.04	0.03	0.06	0.05	0.05	0.06	0.05	0.06
Esfahan	0.01	0.02	0.06	0.04	0.03	0.03	0.03	0.04	0.05	0.09
Ilam	0.00	0.04	0.03	0.04	0.03	0.01	0.00	0.00	0.04	0.02
Tehran-Alborz	0.01	0.01	0.07	0.01	0.00	0.00	0.02	0.03	0.00	0.15
Khorasan Razavi	0.01	0.03	0.07	0.03	0.02	0.02	0.02	0.06	0.05	0.10
Zanjan	0.03	0.06	0.04	0.03	0.06	0.05	0.05	0.06	0.05	0.06
Semnan	0.03	0.06	0.06	0.03	0.03	0.02	0.04	0.07	0.04	0.09
Sistan and Baluchestan	0.00	0.04	0.04	0.04	0.04	0.04	0.03	0.02	0.05	0.03
Fars	0.02	0.04	0.05	0.03	0.04	0.04	0.04	0.05	0.05	0.07
Qazvin	0.05	0.04	0.03	0.05	0.05	0.04	0.04	0.06	0.05	0.07
Kurdistan	0.03	0.07	0.05	0.03	0.05	0.05	0.04	0.06	0.05	0.07
Kerman	0.02	0.04	0.05	0.03	0.04	0.04	0.04	0.05	0.05	0.07
Kermanshah	0.03	0.03	0.04	0.05	0.04	0.03	0.03	0.05	0.06	0.07
Golestan	0.03	0.06	0.04	0.03	0.06	0.05	0.05	0.06	0.05	0.06
Gilan	0.04	0.06	0.04	0.04	0.04	0.06	0.06	0.06	0.05	0.05
Mazandaran	0.04	0.06	0.04	0.03	0.05	0.06	0.05	0.06	0.05	0.06
Markazi	0.04	0.06	0.05	0.04	0.04	0.05	0.05	0.07	0.05	0.06
Hamedan	0.03	0.06	0.04	0.03	0.06	0.05	0.05	0.06	0.05	0.06
Yazd	0.02	0.04	0.06	0.03	0.04	0.05	0.05	0.07	0.05	0.09

Table 11 The Shapley values and weights for cross-efficiency DEA-Game model

	Shapley value	Weight
Gilan	0.025752	0.110765
Ilam	0.142797	0.319411
Khorasan Razavi	0.06719	4.18E−12
Kurdistan	0.038623	4.93E−13
Markazi	0.035782	1.11E−12
Semnan	0.0549	0.062411
Sistan and Baluchestan	0.142157	0.059994
Tehran-Alborz	0.071499	0.181662
Yazd	0.06821	0.179728
Golestan	0.029243	8.03E−13
Esfahan	0.045724	0.046422
Hamedan	0.037037	8.03E−13
Mazandaran	0.024579	1.17E−12
West Azarbaijan	0.033731	8.03E−13
Fars	0.035894	5.55E−13
East Azarbaijan	0.0281	9.28E−13
Kerman	0.04751	5.54E−13
Zanjan	0.025998	7.97E−13
Kermanshah	0.03002	6.38E−12
Qazvin	0.015254	0.039608

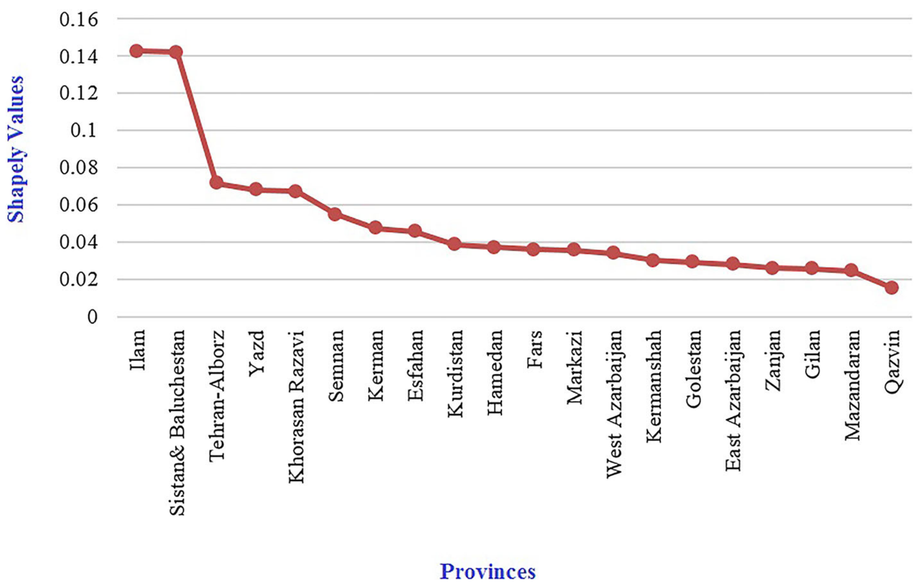

Fig. 2 Shapley value for all provinces

addition, Sistan and Baluchestan as a less developed province of Iran, does not use cleaner fossil fuels such as CNG in transportation sector. It should use CNG instead of other fossil fuels for improving its' score. Among the big provinces, Tehran-Alborz province as capital

Table 12 The results of the DEA-CRS, Cross-efficiency DEA and DEA-Game models

Province	DEA-VRS		Cross-efficiency DEA (traditional)		Cross-efficiency DEA-game		Shapley value
	Score	Rank	Score	Rank	Score	Rank	Rank
Gilan	1	1	0.589	14	0.292	16	18
Ilam	1	1	0.917	1	0.804	1	1
Khorasan Razavi	1	1	0.876	3	0.572	5	5
Kurdistan	1	1	0.668	9	0.354	11	9
Markazi	1	1	0.719	6	0.398	9	12
Semnan	1	1	0.759	5	0.505	6	6
Sistan and Baluchestan	1	1	0.673	8	0.767	2	2
Tehran-Alborz	1	1	0.837	4	0.624	4	3
Yazd	1	1	0.899	2	0.633	3	4
Golestan	0.975	10	0.587	15	0.279	17	15
Esfahan	0.937	11	0.687	7	0.425	7	8
Hamedan	0.859	12	0.638	11	0.357	10	10
Mazandaran	0.838	13	0.662	10	0.299	15	19
West Azarbaijan	0.825	14	0.594	13	0.340	12	13
Fars	0.77	15	0.576	16	0.329	13	11
East Azarbaijan	0.755	16	0.562	17	0.312	14	16
Kerman	0.747	17	0.612	12	0.418	8	7
Zanjan	0.728	18	0.466	18	0.243	19	17
Kermanshah	0.636	19	0.443	19	0.255	18	14
Qazvin	0.632	20	0.366	20	0.177	20	20

of Iran with large population, has ranked fourth. These results show that Tehran-Alborz with most complicated transportation system and highest air pollution has performed well. Although Tehran-Alborz province is the first consumer of gasoline and natural gas and second consumer of oil gas as energy inputs, but it has maximum values of GDP, PKM and TKM in transportation sector, too. It seems that the big provinces should develop other transportation systems such subway or use newer vehicles with lower fuel consumption and emissions. In Iran, only Tehran-Alborz province has the big subway network which helps to reduce energy and greenhouse emissions. Also, Golestan, Gilan and Mazandaran which are located in the forested cover region of Iran with mild climate to absorb undesirable greenhouse gases in atmosphere and high volume of population, vehicles and passengers have performed poorly in final rankings. Renewing transportation systems with lower emissions and increasing public transport infrastructure to decrease consumption of energy inputs can help these provinces to improve their performances. The final ranks of 20 provinces are shown in Table 12. It is observed that, like conventional cross-efficiency DEA, the proposed DEA-Game model can completely rank all DMU. Furthermore, Fig. 4 compares the DEA, cross-efficiency DEA and cross-efficiency DEA-Game models for the provinces. As it can be seen, the efficiency scores generated by DEA-Game are lower than DEA and cross-efficiency DEA models except Sistan and Baluchestan province. According to Table 11, the Shapley value of Sistan and Baluchestan is second top ranked among all provinces. This means Sistan and Baluchestan is a valuable DMU and it can create extra pay-off by joining to the coalition. Also, Table 11 shows that

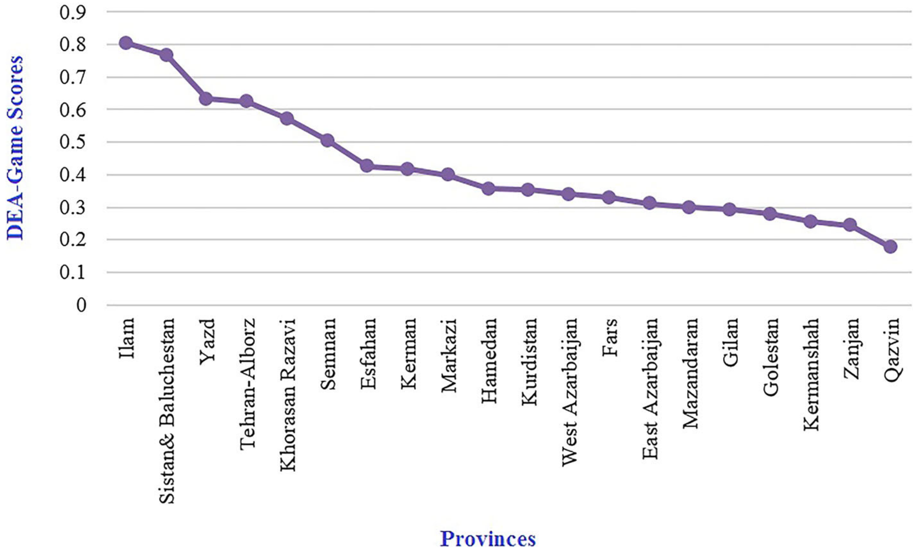

Fig. 3 Efficiency scores generated by DEA-Game model

the weights related to Ilam and Tehran-Alborz provinces are 0.319 and 0.182, respectively which means that these two provinces have the most effects on the cross-efficiency scores. On the other hand, according to the Table 10, the normalized efficiency scores of Sistan and Baluchestan are respectively 0.28 and 0.16 using the weights of Ilam and Tehran-Alborz. The energy efficiency scores for all provinces are rating from 0.177 to 0.804. Generated lower efficiency scores in cross-efficiency DEA-Game causes that the overall mean of efficiency scores decrease to 0.419 which is lower than both DEA-VRS and cross-efficiency DEA-VRS. In general, low energy efficiency of the transportation sector in Iran may mostly results of the worn-out heavy vehicles and obsolete public transportation system which are high energy consumers and high pollution producers. Imposition of restrictive laws on the use of worn-out and obsolete vehicles, helping to equip and modernize the public transportation systems and ultimately encouraging peoples to use the public transportation system may increase energy efficiency in the provinces.

For investigating the relation between the Shapley value and final cross-efficiency DEA-Game, the Spearman correlation test is applied. The results are shown in Table 13. As can be seen, the correlation between ranks generated by different models is significant at the 0.01 level. Indeed, DMU with high Shapley value has the high efficiency score.

6 Conclusion

Economic growth and development in each country requires the use of energy as one of the most important inputs of many sectors like transportation. However, energy consumption and economic growth have some harmful environmental effects. Therefore, in determining the energy efficiency of transportation sector, other factors like technical, economic and environmental factors should be considered. This study examined the energy efficiency in transportation sector of 20 provinces of Iran by using DEA-Game model with undesirable factors. To evaluate the energy efficiency of transportation system, the factors were divided

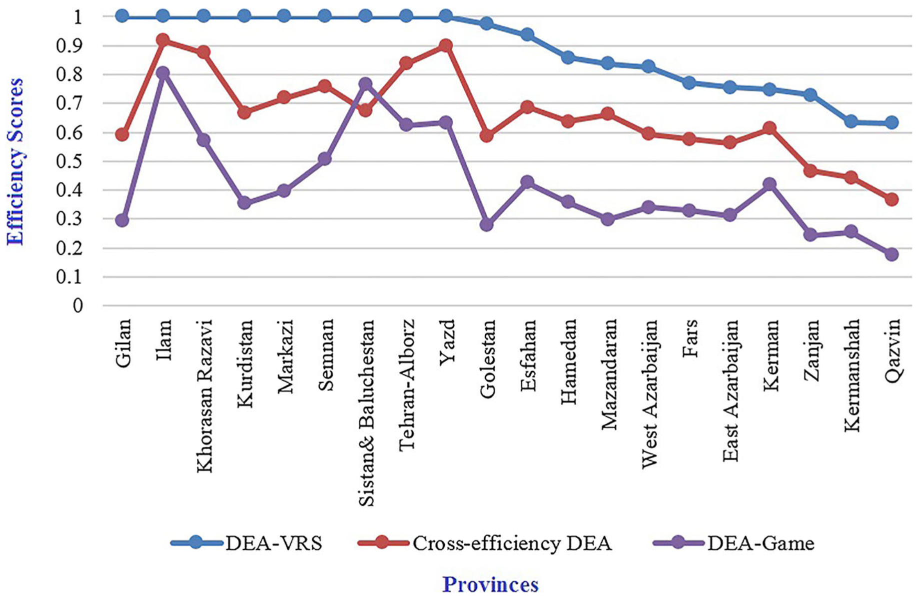

Fig. 4 Comparison between scores generated by DEA-VRS, Cross-efficiency DEA and DEA-Game models

Table 13 The Spearman correlation test among different models

	Cross-efficiency DEA	Cross-efficiency DEA-game	Shapley value
Cross-efficiency DEA	1.000	0.806**	0.947**
Cross-efficiency DEA-Game	–	1.000	0.905**
Shapley value	–	–	1.000

**Correlation is significant at the 0.01 level

to four groups of energy and non-energy inputs, desirable and undesirable outputs. Also, for ranking of the provinces, the cooperative game based on Shapley value was combined with cross-efficiency DEA model. In the cooperative game, each DMU was considered as a player and subset of all DMUs regarded as a coalition. Based on the DEA-cooperative game, the provinces were ranked, fully. The results indicated that smaller provinces which have smaller transportation systems get better ranks. In contrast, big provinces with complex transportation systems performed poorly. Policy makers should popularized public transportation like subways and buses in big provinces. Also, replacing high polluting fossil fuels with clean CNG will help the improvement of energy efficiencies. Furthermore, in provinces like Gilan, Golestan and Mazandaran which are located in the green geography and covered with condense forests, replacing worn-out vehicles with new less fuel consumption ones would increase energy efficiencies. As a result, the proposed approach of this paper is generated the fair weights for fully ranking of DMUs and can be used in other studies. For future studies, readers can apply other fully ranking models such as virtual frontier DEA (VFDEA) and compare the results with the proposed approach.

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