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DEA Malmquist productivity index based on a double-frontier slacks-based model: Iranian road safety assessment

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Abstract

Many governments in the developing world face the social and economic consequences of road accidents and mortalities. Hence, more precise evaluation of regional programs to reduce road fatalities has been a concern for many safety professionals.

Road safety performance is often measured using various extensions of Data Envelopment Analysis (DEA), in particular the model proposed by Charnes, Cooper and Rhodes (CCR), which deals only with the radial efficiency as the objective function neither taking into account input excesses nor output shortfalls. The Slacks-Based Measure (SBM) of efficiency overcomes this shortcoming by taking both measurements mentioned above simultaneously. In this regard, the current study aims to employ the SBM in analyzing road safety performance. It is noteworthy that the efficiency of each Decision Making Unit (DMU) can be pessimistically measured using the slacks-based measure of inefficiency such that the anti-efficient DMUs provide the anti-efficient frontier. The results obtained from the optimistic and pessimistic frontiers are nonlinearly aggregated by means of the Evidential Reasoning (ER) algorithm. Furthermore, a Double-Frontier SBM-based Malmquist Productivity Index (DF-SBM- MPI) is provided to analyze the efficiency and technological changes in safety performance from 2014 to 2016. For this purpose, the standard SBM and Super-SBM models are used to compute the optimistic Malmquist Productivity Index (MPI); similarly, the pessimistic MPI is determined by means of the inverted SBM and Super-SBM models. Finally, the obtained MPIs from the two different points of view are geometrically combined to obtain the overall MPI.

Keywords: Double-frontier slacks-based measurement, Iranian provinces, Road safety performance, ER algorithm, DF-SBM-MPI

1 Introduction

The World Health Organization (WHO) reported that about 1.25 million people annually perish due to road accidents. More often than not, accident victims are from low and middle income countries [1]. In other words, the global contribution of under developed countries to road fatalities is on the rise. Subsequently, road fatalities have recently become a social dilemma in under developed countries. According to the WHO, nearly 18,000 out of 77,447,168 Iranians passed away due to road accidents from 21 March 2013 to 20 March 2014. This means that around 23.2 out of 100,000 people died as a result of road accidents from 2013 to 2014, which is significantly higher than the global average of 17.4 per 100,000 people [1]. As a result of road accidents, Iran lost about six per cent of its gross domestic product [1].

Road safety performance is usually defined as an indicator for assessing countries, states, or provinces in terms of reducing road safety risks with regard to the existing resources. The number of crashes, fatalities, and injuries are usually considered as the three most

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common road safety risk indicators. In this regard, data availability is crucial in selecting the input data as well as road safety risk indicators. In addition, the definition of road safety performance will be different depending on the main purpose of road safety programs provided by governments or local authorities. In the current study, the most successful province in terms of road safety performance is a province that experiences a lower number of fatalities due to the less amount of investment.

Data Envelopment Analysis (DEA) method, originally proposed by Charnes, Cooper and Rhodes (CCR) in 1978 [2], has recently been widely used to assess road safety performance [3–15]. Based on the standard DEA, a Decision Making Unit (DMU) is recognized as an efficient DMU which generates either the maximum output levels with the given input levels or the minimum input levels with the given output levels. The CCR-based DEA model [2] uses a scalar measure to compute the efficiency of DMUs.

The main disadvantage of the CCR model is that it does not directly take into account the input excesses or output shortfalls (input/output slacks). Accordingly, an additive model was proposed by Charnes et al. (1985) to contend with this shortcoming; however it also lacks a scalar measure in the range of [0,1] [16]. Subsequently, Tone (2001) developed a Slacks-Based Measure (SBM) of efficiency in order to take into account both scalar measure and inputs/outputs slacks simultaneously [17]. To the best of our knowledge, no studies have assessed road safety efficiency using SBM-based DEA model. Existing studies have optimistically assessed road safety performance using the traditional CCR model. In other words, each DMU is assessed based only on the distance from the efficient frontier, which is composed of all efficient DMUs. In this situation, a DMU closer to the efficient frontier is more efficient than those that are farther away. On the other hand, the anti-efficiency value of each DMU can be pessimistically measured as the distance from the anti-efficient frontier. Consequently, a DMU farther away from the anti-efficient frontier is more efficient than those that are closer. Obviously, the efficiency results obtained using the optimistic and pessimistic perspectives are not the same, more often than not. In this respect, the present study aims to investigate a double-frontier SBM model to achieve a more realistic evaluation of road safety performance. In this regard, a nonlinear method of integration, namely the ER approach, is employed to integrate the two points of view [18, 19].

In addition, this study is meant to further analyze Iranian road safety performance over a period of time. For this purpose, Malmquist Productivity Index (MPI) is used. Traditionally, MPI values are computed using the optimistic DEA model, but this indicator can be equivalently obtained by utilizing the pessimistic DEA model. In this regard, a novel double-frontier MPI is proposed for a comprehensive evaluation of road safety performance over a three-year period of time.

The rest of the study is organized as follows:

Section 2 reviews the existing studies on road safety evaluation. Section 3 discusses the optimistic and pessimistic SBM models, followed by section 4 that briefly describes the ER approach. Afterwards, the optimistic, pessimistic and integrated MPIs are explained in section 5. Section 6 evaluates Iranian road safety performance not only in each year but also over a period of time by respectively implementing the proposed methods, Double-Frontier SBM aggregated by ER algorithm (DF-SBM-ER) and Double-Frontier SBM-based Malmquist Productivity Index (DF-SBM-MPI). Section 6 respectively implements the proposed methods, DF-SBM-ER and DF-SBM-MPI, in order to practically assess Iranian road safety performance not only during each year but also over a period of time. Conclusions and remarks are finally presented in section 7.

2 Literature review

This section surveys the studies previously carried out on road safety assessment using DEA models. In 2000, Odeck analyzed the productivity of 67 vehicle inspection stations over a two-year period of time (1989-1991), by utilizing an optimistic CCR-based MPI on the basis of an input-oriented model (Appendix 1) with one input (effective days of work) and four outputs including technical controls, usage controls, licensing and administration [3]. Afterwards, Odeck (2006) evaluated the safety performance of the 19 regional road agencies with the assumption of variable return to scale instead of constant return to scales [4]. Additionally, Odeck (2006) analyzed the productivity change of regional road agencies over a three-year period of time by means of an optimistic MPI based on the model proposed by Banker, Charnes and Cooper (BCC) [20] with only three outputs (technical, usage and safety belt controls), while no inputs were taken into account [4].

Hermans et al. (2008) examined the road safety performance of 27 European countries with respect to road accident fatalities using the CCR-based DEA model along with other four weighting methods. They calculated the road safety index for 21 European countries based on seven outputs (i.e., alcohol and drugs, protective systems, speed, vehicle, infrastructure daytime running lights and trauma care), but without input data. It is also found that the DEA model and road safety rank are highly correlated [5]. Hermans et al. [6] further evaluated the European countries in terms of road safety performance, taking into account the above-mentioned seven inputs and two undesirable outputs (number of crashes and fatalities). They came to the obvious conclusion that the inverted DEA model is more suitable for the available data set than economic issues [6].

In 2011, Shen et al. assessed the road safety performance of 19 European countries by developing both multiple-layer CCR and BCC models. They hierarchically categorized all inputs, consisting of 13 road user behaviors, into three layers. Similarly, they classified four defined outputs into two layers, namely injuries and crashes [7]. Also, Shen et al. (2012) assessed the road safety performance of 27 European countries with respect to three desirable inputs, inhabitants, passenger-kilometers and passenger cars, and only one undesirable output, fatalities, by developing a maximization programming model, called DEA-based Road Safety model (DEA-RS). The presented DEA-RS is simply obtained by inverting the traditional CCR model to make it more suitable for the defined data set. Although the DEA-RS was formulated as an output-oriented model (Appendix 1.2), it can also be converted to an input-oriented model, by minimizing the weighted sum of the outputs rather than maximizing the weighted sum of the inputs [8]. In 2013, Shen et al. further evaluated the road safety performance of European countries over a ten-year period of time. For this purpose, they developed a DEA-RS based MPI [9].

In 2013, Egilmez et al. analyzed 50 U.S. states in terms of road safety performance, using an MPI based on the standard input-oriented CCR model with seven inputs (highway safety expenditures, registered vehicles, licenced drivers, vehicle-miles traveled, total road length, overall road condition and safety belt usage) and one output (fatal crashes). They normalized the data set to fit the CCR model. Accordingly, the input data was reduced to five inputs. In addition, the ratio of the total annual time to the fatality rate was introduced as the model's output [10]. Also, in 2015, Shen et al. developed the DEA-RS models with weight restrictions based on either shadow price or a priori knowledge. Then, they employed the proposed models to assess 10 European countries in terms of road safety performance with respect to two outputs, serious injuries and fatalities [11]. All input variables were also defined in the same way as those previously introduced by Shen et al. [8, 9].

Bastos et al. (2015) analyzed the 27 Brazilian states by utilizing a multiple layer DEA method, taking into account two main indicators, namely mortality and fatality rates. They pointed out the obvious fact that the number of fatalities should be used as undesirable output in road safety studies [12]. In this regard, their model was presented based on the inverse of the DEA model provided by Cherchye et al. [21].

Rosic et al. (2017) assessed the 27 Serbian police departments on road safety performance using the DEA and TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) methods. It is worth noting that they applied the DEA models previously presented by Hermans et al. [5] and Shen et al. [8] as well as the corresponding cross-efficiency methods. The number of fatalities and seriously injured people were also defined as two undesirable outputs [13].

Behnood et al. evaluated the Iranian road safety performance using a CCR model that is, in fact, an inverted input-oriented CCR model (Appendix 1), which mathematically defines an efficient DMU as a DMU with less output and more input. However, the input variables seem not to be appropriate for the presented model, since all authorities actually prefer to reduce the fatality rate with the least number of defined inputs, i.e. police operation, emergency medical services, etc. They also measured the efficiency of road safety performance based on a data set of 60 DMUs, including 30 DMUs in 2008, and 30 DMUs in 2009. They did not analyze the road safety performance over a period of time, although they utilized two-year data sets [14].

The literature review reveals that no study has assessed road safety performance using SBM model. In contrast to standard DEA model, SBM assesses road safety performance by considering both input excess and output shortfall. In addition, all previous studies analyzed road safety performance based on the efficient frontier while ignoring the anti-efficient frontier. However, research on double-frontier DEA models has recently been of interest to many researchers [22–24]. Therefore, the main goal of this study is to bridge this gap by analyzing road safety performance based on a double frontier SBM.

3 Methods

3.1 Slacks-based measure (SBM) approach

This section briefly describes the optimistic and pessimistic SBM model. The optimistic SBM model was proposed by Tone in 2001 [17]. Suppose that there is an evaluation problem consisting of n DMUs with m inputs and s outputs respectively defined by $X = x_{ij} \in \mathcal{R}^{m\times n}$, and $Y = y_{rj} \in \mathcal{R}^{s\times n}$. The production possibility set can be defined as follows:

$$P = \{(x, y) |\ x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\} \tag{1}$$

where all data sets are assumed to be positive. The optimistic SBM is mathematically expressed as the following fractional programming model:

$$\begin{aligned}
&\text{Min}\ \rho_{optimistic} = \frac{1-(1/m)\sum_{i=1}^{m} s_i^-/x_{i0}}{1+(1/s)\sum_{r=1}^{s} s_r^+/y_{r0}} \\
&\text{Subject to} \\
&x_{i0} = \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + s_i^-, \qquad i=1,..,m \\
&y_{r0} = \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j - s_r^+, \qquad r=1,..,s \\
&\lambda_j \geq 0, \quad s_i^- \geq 0, \quad s_r^+ \geq 0.
\end{aligned} \tag{2}$$

where the input excess and output shortfall are respectively represented by slacks $s_i^- \in \mathcal{R}^m$ and $s_r^+ \in \mathcal{R}^s$. The SBM model (2) minimizes both input and output inefficiencies, which are respectively defined by the mean rate of input reductions, $(1/m)\sum_{i=1}^{m}(x_{i0}-s_i^-)/x_{i0}$, as well as the inverted mean rate of output expansions, $[(1/s)\sum_{r=1}^{s}(y_{r0}+s_r^+)/y_{r0}]^{-1}$ (*Tone, 2001*).

By multiplying a positive scalar variable $q > 0$ by the denominator and the numerator of the objective function of the fractional program (2) and making some adjustments, the linear program (3) can be achieved as follows:

$$\begin{aligned}
&\text{Min}\ \tau_{optimistic} = q - \frac{1}{m}\sum_{i=1}^{m} S_i^-/x_{i0} \\
&\text{Subject to} \\
&1 = q + (1/s)\sum\nolimits_{r=1}^{s} S_r^+/y_{r0} \\
&qx_{i0} = \sum\nolimits_{j=1}^{n} x_{ij}\Lambda_j + S_i^-, \qquad i=1,..,m \\
&qy_{r0} = \sum\nolimits_{j=1}^{n} y_{rj}\Lambda_j - S_r^+, \qquad r=1,..,s \\
&\Lambda_i \geq 0, \quad S_i^- \geq 0, \quad S_r^+ \geq 0, \qquad q > 0.
\end{aligned} \tag{3}$$

where $\Lambda_j = q\lambda_j$, $S_i^- = qs_i^-$ and $S_r^+ = qs_r^+$.The optimal solution of model (3) is $(\tau^* = \rho^*, q^*, \Lambda_j^*, S_i^{-*}, S_r^{+*})$. Consequently, the optimal solution of (2) is as follow: $(\rho^* = \tau^*, \lambda_j^* = \Lambda_j^*/q^*, s_i^{-*} = S_i^{-*}/q^*, s_r^{+*} = S_r^{+*}/q^*)$. A DMU is efficient if and only if $\rho^*_{optimistic} = \tau^*_{optimistic} = 1$. Such a condition can be obtained when there is no input excess, $s^{-*} = 0$, and output shortfall, $s^{+*} = 0$; otherwise, the DMU is defined as inefficient.

Taking the pessimistic SBM into account, the following production possibility set can be introduced:

$$P = \{(x,y)|\ x \leq X\lambda, y \geq Y\lambda, \lambda \geq 0\} \tag{4}$$

The anti-efficiency of each DMU can be mathematically formulated as follows:

$$\begin{aligned}
&\text{Max}\rho_{pessimistic} = \frac{1+(1/m)\sum_{i=1}^{m} s_i^+/x_{i0}}{1-(1/s)\sum_{r=1}^{s} s_r^-/y_{r0}} \\
&\text{Subject to} \\
&x_{i0} = \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j - s_i^+ \qquad i=1,..,m \\
&y_{r0} = \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j + s_r^- \qquad r=1,..,s \\
&\lambda_j \geq 0, \quad s_i^+ \geq 0, \quad s_r^- \geq 0.
\end{aligned} \tag{5}$$

The pessimistic SBM model (5) maximizes both the mean expansion rate of inputs, $(1/m)\sum_{i=1}^{m}(x_{i0}+s_i^+)/x_{i0}$, and the inverted mean reduction rate of outputs, $[(1/s)\sum_{r=1}^{s}(y_{r0}-s_r^-)/y_{r0}]^{-1}$. The fractional program (5) can also be converted to the following linear program (6) in the same way as the optimistic SBM.

$$\begin{aligned}
&\text{Max}\ \tau_{pessimistic} = q + \frac{1}{m}\sum_{i=1}^{m} S_i^+/x_{i0} \\
&\text{Subject to} \\
&1 = q - (1/s)\sum\nolimits_{r=1}^{s} S_r^-/y_{r0} \\
&qx_{i0} = \sum\nolimits_{j=1}^{n} x_{ij}\Lambda_j - S_i^+ \qquad i=1,..,m \\
&qy_{r0} = \sum\nolimits_{j=1}^{n} y_{rj}\Lambda_j + S_r^- \qquad r=1,..,s \\
&\Lambda_j \geq 0, \quad S_i^- \geq 0, \quad S_r^+ \geq 0, \qquad q > 0.
\end{aligned} \tag{6}$$

All parameters and variables are the same as those of the optimistic SBM. A DMU is anti-efficient if and only if $\rho^*_{pessimistic} = \tau^*_{pessimistic} = 1$. Such a condition indicates that the relative DMU is located on the anti-efficient frontier; hence both slack values are zero.

3.2 Evidential Reasoning (ER) algorithm

The ER algorithm was originally introduced by Yang and Singh in 1994 [25], based on the theory of evidence proposed by Dempster in 1967 [26] and improved by Shafer in 1976 [27]. Suppose that there is a frame of discernment, $\Theta = \{H_1, \ldots, H_N\}$, that contains a set of collectively exhaustive and mutually exclusive propositions. Mass functions (or basic probability assignments) are defined as follows:

$$\begin{aligned}
&m: 2^{\Theta} \rightarrow [0,1] \\
&m(\Phi) = 0 \ \ and \ \ \sum\nolimits_{A \in \Theta} m(A) = 1
\end{aligned} \tag{7}$$

where $m(A)$ represents a belief degree in the interval [0,1], assigned to subset A, and Φ is the empty set. The power set of Θ is expressed by 2^{Θ}. The ER algorithm aggregates the independent evidence, m_1 and m_2, based on the Dumpster's rule of combination, as follows:

$$[m_1 \oplus m_2](C) = \begin{cases} 0, & C = \Phi \\ \frac{1}{k} \sum_{A \cap B = C} m_1(A) m_2(B), & C \neq \Phi \end{cases} \tag{8}$$
$$k = 1 - \sum_{A \cap B = \Phi} m_1(A) m_2(B)$$

where k is a normalization factor. Note that the Dumpster's rule is not compatible in such a situation with thorough conflict between evidence, $\sum_{A \cap B = \Phi} m_1(A)$ $m_2(B) = 1$. In addition, many studies also pointed out that the Dumpster's rule of combination may be inappropriate to deal with the problems with conflicting evidence. In other word, in such a situation, the results might be counter-intuitive, irrational and complex [28–30].

In this regard, the ER algorithm has been proposed to effectively deal with the aforementioned shortcomings. Many studies were carried out based on the ER algorithm as an appropriate method of aggregation in dealing with certain and uncertain decision making problems [15, 25, 31–40].

Suppose that we intend to evaluate a decision making problem with n *DMUs* using G assessment grades as the frame of discernment, $\Theta = \{H_1, \ldots, H_g, \ldots, H_G\}$. It is also assumed that each DMU is assessed according to L pieces of evidence, $E = \{e_1, \ldots, e_l, \ldots, e_L\}$, and L relative weights, $w = (\omega_1, \ldots, \omega_l, \ldots, \omega_L)$. The mathematical expression of each DMU evaluation based on a certain evidence, e_l, is as follows:

$$S(e_l) = \left\{ \left(H_g, \beta_{g,l} \right), g = 1, \ldots, G \right\}, l = 1, \ldots, L \tag{9}$$

where $\beta_{g,l}$ is a belief degree assigned to H_g with respect to evidence e_l. Note that the sum of all beliefs is equal to unity, $\sum_{g=1}^{G} \beta_{g,l} = 1$, in the certain environment and is less than unity in the uncertain conditions, $\sum_{g=1}^{G} \beta_{g,l} < 1$. In brief, $\sum_{g=1}^{G} \beta_{g,l} \leq 1$. Accordingly, the mass functions, including the assigned and unassigned probabilities respectively denoted by $m_{g,l}$ and $m_{\Theta,l}$, are calculated by multiplying the belief degree, $\beta_{g,l}$, by the relative importance degree, ω_l , as follows :

$$m_{g,l} = \omega_l \beta_{g,l}, g = 1, \ldots, G, l = 1, \ldots\ldots, L \tag{10}$$

$$m_{\Theta,l} = 1 - \sum_{g=1}^{G} m_{g,l} = 1 - \omega_l \sum_{g=1}^{G} \beta_{g,l}, l = 1, \ldots\ldots, L \tag{11}$$

In addition, the unassigned probability mass, $m_{\Theta,i}$, can be derived using Eqs. (12) and (13):

$$\overline{m}_{\Theta,l} = 1 - \omega_l, l = \quad 1, \ldots\ldots, L \tag{12}$$

$$\tilde{m}_{\Theta,l} = \omega_l \left(1 - \sum_{g=1}^{G} \beta_{g,l} \right), l = 1, \ldots\ldots, L \tag{13}$$

where $\overline{m}_{\Theta,l}$ and $\overline{m}_{\Theta,l}$ represent the relative importance of evidence e_l and the ignorance respectively.

The ER algorithm aggregates probability masses using Eqs. (14) –(16) as follows:

$$\{H_g\} : m_g = k \begin{bmatrix} \prod_{l=1}^{L} (m_{g,l} + \bar{m}_{\Theta,l} + \tilde{m}_{\Theta,l}) - \\ \prod_{l=1}^{L} (\bar{m}_{\Theta,l} + \tilde{m}_{\Theta,l}) \end{bmatrix}, g = 1, \ldots., G, \tag{14}$$

$$\{H_\Theta\} : \tilde{m}_\Theta = k \left[\prod_{l=1}^{L}, (\bar{m}_{\Theta,l} + \tilde{m}_{\Theta,l}), - \prod_{l=1}^{L}, \bar{m}_{\Theta,l} \right], \tag{15}$$

$$\{H_\Theta\} : \bar{m}_\Theta = k \left[\prod_{l=1}^{L}, \bar{m}_{\Theta,l} \right], \tag{16}$$

and the normalization factor, k, is calculated using Eq. (17):

$$k = \left[\sum_{g=1}^{G} \left(\prod_{l=1}^{L} (m_{g,l} + \overline{m}_{\Theta,l} + \tilde{m}_{\Theta,l}) \right) - (G-1) \prod_{l=1}^{L} (\overline{m}_{\Theta,l} + \tilde{m}_{\Theta,l}) \right]^{-1} \tag{17}$$

In addition, Yang and Xu proposed the recursive ER algorithm as a novel aggregation process as follows [32]:

$$\{H_g\} : m_{g,I(l+1)} = K_{I(l+1)} \left(m_{g,I(l)} m_{g,l+1} + m_{g,I(l)} m_{\Theta,l+1} + m_{\Theta,I(l)} m_{g,l+1} \right) \quad g = 1, \ldots., G \tag{18}$$

$$\{H_\Theta\} : \tilde{m}_{\Theta,I(l+1)} = K_{I(l+1)} \left(\tilde{m}_{\Theta,I(l)} \tilde{m}_{\Theta,l+1} + \overline{m}_{\Theta,I(l)} \tilde{m}_{\Theta,l+1} + \tilde{m}_{\Theta,I(l)} \overline{m}_{\Theta,l+1} \right) \tag{19}$$

$$\{H_\Theta\} : \overline{m}_{\Theta,I(l+1)} = K_{I(l+1)} \left(\overline{m}_{\Theta,I(l)} \overline{m}_{\Theta,l+1} \right) \tag{20}$$

The normalization factor, $K_{I(l+1)}$, is computed as follows:

$$K_{I(l+1)} = \left[1 - \sum_{t=1}^{G} \sum_{\substack{k=1 \\ k \neq t}}^{G} m_{t,I(l)} m_{k,l+1} \right]^{-1}, l = 1, \ldots., L-1 \tag{21}$$

The ultimate assessment distribution can be achieved using Eqs. (22) and (23):

$$\{H_g\} : \beta_g = \frac{m_{g,I(L)}}{1-\overline{m}_{\Theta\ I(L)}}, g = 1, \dots, G, \tag{22}$$

$$\{H_\Theta\} : \beta_\Theta = \frac{\tilde{m}_{\Theta,I(L)}}{1-\overline{m}_{\Theta,I(L)}}, \tag{23}$$

where $\sum_{g=1}^{G} \beta_g + \beta_\Theta = 1$.

3.3 Malmquist Productivity Index (MPI)

Sten Malmquist proposed a quantity index to analyze input consumptions [41]. Fare et al. (1992) suggested a DEA-based MPI to measure the efficiency and technical changes on the basis of two measurements, namely efficiency and the productivity, that were previously proposed by Farrell (1957) and Cave et al. (1982) [42–44]. Subsequently, the DEA-based MPI was successfully applied in many studies to examine the productivity change regarding each DMU over time [3, 10, 45, 46]. Wang and Lan recently proposed the integrated MPI as a geometric mean of both optimistic and pessimistic MPIs [47]. They pointed out that the double-frontier MPI measures the productivity changes more comprehensively than the traditional MPI, as all information is taken into account.

Although most of the carried out studies used the CCR model to construct the MPI; Liu and Wang employed SBM to compute MPI [48]. Therefore, a novel DF-SBM-MPI is proposed to thoroughly analyze the productivity changes, taking into accounts both optimistic and pessimistic points of view simultaneously. In this regard, the pessimistic SBM-based MPI (represented by PMPI) is computed along with the optimistic SBM-based MPI (represented by OMPI); thereafter, the MPIs are geometrically combined to generate DF-SBM-MPI.

The OMPI of each DMU can be achieved as follows:

$$OMPI_0 = \left[\frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)} \cdot \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)}\right]^{1/2} \tag{24}$$

where (x_0^t, y_0^t) and (x_0^{t+1}, y_0^{t+1}) denote the input and output data sets relative to time periods t and $t+1$ respectively. $D_0^t(x_0^t, y_0^t)$ and $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$ respectively represent the optimistic efficiency scores obtained in time periods t and $t+1$, based on the data set relative to the same time period. $D_0^{t+1}(x_0^t, y_0^t)$ denotes the optimistic efficiency value in time period t, on the basis of the data set relative to time period $t+1$ and similarly $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$ measures the relative efficiency in time period $t+1$, according to the data set relative to time period t.

It is also noteworthy that the $OMPI_0$ can be achieved by multiplying the optimistic efficiency change (denoted by *OEC*) by the optimistic technical change (denoted by *OTC*), as follows [44]:

$$\begin{aligned} OMPI_0 &= \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)} \times \left[\frac{D_0^t\left(x_0^t, y_0^t\right)}{D_0^{t+1}\left(x_0^t, y_0^t\right)} \cdot \frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}\right]^{\frac{1}{2}} \\ &= OEC_0 \times OTC_0 \end{aligned} \tag{25}$$

$OEC_0 > 1$ demonstrates an improvement in the efficiency of DMU_0 over time period t to $t+1$, whereas $OEC_0 < 1$ indicates that DMU_0 experienced a diminution in its efficiency. $OEC = 1$ denotes no efficiency change over time period t to $t+1$. Similarly, $OTC_0 > 1$ indicates that DMU_0 achieved a technical progress over time period t to $t+1$, while $OTC_0 < 1$ shows that DMU_0 experienced a technical regression. $OTC_0 = 1$ expresses no technical change over time period t to $t+1$.

All required efficiency scores are computed using the optimistic and pessimistic SBM models (3) and (6), rather than only the optimistic CCR model. The required programming models for computing two single period measures, $D_0^t(x_0^t, y_0^t)$ and $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$, as well as two mixed period measures, $D_0^t(x_0^{t+1}, y_0^{t+1})$ and $D_0^{t+1}(x_0^t, y_0^t)$, are in detail presented in Appendix 2.1. Obviously, $D_0(\cdot) = 1$ means that the DMU_0 is efficient in a given time period, t or $t+1$, with respect to the given data set, (x_0^t, y_0^t) or (x_0^{t+1}, y_0^{t+1}). In such a situation, the optimistic Super-SBM model, as presented in Appendix 3.1, is used for further evaluation of efficient *DMUs*, with $\rho^*_{optimistic} = \tau^*_{optimistic} = 1$ [49]. For this reason, two single and two mixed period measures, called $\tilde{D}_0(\cdot) \geq 1$, can be driven as illustrated in Appendix 4.1.

The $PMPI_0$ regarding DMU_0 can be similarly computed by substituting the pessimistic period measures, $\{d_0^t(x_0^t, y_0^t), d_0^{t+1}(x_0^{t+1}, y_0^{t+1}), d_0^t(x_0^{t+1}, y_0^{t+1}), d_0^{t+1}(x_0^t, y_0^t)\}$, in Eq. (25) which can be achieved by multiplication of the pessimistic efficiency and technical changes, respectively called PEC_0 and PTC_0, as follows:

$$\begin{aligned} PMPI_0 &= \frac{d_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{d_0^t\left(x_0^t, y_0^t\right)} \times \left[\frac{d_0^t\left(x_0^t, y_0^t\right)}{d_0^{t+1}\left(x_0^t, y_0^t\right)} \cdot \frac{d_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{d_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}\right]^{\frac{1}{2}} \\ &= PEC_0 \times PTC_0, \end{aligned} \tag{26}$$

All pessimistic period measures are presented in Appendix 2.2. As shown in Appendix 3.2, the pessimistic Super-SBM model can also be applied for further assessment of anti-efficient *DMUs*, with $d_0(\cdot) = 1$ [50]. In this regard, the pessimistic period measures, $\tilde{d}_0(\cdot) \leq 1$, are driven and illustrated in Appendix 4.2. In the situation where $d_0(\cdot) = 1$, the corresponding $\tilde{d}_0(\cdot)$ is used.

Finally, the double-frontier MPI (represented by $DFMPI_0$) for evaluating the DMU_0 can be computed by the geometric mean of $OMPI_0$ and $PMPI_0$ as follows:

$$\begin{aligned} DFMPI_0 &= [OMPI_0 \times PMPI_0]^{\frac{1}{2}} \\ &= [DFEC_0]^{1/2} \times [DFTC_0]^{1/2} \end{aligned} \tag{27}$$

where $DFEC_0$ and $DFTC_0$ indicate the aggregated efficiency and technical changes over a time period.

$DFMPI_0 > 1$ and $DFMPI_0 < 1$ respectively demonstrate a progress and a regression over time that is more realistic. The productivity of DMU_0 will be unchanged if $DFMPI_0 = 1$.

4 Road safety performance

In this section, a three-year evaluation of Iranian road safety performance is practically carried out by means of a new hybrid approach, DF-SBM-ER. In this regard, the efficiencies obtained from the optimistic and pessimistic SBM models are aggregated by the ER algorithm, as a method of combination. Then, the efficiency and technical changes are examined. This case study includes 31 provinces.

The required data are usually selected based on data availability and safety programs defined by government and authorities. For example, Odeck (2000) considered vehicle technical failures as the main cause of road accidents. They defined these indicators mainly based on the Norwegian safety program [3]. Hermans et al. (2008) also utilized seven risk indicators presented in [51] as the input variables [5]. Shen et al. [8, 9] evaluated the road safety of European countries using a set of three input variables provided by the European Commission [52, 53]. Egilmez and McAvoy [10] assessed 50 U.S. states using an online database of Research and Innovative Technology Administration (RITA) Bureau of Transportation Statistics [54].

The Iran Road Maintenance and Transportation Organization (RMTO) is responsible for the intercity road safety performance. RMTO focuses more on fatality reduction by investing facilities and equipment. All available data are annually published by RMTO [55–57]. In this regard, six inputs and an output were derived from the Statistical Yearbook published annually by RMTO. Behnood et al. also applied RMTO Statistical Yearbook in order to define inputs and outputs variables [14].

The computations are based on the available data set for the years 2014–2016 obtained, including six inputs and one output as follows:

4.1 Inputs

4.1.1 Police station (PS)

The average number of highway police stations along 100 kilometres of road.

4.1.2 Road maintenance depot (RMD)

The average number of stations along 100 kilometres of road.

4.1.3 Equipment and vehicles (E&V)

The average number of both equipment and vehicles along 100 kilometres of road.

4.1.4 Camera (C)

The average number of both fixed speed and monitoring cameras along 100 kilometres of road.

Table 1 Descriptive statistics of data set

Variables	Min	Max	Mean	SD
a) Year 2014 (N=31)				
Inputs				
Police Station (PS)	0.09	1.07	0.3620	0.21626
Road Maintenance Depot (RMD)	0.14	3.47	1.1341	0.71446
Equipment & Vehicles (E&V)	6.92	39.73	20.1556	8.03757
Camera (C)	0.18	5.60	1.4881	1.20887
Emergency Medical Service (EMS)	1.06	7.47	2.3653	1.35491
Road with Lighting System (RLS)	0.92	29.81	7.5306	7.40396
Output				
FR^{-1}	0.13	7.77	1.1632	1.37304
b) Year 2015 (N=31)				
Inputs				
Police Station (PS)	0.11	1.02	0.3591	0.21112
Road Maintenance Depot (RMD)	0.17	3.31	1.1205	0.69042
Equipment & Vehicles (E&V)	9.21	37.91	20.4749	7.23863
Camera (C)	0.42	6.93	1.8415	1.57520
Emergency Medical Service (EMS)	1.20	7.63	2.4252	1.32906
Road with Lighting System (RLS)	0.94	30.42	8.0667	7.81487
Output				
FR^{-1}	0.16	8.03	1.1376	1.40518
c) Year 2016 (N=31)				
Inputs				
Police Station (PS)	0.09	1.06	0.3586	0.21049
Road Maintenance Depot (RMD)	0.18	3.17	1.1215	0.69748
Equipment & Vehicles (E&V)	8.74	39.26	19.8316	7.20473
Camera (C)	0.65	10.49	2.6766	2.45488
Emergency Medical Service (EMS)	1.12	7.32	2.4191	1.31821
Road with Lighting System (RLS)	1.27	31.91	8.2670	7.64173
Output				
FR^{-1}	0.12	5.12	0.8052	0.87499

4.1.5 Emergency medical service (EMS)

The average number of EMS stations along 100 kilometres of road.

4.1.6 Road with lighting system (RLS)

The average length of road equipped with lighting systems along 100 kilometres of road.

4.2 Output

4.2.1 Fatality risk (FR^{-1})

The inverse of fatality risk, including the number of fatalities per mean rate of hourly traffic.

It is supposed that all police stations are similar in terms of the number of officers and patrols. It is also supposed that all other input variables are the same. The period of 2014-2016 was selected due to data availability for the inputs and the output considered. The descriptive statistics of data are reported in Table 1. Table 2 reveals that the selected data set for the years 2014–2016 are highly correlated. Tables 3, 4 and 5 depict the efficiency and anti-efficiency degrees measured by implementing the optimistic and pessimistic SBM models (3) and (6). According to the results reported in column 2 of Table 3, *Fars* is optimistically recognized as an efficient province along with *Alborz, Ilam, Tehran, Khorasan S,*

Table 2 Correlation matrix of all variables

Variables	Police Station (PS)	Road Maintenance Depot (RMD)	Equipment & Vehicles (E&V)	Camera (C)	Emergency Medical Service (EMS)	Road with Lighting System (RLS)	FR^{-1}
a) 2014							
Police Station (PS)	1	0.830**	0.758**	0.727**	0.923**	0.858**	0.798**
Road Maintenance Depot (RMD)		1	0.788**	0.643**	0.797**	0.638**	0.722**
Equipment & Vehicles (E&V)			1	0.659**	0.658**	0.619**	0.571**
Camera (C)				1	0.659**	0.736**	0.718**
Emergency Medical Service (EMS)					1	0.798**	0.838**
Road with Lighting System (RLS)						1	0.733**
FR^{-1}							1
b) 2015							
Police Station (PS)	1	0.821**	0.764**	0.796**	0.914**	0.863**	0.809**
Road Maintenance Depot (RMD)		1	0.790**	0.578**	0.795**	0.647**	0.766**
Equipment & Vehicles (E&V)			1	0.573**	0.676**	0.651**	0.626**
Camera (C)				1	0.673**	0.860**	0.670**
Emergency Medical Service (EMS)					1	0.777**	0.887**
Road with Lighting System (RLS)						1	0.702**
FR^{-1}							1
c) 2016							
Police Station (PS)	1	0.814**	0.796**	0.895**	0.916**	0.867**	0.663**
Road Maintenance Depot (RMD)		1	0.791**	0.695**	0.789**	0.646**	0.653**
Equipment & Vehicles (E&V)			1	0.559**	0.655**	0.660**	0.394*
Camera (C)				1	0.837**	0.866**	0.696**
Emergency Medical Service (EMS)					1	0.788**	0.744**
Road with Lighting System (RLS)						1	0.585**
FR^{-1}							1

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

Table 3 Efficiency results for the 31 Iranian provinces in terms of road safety performance for the year 2014

Province	Optimistic SBM				Pessimistic SBM				Safety performance		
			Assessment distribution				Assessment distribution		Assessment distribution		
	$\tau_{optimistic}$	Rank	H_1	H_2	$\tau_{pessimistic}$	Rank	H_1	H_2	H_1	H_2	Rank
Azerbaijan E	0.2828	24	0.7172	0.2828	0.4346	24	0.4346	0.5654	0.5921	0.4079	24
Azerbaijan W	0.3427	21	0.6573	0.3427	0.3506	21	0.3506	0.6494	0.5048	0.4952	21
Ardabil	0.2414	27	0.7586	0.2414	1.0000	29	1.0000	0.0000	0.9125	0.0875	29
Isfahan	0.3308	22	0.6692	0.3308	0.3659	22	0.3659	0.6341	0.5211	0.4789	22
Alborz	1.0000	1	0.0000	1.0000	0.1093	1	0.1093	0.8907	0.0378	0.9622	1
Ilam	1.0000	1	0.0000	1.0000	0.2083	9	0.2083	0.7917	0.0746	0.9254	7
Bushehr	0.4626	17	0.5374	0.4626	0.2500	15	0.2500	0.7500	0.3715	0.6285	16
Tehran	1.0000	1	0.0000	1.0000	0.1832	8	0.1832	0.8168	0.0650	0.9350	6
Chaharmahal and Bakhtiari	0.6986	9	0.3014	0.6986	0.2250	12	0.2250	0.7750	0.2277	0.7723	11
Khorasan S	1.0000	1	0.0000	1.0000	0.1640	5	0.1640	0.8360	0.0578	0.9422	4
Khorasan R	0.2126	29	0.7874	0.2126	0.5686	28	0.5686	0.4314	0.7103	0.2897	28
Khorasan N	0.6563	11	0.3437	0.6563	0.1787	6	0.1787	0.8213	0.2245	0.7755	10
Khuzestan	1.0000	1	0.0000	1.0000	0.1816	7	0.1816	0.8184	0.0644	0.9356	5
Zanjan	0.2332	28	0.7668	0.2332	0.5059	27	0.5059	0.4941	0.6634	0.3366	27
Semnan	0.4515	18	0.5485	0.4515	0.2536	16	0.2536	0.7464	0.3801	0.6199	17
Sistan and Baluchistan	0.1287	31	0.8713	0.1287	1.0000	29	1.0000	0.0000	0.9552	0.0448	31
Fars	1.0000	1	0.0000	1.0000	0.2540	17	0.2540	0.7460	0.0925	0.9075	8
Qazvin	1.0000	1	0.0000	1.0000	0.1238	3	0.1238	0.8762	0.0430	0.9570	3
Qom	0.5263	12	0.4737	0.5263	0.2118	10	0.2118	0.7882	0.3124	0.6876	12
Kurdistan	0.2649	25	0.7351	0.2649	0.4707	25	0.4707	0.5293	0.6242	0.3758	25
Kerman	0.2856	23	0.7144	0.2856	0.4260	23	0.4260	0.5740	0.5853	0.4147	23
Kermamshah	0.3804	20	0.6196	0.3804	0.2866	20	0.2866	0.7134	0.4425	0.5575	20
Kohgiluyeh and Boyer-Ahmad	0.4649	15	0.5351	0.4649	0.2686	18	0.2686	0.7314	0.3814	0.6186	18
Golestan	0.4712	14	0.5288	0.4712	0.2330	14	0.2330	0.7670	0.3562	0.6438	14
Guilan	0.3988	19	0.6012	0.3988	0.2752	19	0.2752	0.7248	0.4245	0.5755	19
Lorestan	0.1545	30	0.8455	0.1545	1.0000	29	1.0000	0.0000	0.9457	0.0543	30
Mazandaran	0.5023	13	0.4977	0.5023	0.2171	11	0.2171	0.7829	0.3290	0.6710	13
Markazi	0.4632	16	0.5368	0.4632	0.2301	13	0.2301	0.7699	0.3590	0.6410	15
Hormozgan	1.0000	1	0.0000	1.0000	0.1199	2	0.1199	0.8801	0.0416	0.9584	2
Hamedan	0.2456	26	0.7544	0.2456	0.4794	26	0.4794	0.5206	0.6409	0.3591	26
Yazd	0.6968	10	0.3032	0.6968	0.1633	4	0.1633	0.8367	0.1960	0.8040	9

Khuzestan, *Qazvin* and *Hormozgan*, and it is ranked 17th, with an efficiency degree of 0.7460 from the pessimistic point of view, as shown in column 6 of Table 3. Obviously, the optimistic SBM model usually overestimates the efficiencies of Iranian provinces, since about 25 per cent of provinces are recognized as efficient according to the data set belonging to 2014. Consequently, the efficiency results might be biased. Furthermore, both efficiency and anti-efficiency degrees are important for having a better insight into the situation of each province in terms of road safety performance. For example, although *Kermanshah* ranks 20th from both optimistic and pessimistic points of view, the measured efficiency scores are respectively 0.3804 and 0.7134, which may lead to different policies. For this reason, the simultaneous evaluations of road safety performance based on the two perspectives seem to be necessary.

A comprehensive and unique indicator of road safety performance can be obtained by employing the ER algorithm as a method of combination. As presented in

Table 4 Efficiency results for the 31 Iranian provinces in terms of road safety performance for the year 2015

Province	Optimistic SBM				Pessimistic SBM				Safety performance		
			Assessment distribution				Assessment distribution		Assessment distribution		
	$T_{optimistic}$	Rank	H_1	H_2	$\tau_{pessimistic}$	Rank	H_1	H_2	H_1	H_2	Rank
Azerbaijan E	0.2863	23	0.7137	0.2863	0.5547	22	0.5547	0.4453	0.6595	0.3405	21
Azerbaijan W	0.2927	22	0.7073	0.2927	0.5420	20	0.5420	0.4580	0.6485	0.3515	20
Ardabil	0.3970	16	0.6030	0.3970	0.3788	15	0.3788	0.6212	0.4890	0.5110	15
Isfahan	0.2740	25	0.7260	0.2740	0.6164	23	0.6164	0.3836	0.7012	0.2988	23
Alborz	1.0000	1	0.0000	1.0000	0.1438	1	0.1438	0.8562	0.0503	0.9497	1
Ilam	1.0000	1	0.0000	1.0000	0.2667	4	0.2667	0.7333	0.0976	0.9024	3
Bushehr	0.5171	8	0.4829	0.5171	0.2917	7	0.2917	0.7083	0.3651	0.6349	8
Tehran	0.4281	12	0.5719	0.4281	0.3260	11	0.3260	0.6740	0.4381	0.5619	12
Chaharmahal and Bakhtiari	1.0000	1	0.0000	1.0000	0.2880	6	0.2880	0.7120	0.1062	0.8938	5
Khorasan S	0.5001	9	0.4999	0.5001	0.3232	10	0.3232	0.6768	0.3939	0.6061	9
Khorasan R	0.1673	30	0.8327	0.1673	1.0000	25	1.0000	0.0000	0.9409	0.0591	30
Khorasan N	0.4571	11	0.5429	0.4571	0.3426	12	0.3426	0.6574	0.4309	0.5691	11
Khuzestan	1.0000	1	0.0000	1.0000	0.2938	8	0.2938	0.7062	0.1086	0.8914	6
Zanjan	0.3010	21	0.6990	0.3010	0.5300	19	0.5300	0.4700	0.6367	0.3633	19
Semnan	0.3173	18	0.6827	0.3173	0.4899	17	0.4899	0.5101	0.6037	0.3963	17
Sistan and Baluchistan	0.2136	28	0.7864	0.2136	1.0000	25	1.0000	0.0000	0.9233	0.0767	28
Fars	0.2824	24	0.7176	0.2824	0.5508	21	0.5508	0.4492	0.6596	0.3404	22
Qazvin	0.4634	10	0.5366	0.4634	0.3172	9	0.3172	0.6828	0.4118	0.5882	10
Qom	0.4203	14	0.5797	0.4203	1.0000	25	1.0000	0.0000	0.8371	0.1629	25
Kurdistan	0.2615	26	0.7385	0.2615	1.0000	25	1.0000	0.0000	0.9045	0.0955	27
Kerman	0.1914	29	0.8086	0.1914	1.0000	25	1.0000	0.0000	0.9319	0.0681	29
Kermamshah	0.4265	13	0.5735	0.4265	0.3623	14	0.3623	0.6377	0.4612	0.5388	13
Kohgiluyeh and Boyer-Ahmad	1.0000	1	0.0000	1.0000	0.2386	2	0.2386	0.7614	0.0864	0.9136	2
Golestan	0.4128	15	0.5872	0.4128	0.3534	13	0.3534	0.6466	0.4640	0.5360	14
Guilan	0.3162	19	0.6838	0.3162	0.4900	18	0.4900	0.5100	0.6044	0.3956	18
Lorestan	0.1672	31	0.8328	0.1672	1.0000	25	1.0000	0.0000	0.9410	0.0590	31
Mazandaran	0.3851	17	0.6149	0.3851	0.3989	16	0.3989	0.6011	0.5084	0.4916	16
Markazi	0.3026	20	0.6974	0.3026	1.0000	25	1.0000	0.0000	0.8878	0.1122	26
Hormozgan	1.0000	1	0.0000	1.0000	0.2685	5	0.2685	0.7315	0.0983	0.9017	4
Hamedan	0.2295	27	0.7705	0.2295	0.7268	24	0.7268	0.2732	0.7844	0.2156	24
Yazd	0.6286	7	0.3714	0.6286	0.2410	3	0.2410	0.7590	0.2735	0.7265	7

section 3, a frame of discernment, $\Theta = \{H_1, H_2\}$, consisting of two hypotheses, H_1: not-efficient and H_2: efficient, is first defined [18, 19]. There are also two pieces of evidence, including the pessimistic and optimistic efficiencies. Accordingly, $E_j = \{e_{j1}, e_{j2}\}$ can be defined as follows:

$$S(e_{j1}) = \{(H_1, \beta_{j,1,1}), (H_2, \beta_{j,2,1})\}, j = 1, \ldots, n \tag{28}$$

$$S(e_{j2}) = \{(H_1, \beta_{j,1,2}), (H_2, \beta_{j,2,2})\}, j = 1, \ldots, n \tag{29}$$

where $S(e_{j1})$ and $S(e_{j2})$ respectively represent two assessment distributions regarding DMU_0, taking into account the optimistic and pessimistic perspectives. $(\beta_{j,1,1}, \beta_{j,2,1})$ and $(\beta_{j,1,2}, \beta_{j,2,2})$ respectively denote the belief degrees assigned to the propositions H_1 and H_2 based on the SBM models (3) and (6). Obviously, $\beta_{j,1,1} + \beta_{j,2,1} = 1$ and $\beta_{j,1,2} + \beta_{j,2,2} = 1$. Subsequently, the assessment distributions (28) and (29) are transformed to the following mass functions:

$$m_{j,1,1} = \omega_1 \beta_{j,1,1}, m_{j,2,1} = \omega_1 \beta_{j,2,1}, m_{j,\theta,1} = 1 - (m_{j,1,1} + m_{j,2,1}),$$
$$\tilde{m}_{j,\theta,1} = \omega_1 \left(1 - \beta_{j,1,1} - \beta_{j,2,1} \ \ j = 1, \ldots, n\right) \tag{30}$$

Table 5 Efficiency results for the 31 Iranian provinces in terms of road safety performance for the year 2016

Province	Optimistic SBM				Pessimistic SBM				Safety performance		
			Assessment distribution				Assessment distribution		Assessment distribution		
	$T_{optimistic}$	Rank	H_1	H_2	$\tau_{pessimistic}$	Rank	H_1	H_2	H_1	H_2	Rank
Azerbaijan E	0.3343	21	0.6657	0.3343	0.4984	21	0.4984	0.5016	0.5985	0.4015	20
Azerbaijan W	0.2812	25	0.7188	0.2812	0.5939	24	0.5939	0.4061	0.6846	0.3154	24
Ardabil	0.4724	16	0.5276	0.4724	0.3188	15	0.3188	0.6812	0.4075	0.5925	16
Isfahan	0.2353	27	0.7647	0.2353	0.6655	26	0.6655	0.3345	0.7494	0.2506	26
Alborz	1.0000	1	0.0000	1.0000	0.1403	2	0.1403	0.8597	0.0491	0.9509	2
Ilam	1.0000	1	0.0000	1.0000	0.1297	1	0.1297	0.8703	0.0452	0.9548	1
Bushehr	0.5236	11	0.4764	0.5236	0.2935	11	0.2935	0.7065	0.3625	0.6375	10
Tehran	0.1575	31	0.8425	0.1575	1.0000	27	1.0000	0.0000	0.9446	0.0554	31
Chaharmahal and Bakhtiari	0.6007	8	0.3993	0.6007	0.2593	7	0.2593	0.7407	0.2991	0.7009	7
Khorasan S	0.6784	5	0.3216	0.6784	0.2279	6	0.2279	0.7721	0.2398	0.7602	5
Khorasan R	0.2047	29	0.7953	0.2047	1.0000	27	1.0000	0.0000	0.9268	0.0732	29
Khorasan N	0.5569	9	0.4431	0.5569	0.2751	8	0.2751	0.7249	0.3326	0.6674	9
Khuzestan	0.4288	18	0.5712	0.4288	0.3861	18	0.3861	0.6139	0.4742	0.5258	18
Zanjan	0.3922	19	0.6078	0.3922	0.3920	19	0.3920	0.6080	0.4999	0.5001	19
Semnan	0.4869	15	0.5131	0.4869	0.3207	16	0.3207	0.6793	0.4001	0.5999	15
Sistan and Baluchistan	0.2079	28	0.7921	0.2079	1.0000	27	1.0000	0.0000	0.9255	0.0745	28
Fars	0.2984	24	0.7016	0.2984	0.5086	22	0.5086	0.4914	0.6259	0.3741	22
Qazvin	0.6651	6	0.3349	0.6651	0.2275	5	0.2275	0.7725	0.2466	0.7534	6
Qom	0.5034	14	0.4966	0.5034	0.2778	9	0.2778	0.7222	0.3647	0.6353	11
Kurdistan	0.3895	20	0.6105	0.3895	1.0000	27	1.0000	0.0000	0.8508	0.1492	27
Kerman	0.2612	26	0.7388	0.2612	0.6127	25	0.6127	0.3873	0.7065	0.2935	25
Kermamshah	0.5306	10	0.4694	0.5306	0.3082	13	0.3082	0.6918	0.3672	0.6328	12
Kohgiluyeh and Boyer-Ahmad	1.0000	1	0.0000	1.0000	0.1602	3	0.1602	0.8398	0.0564	0.9436	3
Golestan	0.6022	7	0.3978	0.6022	0.2835	10	0.2835	0.7165	0.3121	0.6879	8
Guilan	0.4472	17	0.5528	0.4472	0.3637	17	0.3637	0.6363	0.4496	0.5504	17
Lorestan	0.1849	30	0.8151	0.1849	1.0000	27	1.0000	0.0000	0.9343	0.0657	30
Mazandaran	0.5226	13	0.4774	0.5226	0.3085	14	0.3085	0.6915	0.3720	0.6280	14
Markazi	0.3209	22	0.6791	0.3209	0.4957	20	0.4957	0.5043	0.6049	0.3951	21
Hormozgan	1.0000	1	0.0000	1.0000	0.1880	4	0.1880	0.8120	0.0669	0.9331	4
Hamedan	0.3021	23	0.6979	0.3021	0.5386	23	0.5386	0.4614	0.6410	0.3590	23
Yazd	0.5235	12	0.4765	0.5235	0.3038	12	0.3038	0.6962	0.3687	0.6313	13

$$m_{j,1,2} = \omega_2\, \beta_{j,1,2}, m_{j,2,2} = \omega_2\, \beta_{j,2,2}, m_{j,\theta,2} = 1-\left(m_{j,1,2} + m_{j,2,2}\right),$$
$$\tilde{m}_{j,\theta,2} = \omega_2\left(1-\beta_{j,1,2}-\beta_{j,2,2}\right) \quad j = 1, \ldots, n \tag{31}$$

Eventually, the aggregated distributions can be computed using Eqs. (18)–(21). The final efficiency scores (column 11) and associated ranking results (column 12) for the years 2014–2016 are respectively reported in Tables 3, 4 and 5. Obviously, the discrimination power of DF-SBM-ER is higher than both the optimistic and pessimistic SBM models.

5 Results and discussion

As graphically shown in Figs. 1, 2 and 3, *Alborz, Hormozgan*, and *Qazvin* rank 1st (0.9622), 2nd (0.9584) and 3rd (0.9570) in 2014 respectively; *Alborz, Kohgiluyeh-and--Boyer-Ahmad* and *Ilam* rank 1st (0.9497), 2nd (0.9136) and 3rd (0.9024) in 2015 respectively; *Ilam, Alborz* and *Kohgiluyeh-and-Boyer-Ahmad* rank 1st (0.9548), 2nd (0.9509) and 3rd (0.9436) in 2016 respectively.

Similar results can be obtained using the double frontier CCR model aggregated by ER approach (DF-CCR-ER). These results are compared in Table 6 and Fig. 4. For more discussion on DF-CCR-ER, the

Fig. 1 Iranian road safety performance obtained using DF-SBM-ER for the year 2014

interested readers are referred to [15, 19]. As proved, the efficiency and anti-efficiency degrees obtained by SBM are equal or less than those obtained by the CCR model. Compared with CCR, the SBM based models result in higher optimistic and lower pessimistic degrees of efficiency. As a result, some aggregated results achieved by DF-SBM-ER are greater than those obtained by DF-CCR-ER [15]. In such a situation, the aggregated efficiencies are closer to the pessimistic efficiency compared to the optimistic results.

The efficiency and anti-efficiency results obtained by SBM and Super SBM for evaluating 31 Iranian provinces over two periods of time (2014-2015 and 2015-2016) are summarized in Tables 7 and 8. In order to further analyzethe road safety performance over a period of time (2014–2016), the super efficiency scores of the efficient provinces, $D_0^t(x_0^t, y_0^t) = 1$, are computed by implementing the optimistic Super SBM model (43), $\tilde{D}_0^t(x_0^t, y_0^t)$. For example, the super efficiency values of the eight efficient provinces in 2014, *Alborz*, *Ilam*, *Tehran*, *Khorasan S*, *Khuzestan*, *Fars*, *Qazvin* and *Hormozgan*, were 1.2176, 1.0467, 1.0349, 1.0307, 1.0125, 1.0433, 1.0269 and 1.2585 respectively. Similarly, the super anti-efficiency scores of anti-efficient provinces, $d_0^t(x_0^t, y_0^t) = 1$, are computed by employing the pessimistic Super-SBM model (47), $\tilde{d}_0^t(x_0^t, y_0^t)$.

As shown in Table 7, twelve provinces optimistically improved their efficiency from 2014 to 2015, as $OEC \geq 1$, while only three provinces experienced efficiency progress from the pessimistic point of view, as $PEC \geq 1$. Taking into account the optimistic point of view,

Fig. 2 Iranian road safety performance obtained using DF-SBM-ER for the year 2015

Kohgiluye-and-Boyer-Ahmad showed the highest efficiency progress, with a growth rate of 83.84% from 2014 to 2015, while *Fars* experienced the highest efficiency regression, with a decline of 72.93%. On average, the Iranian road safety performance declined in terms of efficiency change from both the optimistic and pessimistic perspectives, with a rate of 11.61% and 37.27% decline respectively, from 2014–2015. Furthermore, among the twenty two provinces with optimistic technical progress, *Mazandaran* experienced the highest change, with an improvement of 5.58%; meanwhile, *Qom* pessimistically experienced the highest technical change, with a growth rate of 127.83%. It is noted that on average, the technical efficiency of provinces in terms of road safety performance optimistically declined by 2.43% while pessimistically improved 37.79%. Fig. 5 (a) illustrates that the road safety performance of ten provinces optimistically progressed from 2014 to 2015, as $OMPI \geq 1$; additionally, nine provinces pessimistically showed improvement in terms of road safety performance, as $PMPI \geq 1$. Generally speaking, the Iranian road safety performance, however, declined by an average rate of about 14% from both the optimistic and pessimistic perspectives.

As illustrated in Table 8 and Fig. 5 (b), no province technically showed any progress in road safety performance from 2015 to 2016, as $OMPI \leq 1$ and $PMPI \leq 1$. This is mainly because of a significant decrease in average technical change over the period of time from 2015–2016, with 42.05% optimistic decline and a 45.81% pessimistic drop. On average, the efficiency of Iranian provinces optimistically progressed by about 7% from

Fig. 3 Iranian road safety performance obtained using DF-SBM-ER for the year 2016

2015 to 2016; meanwhile, Iranian provinces pessimistically showed an increase of nearly 19%.

The rather different results can be addressed by computing the integrated *OMPI* and *PMPI*. For this purpose, double frontier MPIs are obtained using a geometric integration of *OMPIs* and *PMPIs* through Eq. (27). Table 9 and Fig. 6 provide the achieved double frontier MPIs with associated components, efficiency and technical changes, for all Iranian provinces in terms of road safety performance from 2014–2016. Although technical changes in Iranian provinces optimistically dropped by an average of 2.43% between 2014 and 2015 (Table 7), the double frontier MPI shows an average rise of about 16%.

Fig. 6 graphically displays the double frontier MPIs for two-year (2014–2015 and 2015–2016) and three-year (2014–2016) evaluations. As illustrated in Table 9 and Fig. 6, the overall double frontier MPI demonstrates that most Iranian provinces were unproductive in road safety performance from 2014 to 2016. Iranian road safety performance declined by an average of 26.06%, mainly due to technical negative changes (19.39% decrease), over the time period 2014–2016. During the time period 2015–2016, the road safety performance of Iranian provinces dropped by an average rate of 36.68%, mainly due to a significant reduction of about 44% in technical changes, while the average integrated efficiency progressed with a mean rate of around 13%. During the time period 2014–2015, Iranian road safety performance declined by an average of 13.66%, largely owing to a considerable decrease of 25.54% in efficiency changes, while the integrated technical changes improved at a mean rate of about 16%.

Table 6 Comparisons between the Efficiency results for Iranian road safety performance obtained using DF-SBM-ER and DF-CCR-ER [15] methods

Province	2014				2015				2016			
	DF-CCR-ER		DF-SBM-ER		DF-CCR-ER		DF-SBM-ER		DF-CCR-ER		DF-SBM-ER	
	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank
Azerbaijan E	0.3253	24	0.4079	24	0.3362	20	0.3405	21	0.2952	22	0.4015	20
Azerbaijan W	0.3463	23	0.4952	21	0.2656	24	0.3515	20	0.2104	25	0.3154	24
Ardabil	0.1126	29	0.0875	29	0.4106	14	0.5110	15	0.6326	14	0.5925	16
Isfahan	0.3918	21	0.4789	22	0.3411	19	0.2988	23	0.1364	27	0.2506	26
Alborz	0.9289	2	0.9622	1	0.9197	1	0.9497	1	0.9348	1	0.9509	2
Ilam	0.8053	8	0.9254	7	0.7952	6	0.9024	3	0.9049	2	0.9548	1
Bushehr	0.5988	12	0.6285	16	0.6627	9	0.6349	8	0.6492	13	0.6375	10
Tehran	0.7614	11	0.9350	6	0.3876	15	0.5619	12	0.0669	31	0.0554	31
Chaharmahal and Bakhtiari	0.8134	7	0.7723	11	0.8027	5	0.8938	5	0.5905	16	0.7009	7
Khorasan S	0.8974	3	0.9422	4	0.6862	8	0.6061	9	0.8260	6	0.7602	5
Khorasan R	0.1823	27	0.2897	28	0.093	30	0.0591	30	0.0914	28	0.0732	29
Khorasan N	0.8215	5	0.7755	10	0.6196	10	0.5691	11	0.6889	9	0.6674	9
Khuzestan	0.8014	9	0.9356	5	0.719	7	0.8914	6	0.5897	17	0.5258	18
Zanjan	0.2718	25	0.3366	27	0.3508	17	0.3633	19	0.4795	19	0.5001	19
Semnan	0.5688	16	0.6199	17	0.2918	23	0.3963	17	0.6559	12	0.5999	15
Sistan and Baluchistan	0.0613	31	0.0448	31	0.1303	27	0.0767	28	0.0832	29	0.0745	28
Fars	0.7827	10	0.9075	8	0.3437	18	0.3404	22	0.3343	21	0.3741	22
Qazvin	0.8973	4	0.9570	3	0.5304	12	0.5882	10	0.8273	5	0.7534	6
Qom	0.5051	18	0.6876	12	0.2972	22	0.1629	25	0.6868	10	0.6353	11
Kurdistan	0.1313	28	0.3758	25	0.1591	26	0.0955	27	0.1897	26	0.1492	27
Kerman	0.3717	22	0.4147	23	0.1001	29	0.0681	29	0.2477	23	0.2935	25
Kermamshah	0.4929	19	0.5575	20	0.5547	11	0.5388	13	0.5982	15	0.6328	12
Kohgiluyeh and Boyer-Ahmad	0.5853	14	0.6186	18	0.871	3	0.9136	2	0.8818	4	0.9436	3
Golestan	0.5505	17	0.6438	14	0.427	13	0.5360	14	0.7139	8	0.6879	8
Guilan	0.4532	20	0.5755	19	0.302	21	0.3956	18	0.5543	18	0.5504	17
Lorestan	0.0675	30	0.0543	30	0.0812	31	0.0590	31	0.0791	30	0.0657	30
Mazandaran	0.5878	13	0.6710	13	0.3778	16	0.4916	16	0.7595	7	0.6280	14
Markazi	0.5827	15	0.6410	15	0.1968	25	0.1122	26	0.3491	20	0.3951	21
Hormozgan	0.9335	1	0.9584	2	0.879	2	0.9017	4	0.8869	3	0.9331	4
Hamedan	0.1839	26	0.3591	26	0.1265	28	0.2156	24	0.2269	24	0.3590	23
Yazd	0.8162	6	0.8040	9	0.8378	4	0.7265	7	0.6600	11	0.6313	13

As shown in Fig. 6 and Table 9, only three provinces, *Ardabil, Zanjan and Kohgiluyeh-and-Boyer-Ahmad*, progressed in road safety performance with growth rates of 32.95%, 3.27% and 10.44% respectively. The main reason for their improvement was efficiency enhancement, while they experienced a decline in technology from 2014 to 2016. On the other hand, *Tehran* experienced the most negative growth in road safety performance during the three-year evaluation (2014–2016) by taking into account the optimistic and pessimistic points of view, with a mean rate of 66.96% decline in MPI; meanwhile, it achieved a negative growth not only in efficiency but also in technology, with mean rates of 60.67% (decrease) and 16% (decrease) respectively. Therefore, it can be concluded that *Tehran's* negative growth in road safety performance was mainly influenced by negative changes in efficiency, since it is technically recognized as one of the top six provinces. As clearly shown in Tables 3, 4 and 5, the efficiency of *Tehran* optimistically declined from 1.00 (super efficiency of 1.0349) (rank 1st) in 2014 to 0.4281 (rank 12th) in 2015 and then to 0.1575 (rank 31th) in 2016. From the pessimistic point of view, the efficiency of *Tehran* decreased from

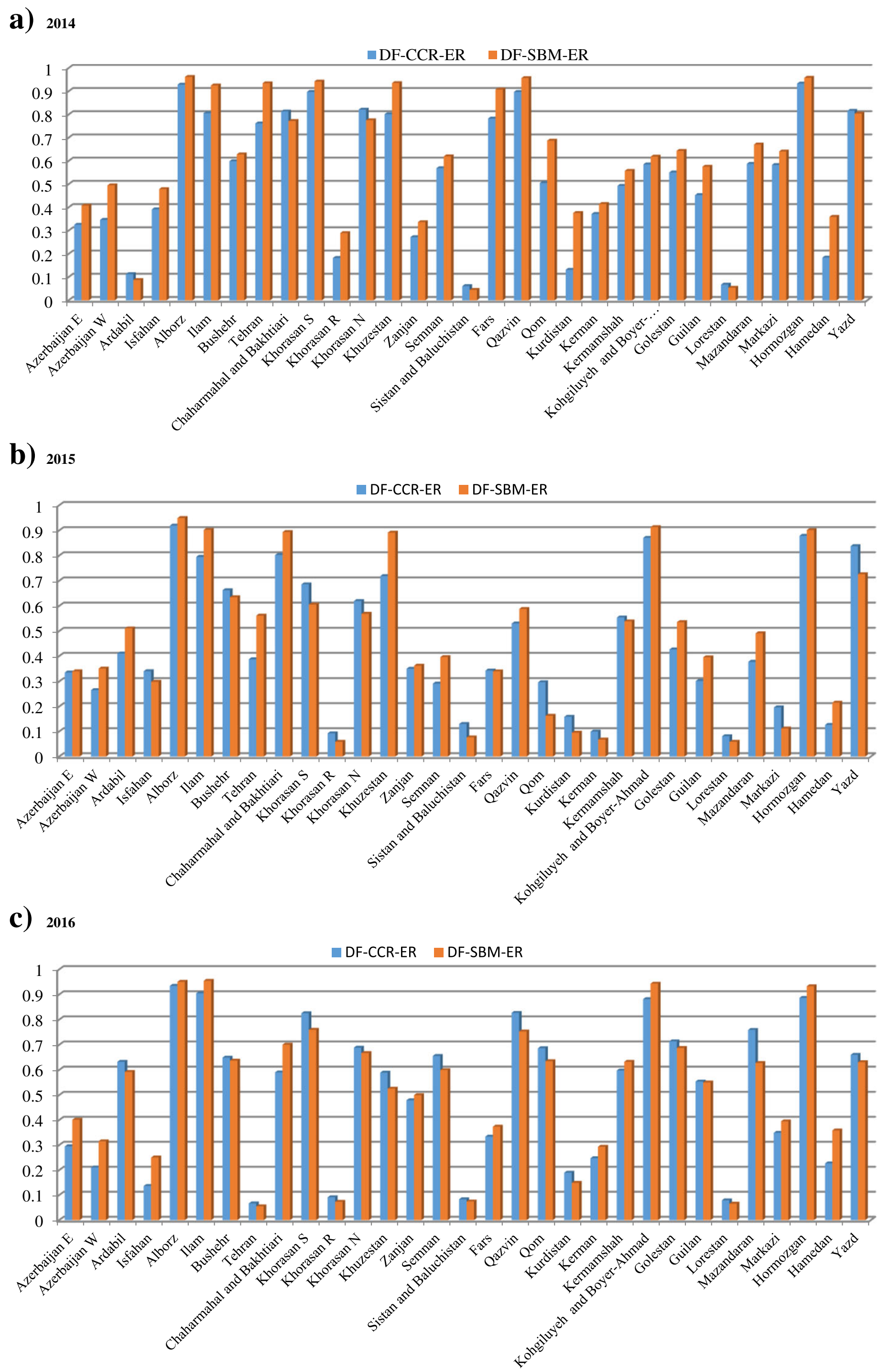


Fig. 4 Comparisons between the efficiency results obtained using DF-CCR-ER and DF-SBM-ER [15] methods

0.8168 (rank 8^{th}) in 2014 to 0.6740 (rank 11^{th}) in 2015 and then to 0.00 (rank 27^{th}) in 2016.

More precisely, the MPI values alone are not enough to evaluate a province in terms of road safety performance, and a province should also be productive with respect to both technical and efficiency components. Figures 7, 8 and 9 depict the status of Iranian provinces in terms of road safety performance in Cartesian coordinates, with efficiency changes as the vertical axis and technical changes as the horizontal axis. The coordinates

Table 7 OMPI and PMPI values for the 31 Iranian provinces (2014-2015)

Provinces	$D_0^{14}(x_0^{14},y_0^{14})$	$D_0^{14}(x_0^{15},y_0^{15})$	$D_0^{15}(x_0^{15},y_0^{15})$	$D_0^{15}(x_0^{14},y_0^{14})$	OEC	OTC	OMPI
	$\tilde{\mathbf{D}}_0^{14}(\mathbf{x}_0^{14},\mathbf{y}_0^{14})$	$\tilde{\mathbf{D}}_0^{14}(\mathbf{x}_0^{15},\mathbf{y}_0^{15})$	$\tilde{\mathbf{D}}_0^{15}(\mathbf{x}_0^{15},\mathbf{y}_0^{15})$	$\tilde{\mathbf{D}}_0^{15}(\mathbf{x}_0^{14},\mathbf{y}_0^{14})$			
OMPI							
Azerbaijan E	0.2828	0.2870	0.2863	0.2830	1.0125	1.0008	1.0133
Azerbaijan W	0.3427	0.3049	0.2927	0.3297	0.8541	1.0404	0.8886
Ardabil	0.2414	0.4168	0.3970	0.2300	1.6444	1.0496	1.7260
Isfahan	0.3308	0.2710	0.2740	0.3373	0.8284	0.9848	0.8158
Alborz	*1.2176*	*1.2753*	*1.7734*	0.9535	1.4565	0.9583	1.3957
Ilam	*1.0467*	0.9334	*1.1475*	*1.1850*	1.0963	0.8476	0.9293
Bushehr	0.4626	0.5409	0.5171	0.4429	1.1179	1.0453	1.1684
Tehran	*1.0349*	0.4502	0.4281	*1.0417*	0.4136	1.0221	0.4228
Chaharmahal and Bakhtiari	0.6986	0.6110	*1.0309*	*1.0492*	1.4757	0.6282	0.9270
Khorasan S	*1.0307*	0.5081	0.5001	*1.0616*	0.4852	0.9932	0.4819
Khorasan R	0.2126	0.1705	0.1673	0.2132	0.7872	1.0078	0.7934
Khorasan N	0.6563	0.4767	0.4571	0.6751	0.6965	1.0069	0.7013
Khuzestan	*1.0125*	0.5557	*1.0381*	*1.0681*	1.0253	0.7123	0.7303
Zanjan	0.2332	0.3123	0.3010	0.2247	1.2909	1.0375	1.3394
Semnan	0.4515	0.3326	0.3173	0.4315	0.7027	1.0474	0.7360
Sistan and Baluchistan	0.1287	0.1952	0.2136	0.1314	1.6601	0.9459	1.5703
Fars	*1.0433*	0.2946	0.2824	*1.0691*	0.2707	1.0091	0.2731
Qazvin	*1.0269*	0.4847	0.4634	*1.0210*	0.4513	1.0257	0.4629
Qom	0.5263	0.4422	0.4203	0.5006	0.7986	1.0517	0.8399
Kurdistan	0.2649	0.2674	0.2615	0.2584	0.9874	1.0238	1.0109
Kerman	0.2856	0.2003	0.1914	0.2728	0.6701	1.0467	0.7014
Kermamshah	0.3804	0.4431	0.4265	0.3665	1.1211	1.0384	1.1642
Kohgiluyeh and Boyer-Ahmad	0.4649	0.6942	*1.0360*	0.4577	2.2285	0.8249	1.8384
Golestan	0.4712	0.4334	0.4128	0.4491	0.8761	1.0495	0.9195
Guilan	0.3988	0.3314	0.3162	0.3809	0.7931	1.0474	0.8307
Lorestan	0.1545	0.1744	0.1672	0.1482	1.0822	1.0426	1.1283
Mazandaran	0.5023	0.4069	0.3851	0.4760	0.7668	1.0558	0.8096
Markazi	0.4632	0.3168	0.3026	0.4436	0.6534	1.0455	0.6831
Hormozgan	*1.2585*	0.6100	*1.0160*	*1.2320*	0.8073	0.7831	0.6322
Hamedan	0.2456	0.2388	0.2295	0.2361	0.9345	1.0404	0.9723
Yazd	0.6968	0.6599	0.6286	0.6669	0.9021	1.0473	0.9448
Mean					*0.8839*	*0.9757*	*0.8625*
Provinces	$d_0^{14}(x_0^{14},y_0^{14})$	$d_0^{14}(x_0^{15},y_0^{15})$	$d_0^{15}(x_0^{15},y_0^{15})$	$d_0^{15}(x_0^{14},y_0^{14})$	PEC	PTC	PMPI
	$\boldsymbol{d}_0^{14}(\boldsymbol{x}_0^{14},\boldsymbol{y}_0^{14})$	$\tilde{\boldsymbol{d}}_0^{14}(\boldsymbol{x}_0^{15},\boldsymbol{y}_0^{15})$	$\tilde{\boldsymbol{d}}_0^{15}(\boldsymbol{x}_0^{15},\boldsymbol{y}_0^{15})$	$\tilde{\boldsymbol{d}}_0^{15}(\boldsymbol{x}_0^{14},\boldsymbol{y}_0^{14})$			
PMPI							
Azerbaijan E	2.3009	2.3417	1.8027	1.7792	0.7835	1.2961	1.0155
Azerbaijan W	2.8521	2.5745	1.8450	2.0620	0.6469	1.3893	0.8987
Ardabil	*0.9797*	3.9403	2.6402	*0.9721*	2.6951	1.2264	3.3052
Isfahan	2.7331	2.2582	1.6224	2.0312	0.5936	1.3685	0.8124
Alborz	9.1483	9.6453	6.9547	6.5986	0.7602	1.3866	1.0542
Ilam	4.8018	4.3584	3.7500	4.0278	0.7810	1.1771	0.9193

Table 7 OMPI and PMPI values for the 31 Iranian provinces (2014-2015) *(Continued)*

Bushehr	4.0002	2.7508	3.4279	2.9205	0.8569	1.0484	0.8984
Tehran	5.4571	4.2718	3.0670	4.2371	0.5620	1.3393	0.7527
Chaharmahal and Bakhtiari	4.4454	4.3437	3.4720	3.5808	0.7810	1.2462	0.9734
Khorasan S	6.0988	4.1753	3.0937	4.6462	0.5073	1.3310	0.6752
Khorasan R	1.7587	*0.9927*	*0.9089*	1.2701	0.5168	1.2297	0.6355
Khorasan N	5.5964	4.0740	2.9191	3.9972	0.5216	1.3979	0.7291
Khuzestan	5.5058	4.8922	3.4037	3.8011	0.6182	1.4429	0.8920
Zanjan	1.9768	2.6323	1.8868	1.3178	0.9544	1.4466	1.3807
Semnan	3.9429	3.0174	2.0413	2.8193	0.5177	1.4378	0.7444
Sistan and Baluchistan	*0.7627*	*0.9300*	*0.9427*	*0.7609*	1.2361	0.9944	1.2291
Fars	3.9377	2.4512	1.8157	3.3864	0.4611	1.2529	0.5777
Qazvin	8.0790	2.4512	3.1530	5.6208	0.3903	1.0571	0.4125
Qom	4.7212	3.7199	*0.9994*	3.3855	0.2117	2.2783	0.4823
Kurdistan	2.1244	2.1420	*0.9609*	*0.9580*	0.4523	2.2233	1.0057
Kerman	2.3477	1.6414	*0.9895*	1.7472	0.4215	1.4929	0.6292
Kermamshah	3.4888	3.9413	2.7598	2.3755	0.7910	1.4482	1.1456
Kohgiluyeh and Boyer-Ahmad	3.7229	5.5251	4.1917	2.7982	1.1259	1.3243	1.4910
Golestan	4.2919	3.9702	2.8295	3.0585	0.6592	1.4032	0.9251
Guilan	3.6343	2.8922	2.0408	2.4890	0.5615	1.4385	0.8078
Lorestan	*0.9500*	1.2498	*0.9032*	*0.8539*	0.9508	1.2407	1.1796
Mazandaran	4.6067	3.2851	2.5066	3.0967	0.5441	1.3963	0.7598
Markazi	4.3466	2.3358	*0.9889*	3.0433	0.2275	1.8367	0.4179
Hormozgan	8.3428	5.0643	3.7247	6.0590	0.4465	1.3683	0.6109
Hamedan	2.0858	2.0317	1.3760	1.4272	0.6597	1.4690	0.9691
Yazd	6.1221	5.7688	4.1485	4.2521	0.6776	1.4149	0.9588
Mean					*0.6273*	*1.3779*	*0.8643*

of the origin is also defined as the point (1,1), where the vertical and technical axes intersect.

Although the optimistic MPIs indicate that ten provinces are productive in road safety performance (Table 7), Fig. 7. a displays that six provinces were located in the 1st quadrant, which means that these provinces optimistically increased their efficiency and technology from 2014–2015. Pessimistically, only two provinces, *Ardabil* and *Kohgiluyeh-and-Boyer-Ahmad*, were located in the 1st quadrant (Fig. 7.b), and the pessimistic MPI (Table 7) shows that nine provinces are productive. As shown in Fig. 7.c, the double-frontier assessment also demonstrates that five provinces simultaneously enhanced their productivity on road safety, taking into account both components, from 2014–2015. Briefly, the Iranian provinces were mostly productive in terms of technological advancement, since most provinces were in the 1st and 2nd quadrants from 2014–2015.

As shown in Fig. 8 (a) –(c), unfortunately, no provinces were positioned in the first quadrant, which means that all provinces declined their productivity from 2015–2016. On the other hand, most provinces were in the third quadrant, which means that Iranian provinces were mostly productive in terms of efficiency enhancement in 2015–2016.

Generally speaking, the three-year assessment from 2014 to 2016, as illustrated in Fig. 9, indicates that most Iranian provinces were located in the 3th and 4th quadrants meaning that they are in general unsuccessful in road safety performance in terms of technology advancement; meanwhile, eleven provinces progressed in road safety performance in terms of efficiency improvement.

For more discussion, the input and output slack variables can be further analyzed. For example, the existing data set, slack values and the deviations of input and output variables for *Qom* province based on the efficient frontier are shown in Tables 10, 11 and 12 respectively. As illustrated, the maximum deviation for *Qom* province is related to the input variable *RLS* with a deviation of about 67%. The results also demonstrate that there is no deviation in the input variable of *EMS*. Similarly, the relative deviation of input and output variables for all

Table 8 OMPI and PMPI values for the 31 Iranian provinces (2015-2016)

Provinces	$D_0^{15}(x_0^{15}, y_0^{15})$	$D_0^{15}(x_0^{16}, y_0^{16})$	$D_0^{16}(x_0^{16}, y_0^{16})$	$D_0^{16}(x_0^{15}, y_0^{15})$	OEC	OTC	OMPI
	$\tilde{\boldsymbol{D}}_{\mathbf{0}}^{\mathbf{15}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{15}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{15}})$	$\tilde{\boldsymbol{D}}_{\mathbf{0}}^{\mathbf{15}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{16}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{16}})$	$\tilde{\boldsymbol{D}}_{\mathbf{0}}^{\mathbf{16}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{16}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{16}})$	$\tilde{\boldsymbol{D}}_{\mathbf{0}}^{\mathbf{16}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{15}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{15}})$			
OMPI							
Azerbaijan E	0.2863	0.1908	0.3343	0.5138	1.1676	0.5640	0.6585
Azerbaijan W	0.2927	0.1617	0.2812	0.5291	0.9606	0.5641	0.5419
Ardabil	0.3970	0.2940	0.4724	0.6423	1.1899	0.6202	0.7380
Isfahan	0.2740	0.1480	0.2353	0.4553	0.8587	0.6152	0.5282
Alborz	*1.7734*	0.6387	*1.5789*	*2.1783*	0.8903	0.5739	0.5109
Ilam	*1.1475*	*1.0624*	*1.3190*	*1.3890*	1.1494	0.8158	0.9376
Bushehr	0.5171	0.3292	0.5236	*1.0139*	1.0125	0.5663	0.5733
Tehran	0.4281	0.0988	0.1575	*1.0094*	0.3679	0.5157	0.1897
Chaharmahal and Bakhtiari	*1.0309*	0.3343	0.6007	*1.0945*	0.5827	0.7240	0.4219
Khorasan S	0.5001	0.4181	0.6784	*1.0646*	1.3565	0.5381	0.7299
Khorasan R	0.1673	0.1249	0.2047	0.2801	1.2233	0.6039	0.7387
Khorasan N	0.4571	0.3370	0.5569	0.7962	1.2183	0.5894	0.7181
Khuzestan	*1.0381*	0.2455	0.4288	*1.2626*	0.4131	0.6862	0.2834
Zanjan	0.3010	0.2409	0.3922	0.5116	1.3030	0.6011	0.7832
Semnan	0.3173	0.3053	0.4869	0.5058	1.5347	0.6271	0.9625
Sistan and Baluchistan	0.2136	0.1267	0.2079	0.3412	0.9732	0.6176	0.6011
Fars	0.2824	0.1850	0.2984	0.4959	1.0566	0.5941	0.6278
Qazvin	0.4634	0.3990	0.6651	*1.0423*	1.4351	0.5165	0.7412
Qom	0.4203	0.3252	0.5034	*1.0056*	1.1977	0.5196	0.6223
Kurdistan	0.2615	0.2211	0.3895	0.4603	1.4892	0.5679	0.8457
Kerman	0.1914	0.1552	0.2612	0.3279	1.3649	0.5890	0.8038
Kermamshah	0.4265	0.2913	0.5306	*1.0175*	1.2441	0.4797	0.5968
Kohgiluyeh and Boyer-Ahmad	*1.0360*	0.5375	*1.1429*	*1.2945*	1.1032	0.6135	0.6768
Golestan	0.4128	0.3147	0.6022	*1.0148*	1.4589	0.4610	0.6726
Guilan	0.3162	0.2589	0.4472	0.5545	1.4141	0.5746	0.8125
Lorestan	0.1672	0.1122	0.1849	0.3008	1.1056	0.5809	0.6422
Mazandaran	0.3851	0.3095	0.5226	*1.0263*	1.3570	0.4714	0.6397
Markazi	0.3026	0.1894	0.3209	0.5100	1.0604	0.5919	0.6276
Hormozgan	*1.0160*	0.5313	*1.1155*	*1.3389*	1.0979	0.6012	0.6601
Hamedan	0.2295	0.1696	0.3021	0.4176	1.3165	0.5554	0.7311
Yazd	0.6286	0.3213	0.5235	*1.2915*	0.8328	0.5465	0.4551
Mean					*1.0706*	*0.5795*	*0.6204*
Provinces	$d_0^{15}(x_0^{15}, y_0^{15})$	$d_0^{15}(x_0^{16}, y_0^{16})$	$d_0^{16}(x_0^{16}, y_0^{16})$	$d_0^{16}(x_0^{15}, y_0^{15})$	PEC	PTC	PMPI
	$\boldsymbol{d}_{\mathbf{0}}^{\mathbf{15}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{15}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{15}})$	$\tilde{\boldsymbol{d}}_{\mathbf{0}}^{\mathbf{15}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{16}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{16}})$	$\tilde{\boldsymbol{d}}_{\mathbf{0}}^{\mathbf{16}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{16}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{16}})$	$\tilde{\boldsymbol{d}}_{\mathbf{0}}^{\mathbf{16}}(\boldsymbol{x}_{\mathbf{0}}^{\mathbf{15}}, \boldsymbol{y}_{\mathbf{0}}^{\mathbf{15}})$			
PMPI							
Azerbaijan E	1.8027	*0.9952*	2.0065	3.4933	1.1130	0.5059	0.5631
Azerbaijan W	1.8450	*0.9132*	1.6839	3.3195	0.9126	0.5490	0.5011
Ardabil	2.6402	1.9507	3.1363	4.2084	1.1879	0.6247	0.7420
Isfahan	1.6224	*0.8902*	1.5026	2.9699	0.9261	0.5689	0.5269
Alborz	6.9547	4.5652	7.1264	10.8206	1.0247	0.6417	0.6575
Ilam	3.7500	3.6444	7.7097	8.4609	2.0559	0.4577	0.9410

Table 8 OMPI and PMPI values for the 31 Iranian provinces (2015-2016) *(Continued)*

Bushehr	3.4279	2.1886	3.4073	5.6397	0.9940	0.6248	0.6211
Tehran	3.0670	*0.6598*	*0.8579*	4.7441	0.2797	0.7051	0.1972
Chaharmahal and Bakhtiari	3.4720	2.0628	3.8560	6.8044	1.1106	0.5225	0.5802
Khorasan S	3.0937	2.5899	4.3876	5.8182	1.4182	0.5602	0.7945
Khorasan R	*0.9089*	*0.7301*	*0.9875*	1.7403	1.0864	0.6214	0.6751
Khorasan N	2.9191	2.1175	3.6344	4.9800	1.2451	0.5844	0.7276
Khuzestan	3.4037	*0.9210*	2.5899	6.0655	0.7609	0.4467	0.3399
Zanjan	1.8868	1.5159	2.5513	3.3254	1.3522	0.5806	0.7851
Semnan	2.0413	1.9541	3.1181	3.2418	1.5275	0.6282	0.9595
Sistan and Baluchistan	*0.9427*	*0.7047*	*0.8512*	2.1527	0.9029	0.6021	0.5436
Fars	1.8157	*0.9518*	1.9661	3.2007	1.0828	0.5240	0.5674
Qazvin	3.1530	2.7874	4.3957	5.1310	1.3941	0.6242	0.8703
Qom	*0.9994*	*0.9206*	3.5998	4.7038	3.6019	0.2331	0.8396
Kurdistan	*0.9609*	*0.9374*	*0.9770*	2.3753	1.0168	0.6230	0.6334
Kerman	*0.9895*	*0.9189*	1.6322	2.1255	1.6495	0.5120	0.8445
Kermamshah	2.7598	1.8778	3.2442	4.7679	1.1755	0.5788	0.6804
Kohgiluyeh and Boyer-Ahmad	4.1917	3.4689	6.2438	8.0350	1.4896	0.5384	0.8019
Golestan	2.8295	2.0083	3.5271	4.6297	1.2466	0.5899	0.7354
Guilan	2.0408	1.5210	2.7493	3.3825	1.3472	0.5777	0.7783
Lorestan	*0.9032*	*0.7246*	*0.9922*	1.9070	1.0985	0.5881	0.6461
Mazandaran	2.5066	*0.9784*	3.2417	4.0088	1.2933	0.4344	0.5618
Markazi	*0.9889*	*0.9340*	2.0174	3.3470	2.0401	0.3698	0.7545
Hormozgan	3.7247	3.0950	5.3188	7.2127	1.4280	0.5482	0.7828
Hamedan	1.3760	*0.9527*	1.8566	2.5482	1.3493	0.5264	0.7103
Yazd	4.1485	2.0537	3.2917	7.1689	0.7935	0.6009	0.4768
Mean					1.1926	0.5419	0.6462

provinces can be achieved for 2014-2016. The average deviation of input and output variables are demonstrated in Fig. 10. It has to be noted that an efficient province, in this regard, is a province with fewer investments in road safety and, consequently, fewer fatalities. As shown in Fig. 10, Iranian provinces experienced a high deviation in road fatalities; i.e. 75% on average. The results also demonstrate that the deviation of road fatality rate has been reduced to some extent from 2014 (around 91%) to 2016 (about 75%). Regarding the input variables, the highest deviation was related to *E&V*, which indicates an improper distribution of this variable in provinces, with a deviation of around 58% in 2016, 50% in 2015, and 33% in 2014. The second highest deviation regarding the input variables in 2015 and 2016 was related to the variable *PS*, with a deviation of more than 30%, compared to a deviation of about 21% in 2014, which ranked 3rd. Furthermore, the lowest deviation in 2016 was related to variable *C*, with a deviation of about 11%, compared to a deviation of more than 16% in 2014 and 24% in 2015. This result shows the improved distribution of cameras in 2016. Apart from fatality risk and cameras, the deviation of other variables from ideal situation has increased in 2016 compared to the years 2014 and 2015, which requires special attention from the Iranian government in their future planning. Generally speaking, although the average deviation of the fatality rate has been improved by 17.6%, Iranian provinces have not succeeded in reducing the deviation of input variables over the period 2014-2016.

For more discussion, the deviations of input and output variables for the year 2016 are shown in detail in Fig. 11. As can be noted, there are no deviations for efficient provinces taking into account all input and output variables (*Ilam, Alborz, Kohgiluyeh-and-Boyer-Ahmad, and Hormozgan*). In addition to the efficient provinces, Fig. 11.a illustrates that *Bushehr* and *Sistan-and-Baluchistan* have also experienced a deviation of less than 10% in terms

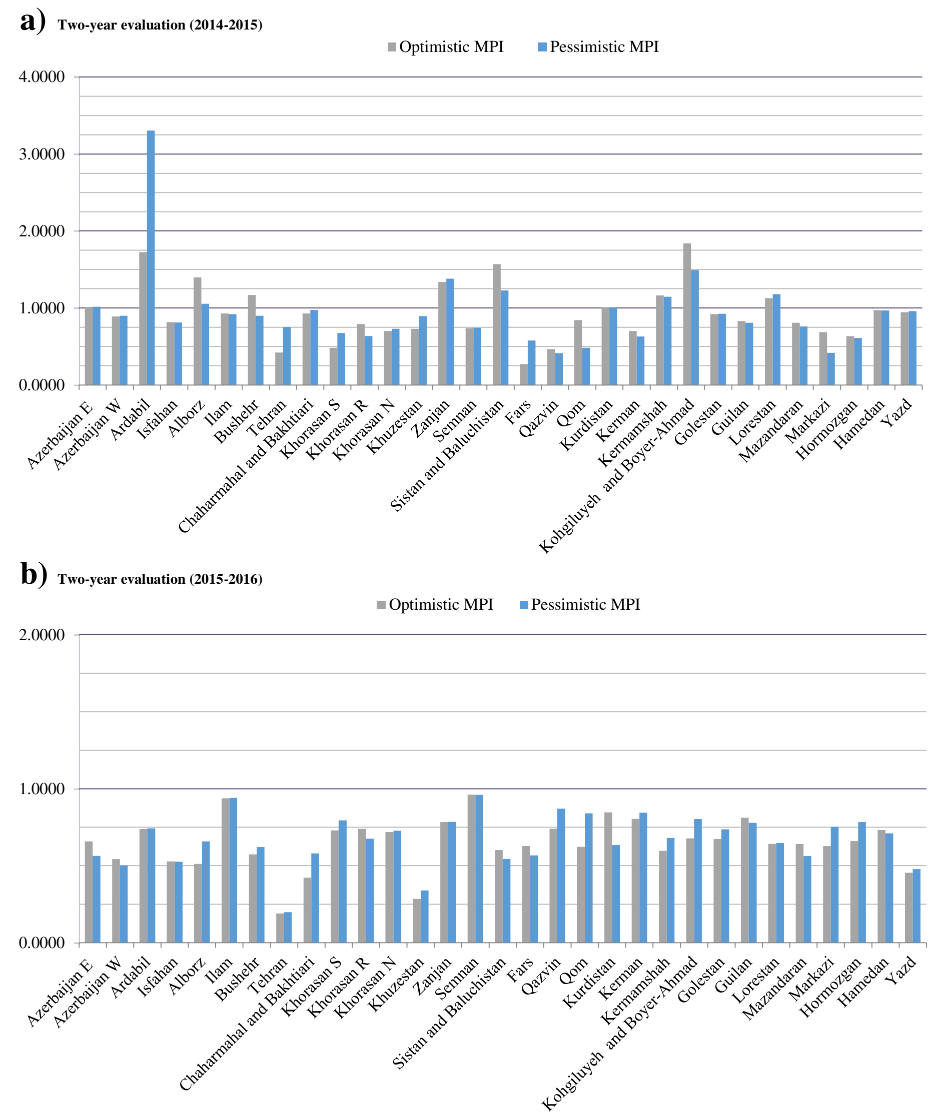


Fig. 5 Comparison of Malmquist productivity index values from the two points of view, (a) optimistic MPI and (b) pessimistic MPI

of PS. As shown in Fig. 11.a, about 25% of provinces experienced a deviation of more than 50%. It is worth noting that the highest deviation regarding PS variable is related to *Khuzestan* followed by *Kermanshah* and *Azerbaijan E.*

Figure 11.b shows that there is no deviation in *RMD* for *Ardebil, Tehran, Khuzestan, Semnan,* and *Mazandaran*. Apparently, *Khuzestan* and *Mazandaran* have experienced no deviation in *RMD* in contrast to their high deviation in *PS.* Fig. 11.c also presents that about 77% of provinces have experienced a deviation of more than 50% in *E&V*. As illustrated in Fig. 11.d, about half the provinces have effectively invested in *C* without any deviation and five provinces have marginally deviated from the ideal position with a deviation of less than 10%. Although *Qom* province has received a deviation of more than 50% in *C*, it has experienced no deviation in *EMS* (Fig. 11.e). *Tehran*, *Markazi,* and *Yazd* have also invested in *EMS* effectively. The deviations of about 22% Iranian provinces from the ideal were more than 50%. Figure 11.e also shows that, similar to *PS* and *E&V*, the deviation of *Khuzestan* province in *EMS* is critically high and needs to be reconsidered by the authorities. According to Fig. 11.f, any deviation from the ideal is observed for twelve provinces while there is a deviation of more than 50% for about 25% of provinces. Figure 11.g provides some information about road fatality risk. The results confirm that nine provinces have succeeded in reducing road fatalities with no deviation from Ideal;

Table 9 The double-frontier MPI for the three-year evaluation (2014-2016)

Provinces	2014/2015			2015/2016			2014/2016		
	EC	*TC*	*MPI*	*EC*	*TC*	*MPI*	*EC*	*TC*	*MPI*
Azerbaijan E	0.8907	1.1389	1.0144	1.1400	0.5342	0.6090	1.0076	0.7800	0.7860
Azerbaijan W	0.7433	1.2023	0.8937	0.9363	0.5565	0.5211	0.8343	0.8180	0.6824
Ardabil	2.1052	1.1346	2.3885	1.1889	0.6224	0.7400	1.5820	0.8404	1.3295
Isfahan	0.7012	1.1609	0.8141	0.8918	0.5916	0.5276	0.7908	0.8287	0.6553
Alborz	1.0523	1.1527	1.2130	0.9551	0.6068	0.5796	1.0025	0.8364	0.8385
Ilam	0.9253	0.9989	0.9242	1.5372	0.6111	0.9393	1.1926	0.7813	0.9318
Bushehr	0.9787	1.0468	1.0246	1.0032	0.5948	0.5967	0.9909	0.7891	0.7819
Tehran	0.4822	1.1700	0.5641	0.3208	0.6030	0.1935	0.3933	0.8400	0.3304
Chaharmahal and Bakhtiari	1.0736	0.8848	0.9499	0.8044	0.6150	0.4948	0.9293	0.7377	0.6855
Khorasan S	0.4961	1.1497	0.5704	1.3870	0.5490	0.7615	0.8295	0.7945	0.6591
Khorasan R	0.6379	1.1132	0.7101	1.1528	0.6126	0.7062	0.8575	0.8258	0.7081
Khorasan N	0.6027	1.1864	0.7151	1.2316	0.5869	0.7228	0.8616	0.8344	0.7189
Khuzestan	0.7962	1.0138	0.8071	0.5606	0.5536	0.3104	0.6681	0.7492	0.5005
Zanjan	1.1100	1.2251	1.3599	1.3274	0.5908	0.7842	1.2138	0.8508	1.0327
Semnan	0.6032	1.2272	0.7402	1.5311	0.6277	0.9610	0.9610	0.8776	0.8434
Sistan and Baluchistan	1.4325	0.9699	1.3893	0.9374	0.6098	0.5716	1.1588	0.7690	0.8912
Fars	0.3533	1.1244	0.3972	1.0696	0.5580	0.5968	0.6147	0.7921	0.4869
Qazvin	0.4197	1.0413	0.4370	1.4145	0.5678	0.8032	0.7705	0.7689	0.5924
Qom	0.4112	1.5479	0.6365	2.0770	0.3480	0.7229	0.9241	0.7340	0.6783
Kurdistan	0.6683	1.5087	1.0083	1.2305	0.5948	0.7319	0.9068	0.9473	0.8591
Kerman	0.5315	1.2501	0.6644	1.5005	0.5491	0.8239	0.8930	0.8285	0.7398
Kermamshah	0.9417	1.2263	1.1549	1.2093	0.5269	0.6372	1.0672	0.8039	0.8579
Kohgiluyeh and-Boyer-Ahmad	1.5840	1.0452	1.6556	1.2819	0.5747	0.7367	1.4250	0.7750	1.1044
Golestan	0.7600	1.2136	0.9223	1.3486	0.5215	0.7033	1.0124	0.7955	0.8054
Guilan	0.6673	1.2275	0.8192	1.3802	0.5762	0.7952	0.9597	0.8410	0.8071
Lorestan	1.0143	1.1374	1.1537	1.1021	0.5845	0.6441	1.0573	0.8153	0.8620
Mazandaran	0.6459	1.2142	0.7843	1.3247	0.4525	0.5995	0.9250	0.7413	0.6857
Markazi	0.3855	1.3858	0.5343	1.4708	0.4679	0.6882	0.7530	0.8052	0.6064
Hormozgan	0.6003	1.0352	0.6214	1.2521	0.5741	0.7188	0.8670	0.7709	0.6684
Hamedan	0.7852	1.2362	0.9707	1.3328	0.5407	0.7206	1.0230	0.8176	0.8363
Yazd	0.7819	1.2173	0.9518	0.8129	0.5730	0.4658	0.7972	0.8352	0.6659
Mean	0.7446	1.1595	0.8634	1.1299	0.5604	0.6332	0.9173	0.8061	0.7394

however, fifteen provinces have significantly deviated from ideal with a deviation of more than 50%. So, it can be stated that although Iranian provinces have generally succeeded in fatality reduction in 2016 compared to 2014 and 2015 (Fig. 10), output shortfalls are still considerable.

In summary, the input excesses, as well as the output shortfalls regarding each province, can be highlighted using Figs. 10 and 11, respectively. The findings would also be appropriate for the provincial authorities to address safety issues in their future planning.

6 Conclusions

The DEA models have been recently employed as an effective tool to measure road safety performance worldwide. The existing studies mostly applied the CCR and BCC models for safety measurement, which are on the basis of efficiency ratio and neither considered input excess nor output shortfall. In this respect, the SBM is employed in the current study, which not only measures the efficiency ratio but also takes account of slacks. It is also noted that the safety performance of each DMU (countries, states or provinces) has been previously assessed using the traditional CCR model based only on

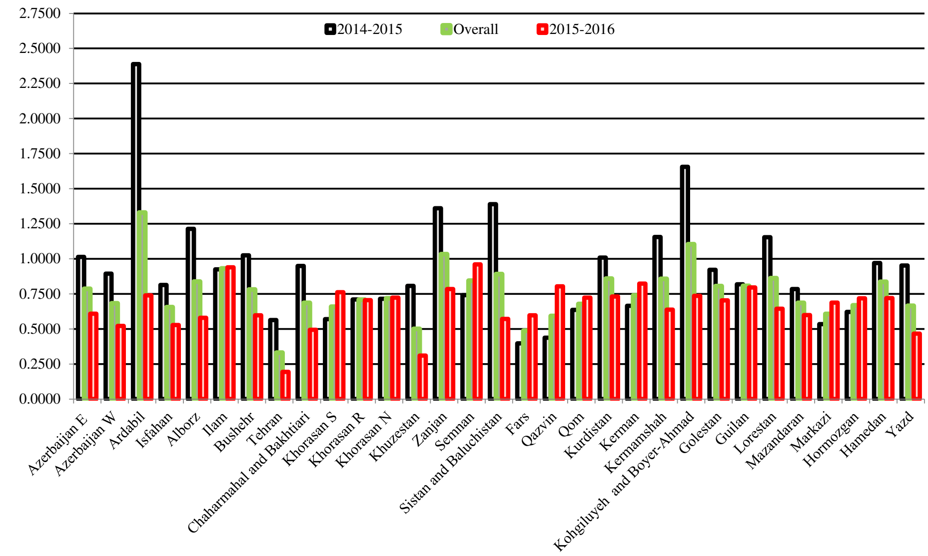


Fig. 6 The results of double-frontier MPI for the 31 Iranian provinces

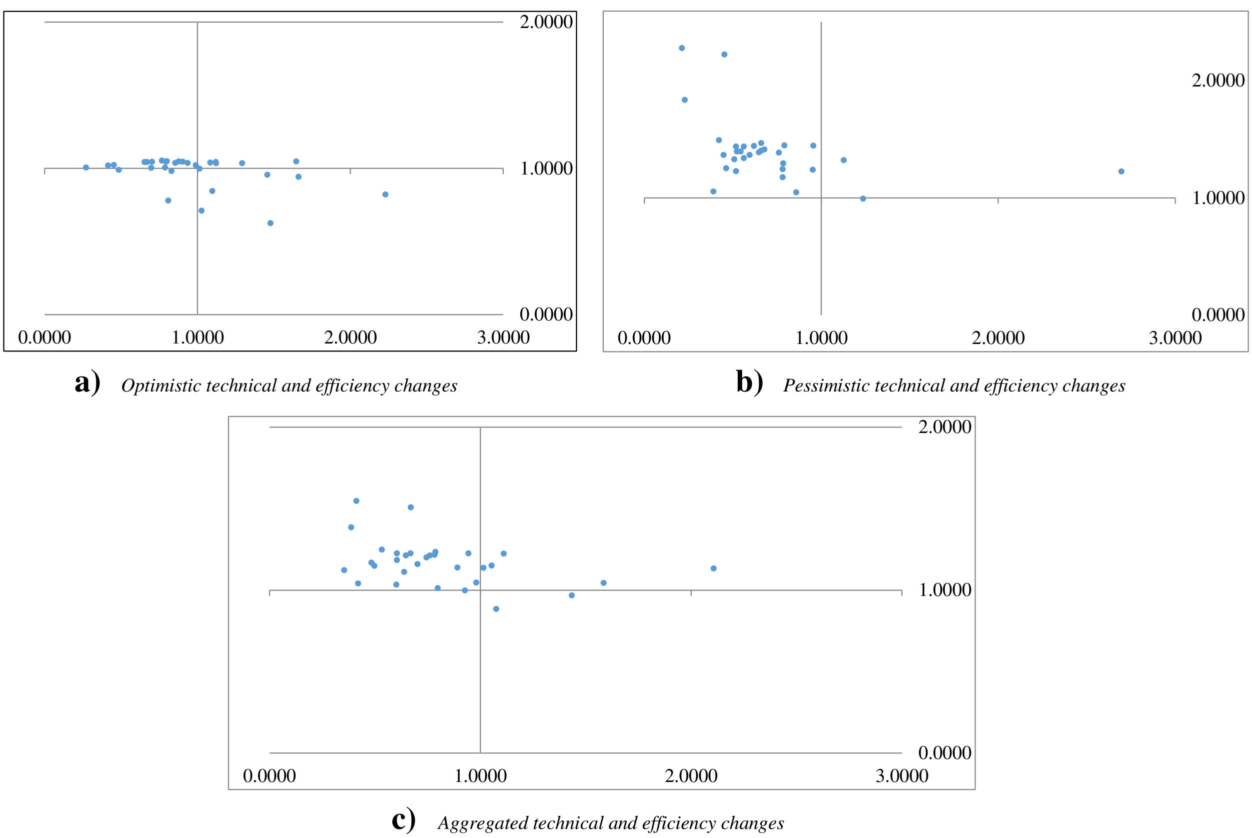


Fig. 7 The results of negative or positive productivity growth in connection with technical and efficiency changes for the 31 Iranian provinces from 2014–2015. Vertical axes: efficiency change. Horizontal axes: technical change

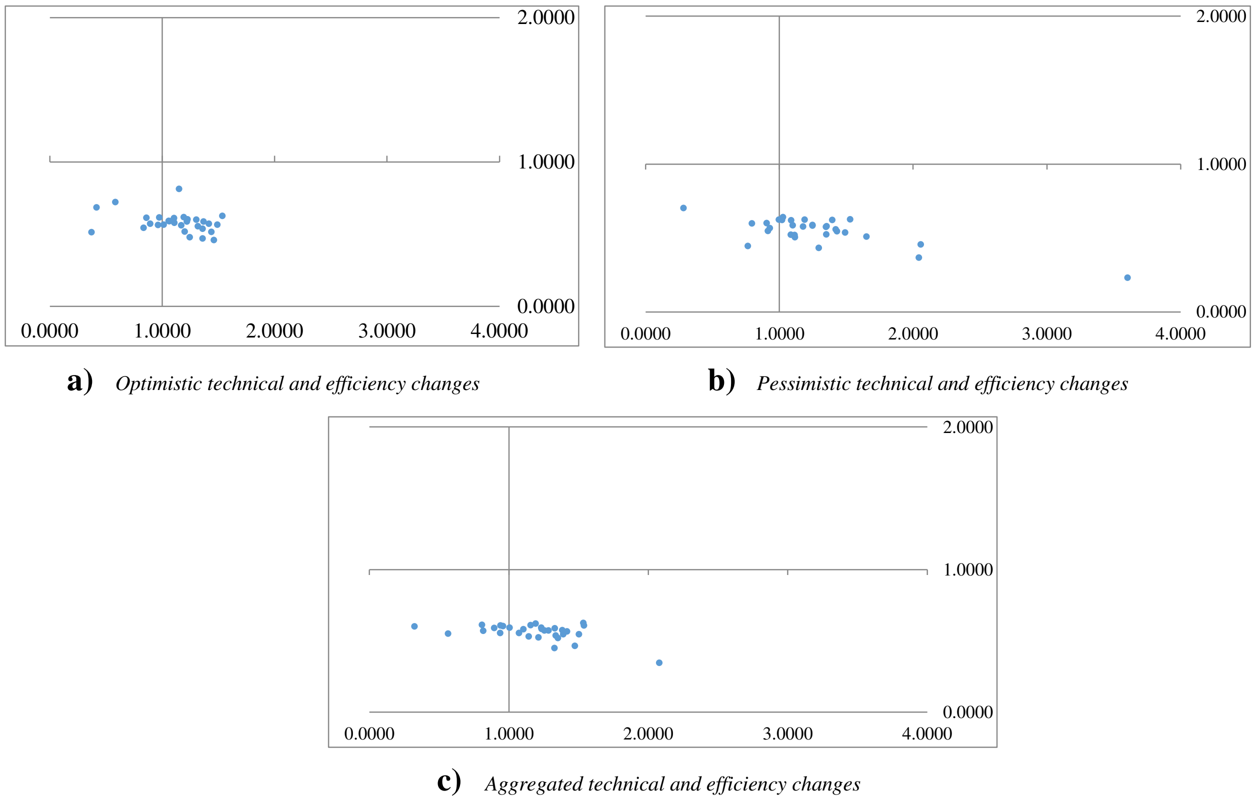


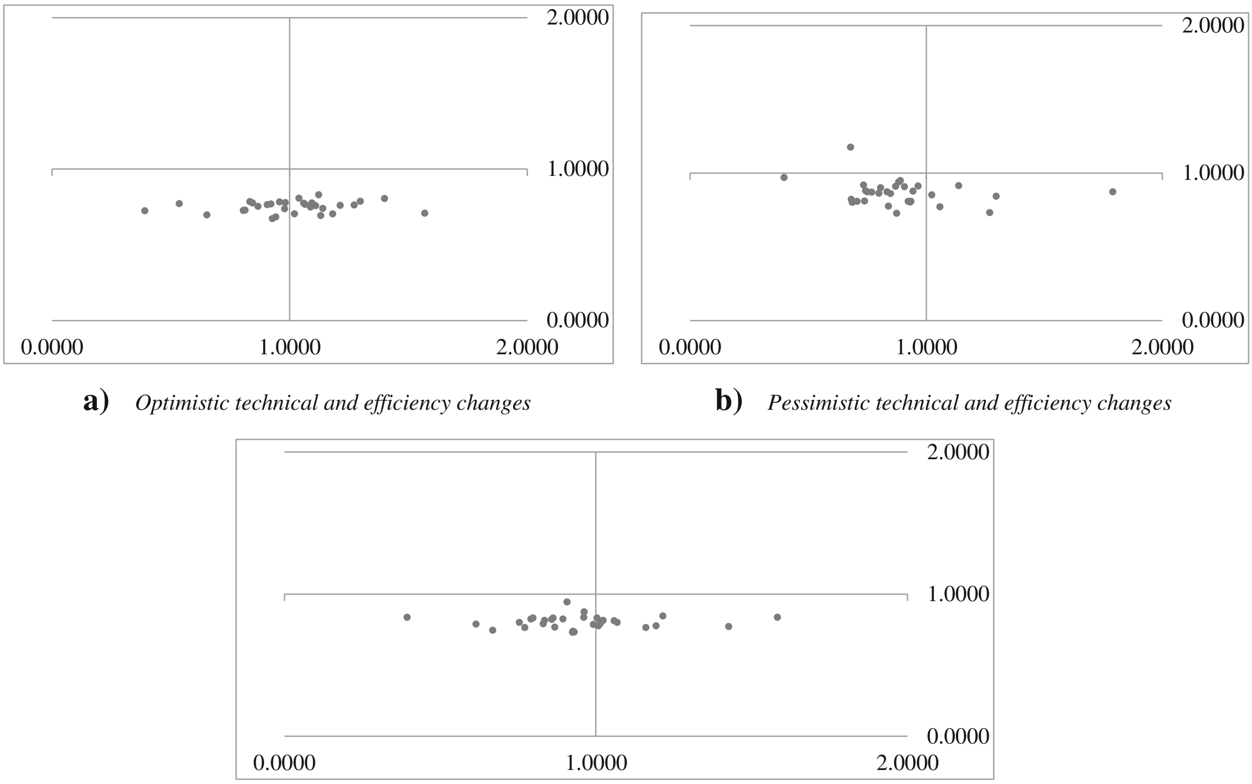
Fig. 8 The results of negative or positive productivity growth in connection with technical and efficiency changes for the 31 Iranian provinces from 2015–2016. Vertical axes: efficiency change. Horizontal axes: technical change

the efficient frontier, but it can be equivalently measured by taking into account the anti-efficient frontier. To bridge this gap, the present study comprehensively examined Iranian road safety performance using a novel double frontier SBM model taking into account the efficient and anti-efficient frontiers simultaneously. The ER approach was then employed as a suitable method to aggregate the obtained results from both optimistic and pessimistic points of view. This is because of the fact that the additive independence condition may not be satisfied, since both the optimistic and pessimistic efficiency results are computed from the same data source.

To evaluate Iranian road safety performance, the input and output variables were selected based on policy relevance and data availability. For this purpose, the RMTO Statistical Yearbook was used as the main source of information. As a result, six input variables, including *PS, RMD, E&V, C, EMS, and RLS,* and an output variable, FR^{-1}, were selected for assessing the road safety performance. Analysis of Iranian road safety performance using the proposed DF-SBM-ER illustrates that *Alborz* ranked 2nd in the year 2014; meanwhile, it was the most efficient province in 2015 and 2016.

It is certainly crucial for the authorities to examine the strengths and weaknesses of their managerial decisions regarding each province. For this reason, the MPI has been recognized as an appropriate method for further analysis of each province in terms of road safety performance. Although the previous studies, more or less, utilized the optimistic MPI values for assessing DMUs, the current study carried out an in-depth analysis to assess Iranian provinces regarding road safety performance by investigating a novel DF-SBM-MPI, which simultaneously takes into account both efficiency changes and frontier shifts from the optimistic and pessimistic points of view over a period of time. The significant difference between the results obtained from the optimistic and pessimistic MPIs obviously confirms that taking account of the anti-efficient frontier is essential for a more comprehensive analysis of performance changes. The results will also assist the authorities to decide whether the strategic frontier shift is appropriate or not.

On average, the Iranian provinces' productivity in terms of road safety declined with a rate of 13.66% from 2014 to 2015, although the technology frontier shifted



a) *Optimistic technical and efficiency changes*

b) *Pessimistic technical and efficiency changes*

c) *Aggregated technical and efficiency changes*

Fig. 9 The results of negative or positive productivity growth in connection with technical and efficiency changes for the 31 Iranian provinces from 2014–2016. Vertical axes: efficiency change. Horizontal axes: technical change

with a positive rate of around 16%. This means that the main reason for productivity reduction from 2014–2015 is the significant decline in provinces' efficiency, by an average of 25.54%. On the contrary, the Iranian road safety performance technologically regressed, with an average reduction rate of 44 % from 2015–2016; meanwhile, Iranian provinces experienced an improvement in efficiency changes, with an average reduction rate of 13%. Generally speaking, the provinces' productivity in terms of road safety significantly decreased from 2015 to 2016, with a geometric mean rate of about 37%.

Finally, taking into account the period 2014–2016, Iranian road safety declined with a mean rate of about 26%, due to a reduction in efficiency changes (around 8%) as well as a slight negative shift in technology frontier (about 19%).

In brief, the conducted in-depth analysis reveals that Iranian provinces were successful in technical changes from 2014–2015, while from 2015–2016, they effectively improved their efficiencies, which is, of course, admirable. It is also worth mentioning that although the productivity of nine provinces on road safety was generally enhanced from 2014–2015; only five provinces fully

Table 10 Data analysis. The input and output slacks for Qom province

Years	s_i^-						s_r^+
	Police Station (PS)	Road Maintenance Depot (RMD)	Equipment & Vehicles (E&V)	Camera (C)	Emergency Medical Service (EMS)	Road with Lighting System (RLS)	FR^{-1}
2014	*0.1798190*	*0.02497436*	*11.87315*	*1.643356*	*0.0000*	*17.60741*	*0.6274015*
2015	*0.2163227*	*0.1130736*	*14.54769*	*4.877088*	*0.0000*	*18.53491*	*0.9212618*
2016	*0.1963451*	*0.1026324*	*11.06201*	*4.118692*	*0.0000*	*16.82283*	*0.3757682*

Table 11 Data analysis. The existing dataset for Qom province

Years	*Input(i)*						*Output (r)*
	Police Station (PS)	Road Maintenance Depot (RMD)	Equipment & Vehicles (E&V)	Camera (C)	Emergency Medical Service (EMS)	Road with Lighting System (RLS)	FR^{-1}
2014	0.55944	1.25874	26.01399	3.63636	2.65734	26.43357	2.13776
2015	0.58997	1.32743	28.46608	6.93215	2.80236	27.87611	2.02564
2016	0.53548	1.20482	21.15127	7.76439	2.54351	25.30120	1.40260

progressed in road safety performance regarding both efficiency and technical changes.

It is suggested applying the proposed method in other aspects of transportation management. Using different nonlinear methods of aggregation rather than the ER algorithm would also be an interesting topic for future road safety research. In addition, it is suggested extending the method by using some weight restrictions on input variables. In this regard, some group decision-making methods can be applied to investigate the importance of each variable. Furthermore, proposing a double frontier Assurance Region SBM model can be of interest to the safety experts.

As mentioned earlier, Iranian safety experts suffer from lack of data. Road safety experts around the world are encouraged to conduct a research study based on the proposed method by defining some new input and output variables subject to data availability. They can define input variables such as “barriers to accidents”, “traffic calming devices”, “police officers or patrol units”, “financial resources” (i.e. the amount of money spent on police patrols and highway maintenance) and “manpower”; meanwhile, “the number of seriously injured people” and “the number of road accidents” can also be used to define a new output variable.

As discussed in the literature, a number of studies have been carried out to assess the road safety performance of European countries using DEA models based only on the efficient frontier, which could not lead to a comprehensive assessment. The current study is the first attempt to assess road safety performance by considering

Table 12 Data analysis. Deviations of the input and output variables for Qom province

Years	Input						Output
	Police Station (PS)	Road Maintenance Depot (RMD)	Equipment & Vehicles (E&V)	Camera (C)	Emergency Medical Service (EMS)	Road with Lighting System (RLS)	FR^{-1}
2014	*0.32143*	*0.01984*	*0.45641*	*0.45192*	*0.00000*	*0.66610*	*0.29349*
2015	*0.36667*	*0.08518*	*0.51105*	*0.70355*	*0.00000*	*0.66490*	*0.45480*
2016	*0.36667*	*0.08518*	*0.52300*	*0.53046*	*0.00000*	*0.66490*	*0.26791*

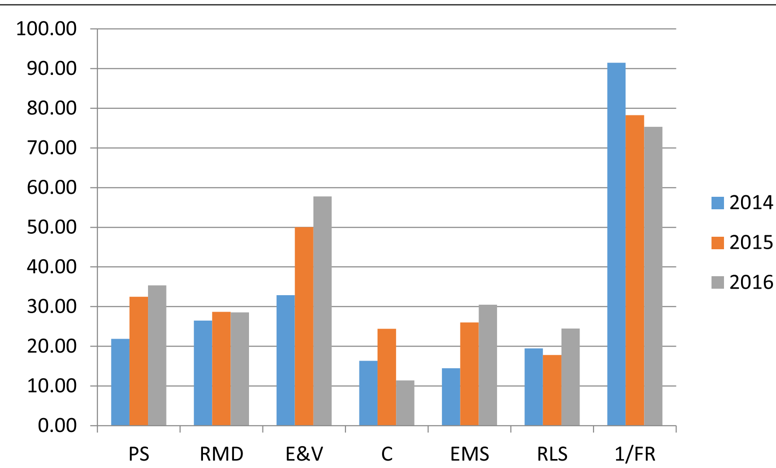


Fig. 10 The average deviation of input and output variables from the ideal situation for the years 2014-2016

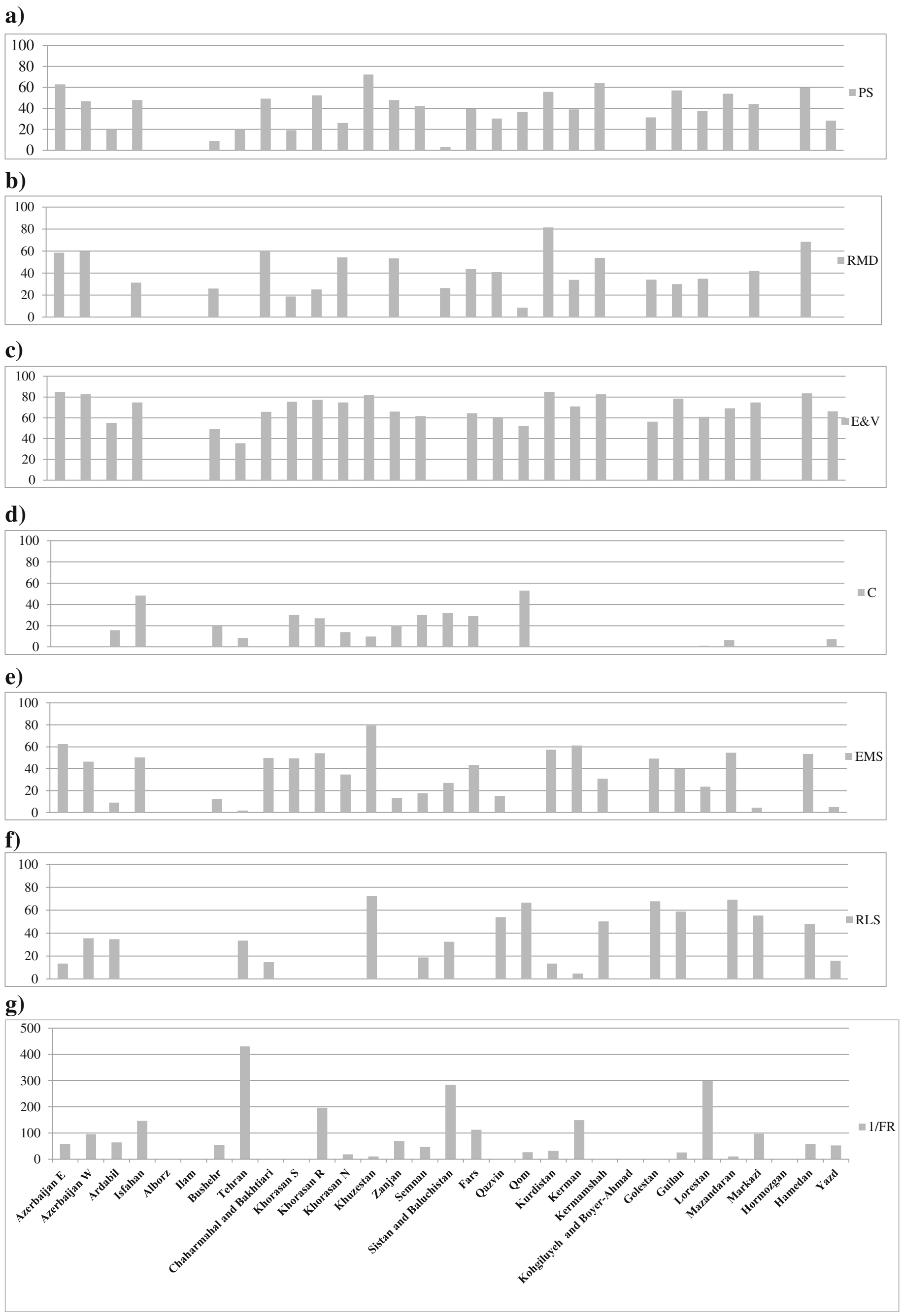


Fig. 11 Deviations of input and output variables for Iranian provinces in 2016

the best-practice and the worst-practice frontiers. Since the focus of this study is on the basic characteristics of the proposed method, further applications are suggested as the future direction of the current research. The European countries can apply the proposed approach to assess their road safety performance more comprehensively. The input excesses and the output shortfalls obtained from the slack variables analysis can also provide the European authorities with a deeper insight into the road safety performance. In addition, the DF-SBM-ER can be further used by the European Commission to assess other aspects of transportation such as European rail transport, European air transport, and European maritime transport.

7 Appendix 1

Suppose that there is an evaluation problem for assessing n DMUs with m inputs and s outputs.

7.1 1.1. The input-oriented CCR

The optimistic input-oriented CCR model is mathematically as follows [2, 58]:

$$\begin{aligned} &\theta_0 = \max \sum\nolimits_{r=1}^{s} u_r y_{r0} \\ &\text{Subject to :} \\ &\sum\nolimits_{i=1}^{m} v_i x_{i0} = 1, \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1, \ldots, n \\ &u_r, v_i \ge 0, r = 1, \ldots, s, \qquad i = 1, \ldots m \end{aligned} \tag{32}$$

where u_r and v_i denote the realtive weights of the outputs and the inputs, respectively. x_{ij} and y_{rj} also express the i^{th} input and the r^{th} output of DMU_j. θ_0 denotes the efficiency degree of a given DMU_0 with the given inputs (x_{i0}) and the given outputs (y_{r0}).

The pessimistic or inverted input-oriented CCR model can be mathematically formulated as follows:

$$\begin{aligned} &\theta_0^{-1} = \min \sum\nolimits_{r=1}^{s} u_r y_{r0} \\ &\text{Subject to :} \\ &\sum\nolimits_{i=1}^{m} v_i x_{i0} = 1, \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1, \ldots, n \\ &u_r, v_i \ge 0, r = 1, \ldots, s, \qquad i = 1, \ldots m \end{aligned} \tag{33}$$

7.2 1.2. The output-oriented CCR

The optimistic output-oriented CCR model is mathematically as follows [2, 58]:

$$\begin{aligned} &\theta_0 = \min \sum\nolimits_{i=1}^{m} v_i x_{i0} \\ &\text{Subject to:} \\ &\sum\nolimits_{r=1}^{s} u_r y_{r0} = 1, \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1, \ldots, n \\ &u_r, v_i \ge 0, r = 1, \ldots, s, \qquad i = 1, \ldots m \end{aligned} \tag{34}$$

where u_r and v_i denote the realtive weights of the outputs and the inputs, respectively. x_{ij} and y_{rj} also express the i^{th} input and the r^{th} output of DMU_j. θ_0 denotes the efficiency degree of a given DMU_0 with the given inputs (x_{i0}) and the given outputs (y_{r0}).

The pessimistic or inverted output-oriented CCR model can be mathematically formulated as follows:

$$\begin{aligned} &\theta_0^{-1} = mix \sum\nolimits_{i=1}^{m} v_i x_{i0} \\ &\text{Subject to :} \\ &\sum\nolimits_{r=1}^{s} u_r y_{r0} = 1, \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1, \ldots, n \\ &u_r, v_i \ge 0, r = 1, \ldots, s, \qquad i = 1, \ldots m \end{aligned} \tag{35}$$

8 Appendix 2

Suppose that there is an evaluation problem for assessing n DMUs with m inputs and s outputs.

8.1 2.1. The optimistic SBM

The optimistic SBM in time t, $D_0^t(x_0^t, y_0^t)$, can be mathematically represented as follows:

$$\begin{aligned} &D_0^t(x_0^t, y_0^t) = \text{Min}\ \rho = q - \frac{1}{m} \sum_{i=1}^{m} S_i^- / x_{i0}^t \\ &\text{Subject to} \\ &1 = q + (1/s) \sum\nolimits_{r=1}^{s} S_r^+ / y_{r0} \\ &q\, x_{i0}^t = \sum\nolimits_{j=1}^{n} x_{ij}^t \Lambda_j + S_i^-, \qquad i = 1, .., m \\ &q\, y_{r0}^t = \sum\nolimits_{j=1}^{n} y_{rj}^t \Lambda_j - S_r^+, \qquad r = 1, .., s \\ &\Lambda_j \ge 0, \quad S_i^- \ge 0, \quad S_r^+ \ge 0, \qquad q > 0 \end{aligned} \tag{36}$$

Similarly, the optimistic SBM in time $t+1$, $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$, can be obtained by substituting $(x_{i0}^{t+1}, x_{ij}^{t+1}, y_{r0}^{t+1}, y_{rj}^{t+1})$ with $(x_{i0}^t, x_{ij}^t, y_{r0}^t, y_{rj}^t)$ in model (36). As a result, $D_0^t(x_0^{t+1}, y_0^{t+1})$, can be represented as follows:

$$\begin{aligned} &D_0^t(x_0^{t+1}, y_0^{t+1}) = \text{Min}\ \rho = q - \frac{1}{m} \sum_{i=1}^{m} S_i^- / x_{i0}^{t+1} \\ &\text{Subject to} \\ &1 = q + (1/s) \sum\nolimits_{r=1}^{s} S_r^+ / y_{r0} \\ &q\, x_{i0}^{t+1} = \sum\nolimits_{j=1}^{n} x_{ij}^t \Lambda_j + S_i^-, \qquad i = 1, .., m \\ &q\, y_{r0}^{t+1} = \sum\nolimits_{j=1}^{n} y_{rj}^t \Lambda_j - S_r^+, \qquad r = 1, .., s \\ &\Lambda_j \ge 0, \quad S_i^- \ge 0, \quad S_r^+ \ge 0, \qquad q > 0 \end{aligned} \tag{37}$$

Likewise, the second mixed period of measure, $D_0^{t+1}(x_0^t, y_0^t)$, can be computed by substituting ($x_{i0}^t, x_{ij}^{t+1}, y_{r0}^t, y_{rj}^{t+1}$) with ($x_{i0}^{t+1}, x_{ij}^t, y_{r0}^{t+1}, y_{rj}^t$) in model (37).

8.2 2.2. The pessimistic point of view

The pessimistic SBM in time t, $d_0^t(x_0^t, y_0^t)$, can be formulated as follows:

$$d_0^t(x_0^t, y_0^t) = \text{Max } \rho = q + \frac{1}{m}\sum_{i=1}^{m} S_i^+/x_{i0}^t$$
$$\text{Subject to}$$
$$1 = q - (1/s)\sum_{r=1}^{s} S_r^-/y_{r0}$$
$$q\, x_{i0}^t = \sum_{j=1}^{n} x_{ij}^t \Lambda_j - S_i^+, \qquad i = 1,..,m$$
$$q\, y_{r0}^t = \sum_{j=1}^{n} y_{rj}^t \Lambda_j + S_r^-, \qquad r = 1,..,s$$
$$\Lambda_j \geq 0, \quad S_i^+ \geq 0, \quad S_r^- \geq 0, \qquad q > 0 \tag{38}$$

By substituting $(x_{i0}^{t+1}, x_{ij}^{t+1}, y_{r0}^{t+1}, y_{rj}^{t+1})$with$(x_{i0}^t, x_{ij}^t, y_{r0}^t, y_{rj}^t)$ in model (38), the pessimistic SBM in time $t+1$, $d_0^{t+1}(x_0^{t+1}, y_0^{t+1})$, can be computed. Moreover, the first mixed period measure, $d_0^t(x_0^{t+1}, y_0^{t+1})$, can be formulated as follows:

$$d_0^t(x_0^{t+1}, y_0^{t+1}) = \text{Min } \rho = q + \frac{1}{m}\sum_{i=1}^{m} S_i^+/x_{i0}^{t+1}$$
$$\text{Subject to}$$
$$1 = q + (1/s)\sum_{r=1}^{s} S_r^-/y_{r0}$$
$$q\, x_{i0}^{t+1} = \sum_{j=1}^{n} x_{ij}^t \Lambda_j - S_i^+, \qquad i = 1,..,m$$
$$q\, y_{r0}^{t+1} = \sum_{j=1}^{n} y_{rj}^t \Lambda_j + S_r^-, \qquad r = 1,..,s$$
$$\Lambda_j \geq 0, \quad S_i^+ \geq 0, \quad S_r^- \geq 0, \qquad q > 0 \tag{39}$$

Likewise, the second mixed period of measure, $d_0^{t+1}(x_0^t, y_0^t)$, can be computed by substituting $(x_{i0}^t, x_{ij}^{t+1}, y_{r0}^t, y_{rj}^{t+1})$ with $(x_{i0}^{t+1}, x_{ij}^t, y_{r0}^{t+1}, y_{rj}^t)$ in model (39).

9 Appendix 3

9.1 3.1. The optimistic Super-SBM [49]

Suppose that DMU $(\boldsymbol{x_0}, \boldsymbol{y_0})$ is efficient. The production possibility set is defined as follows:

$$P\backslash(x_0, y_0) = \left\{ (\bar{x}, \bar{y}) | \bar{x} \geq \sum_{j=1 \neq 0}^{n} \lambda_j x_j, \bar{y} \leq \sum_{j=1 \neq 0}^{n} \lambda_j y_j, \bar{y} \geq 0, \lambda_j \geq 0 \right\} \tag{40}$$

$\overline{P}\backslash(x_0, y_0)$is further defined as a subset of $P\backslash(x_0, y_0)$:

$$\overline{P}\backslash(x_0, y_0) = P\backslash(x_0, y_0) \cap \{\bar{x} \geq x_0 \text{ and } \bar{y} \leq y_0\} \tag{41}$$

The optimistic Super-SBM is mathematically represented as follows:

$$\delta^* = \text{Min } \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i/x_{i0}}{\frac{1}{r}\sum_{r=1}^{s} \bar{y}_r/y_{r0}}$$
$$\text{Subject to}$$
$$\bar{x}_i \geq \sum_{j=1 \neq 0}^{n} \lambda_j x_{ij}, \qquad i = 1,..,m$$
$$\bar{y}_r \leq \sum_{j=1 \neq 0}^{n} \lambda_j y_{rj}, \qquad r = 1,..,s$$
$$\bar{x}_i \geq x_{i0}, \qquad \bar{y}_r \leq y_{r0}$$
$$\bar{y}_r \geq 0, \qquad \lambda_j \geq 0 \tag{42}$$

Using Charnes-Cooper transformation, the fractional programming model (42) is transformed into the following linear programming model:

$$\tau^* = \text{Min } \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i/x_{i0}$$
$$\text{Subject to}$$
$$1 = \frac{1}{s}\sum_{r=1}^{s} \tilde{y}_r/y_{r0},$$
$$\tilde{x}_i \geq \sum_{j=1 \neq 0}^{n} \Lambda_j x_{ij}, \qquad i = 1,..,m$$
$$\tilde{y}_r \leq \sum_{j=1 \neq 0}^{n} \Lambda_j y_{rj}, \qquad r = 1,..,s$$
$$\tilde{x}_i \geq q x_{i0}, \qquad \tilde{y}_r \leq q y_r$$
$$\tilde{y}_r \geq 0, \qquad \Lambda_j \geq 0 \qquad q \geq 0 \tag{43}$$

The optimal solution of model (43) is $(\tau^*, \tilde{x}_i^*, \tilde{y}_r^*, \Lambda_j^*, q^*)$. Subsequently, the optimal solution of Super-SBM is $(\delta^* = \tau^*, \lambda_j^* = \Lambda_j^*/q^*, \bar{x}_i^* = \tilde{x}_i^*/q^*, \bar{y}_r^* = \tilde{y}_r^*/q^*)$.

9.2 3.2. The pessimistic Super-SBM

The production possibility set can be defined as follows:

$$P\backslash(x_0, y_0) = \left\{ (\bar{x}, \bar{y}) | \bar{x} \leq \sum_{j=1 \neq 0}^{n} \lambda_j x_j, \bar{y} \geq \sum_{j=1 \neq 0}^{n} \lambda_j y_j, \bar{x} \geq 0, \lambda_j \geq 0 \right\} \tag{44}$$

Furthermore, $\overline{P}\backslash(x_0, y_0)$ can be defined as a subset of (x_0, y_0):

$$\overline{P}\backslash(x_0, y_0) = P\backslash(x_0, y_0) \cap \{\bar{x} \leq x_0 \text{ and } \bar{y} \geq y_0\} \tag{45}$$

The pessimistic Super-SBM can be formulated as follows:

$$\delta^* = \text{Max } \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \bar{y}_r / y_{r0}}$$

Subject to

$$\begin{aligned}
&\bar{x}_i \le \sum\nolimits_{j=1\neq 0}^{n} \lambda_j x_{ij}, && i = 1,..,m \\
&\bar{y}_r \ge \sum\nolimits_{j=1\neq 0}^{n} \lambda_j y_{rj}, && r = 1,..,s \\
&\bar{x}_i \le x_{i0}, \quad \bar{y}_r \ge y_{r0} \\
&\bar{x}_i \ge 0, \quad \lambda_j \ge 0
\end{aligned} \tag{46}$$

Subsequently, the following linear programming model can be pessimistically obtained using the Charnes-Cooper transformation technique:

$$\tau^* = \text{Max } \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i / x_{i0}$$

Subject to

$$\begin{aligned}
&1 = \frac{1}{s}\sum\nolimits_{r=1}^{s} \tilde{y}_r / y_{r0}, \\
&\tilde{x}_i \le \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j x_{ij}, && i = 1,..,m \\
&\tilde{y}_r \ge \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j y_{rj}, && r = 1,..,s \\
&\tilde{x}_i \le q x_{i0}, \quad \tilde{y}_r \ge q y_{r0} \\
&\tilde{x}_i \ge 0, \quad \Lambda_j \ge 0 \quad q \ge 0
\end{aligned} \tag{47}$$

The optimal solution of (47) is $(\tau^*, \tilde{x}_i^*, \tilde{y}_r^*, \Lambda_j^*, q^*)$. Subsequently, the optimal solution of Super-SBM is $(\delta^* = \tau^*, \lambda_j^* = \Lambda_j^*/q^*, \bar{x}_i^* = \tilde{x}_i^*/q^*, \bar{y}_r^* = \tilde{y}_r^*/q^*)$.

10 Appendix 4

10.1 4.1. The optimistic point of view

In the situation that $D_0^t(x_0^t, y_0^t) = 1$, DMU_0 is efficient based on the data set belonging to time period t. Therefore, the super efficiency score, $\tilde{D}_0^t(x_0^t, y_0^t)$, is optimistically measured as follows:

$$\tilde{D}_0^t(x_0^t, y_0^t) = \text{Min } \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i^t / x_{i0}^t$$

Subject to

$$\begin{aligned}
&1 = \frac{1}{s}\sum\nolimits_{r=1}^{s} \tilde{y}_r^t / y_{r0}^t, \\
&\tilde{x}_i^t \ge \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j x_{ij}^t, && i = 1,..,m \\
&\tilde{y}_r^t \le \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j y_{rj}^t, && r = 1,..,s \\
&\tilde{x}_i^t \ge q x_{i0}^t, \\
&\tilde{y}_r^t \le q y_{r0}^t \\
&\tilde{y}_r^t \ge 0, \quad \Lambda_j \ge 0 \quad q \ge 0
\end{aligned} \tag{48}$$

By substituting $(x_{i0}^{t+1}, \tilde{x}_i^{t+1}, x_{ij}^{t+1}, y_{r0}^{t+1}, \tilde{y}_r^{t+1}, y_{rj}^{t+1})$ with $(x_{i0}^t, \tilde{x}_i^t, x_{ij}^t, y_{r0}^t, \tilde{y}_r^t, y_{rj}^t)$ in model (48), the super efficiency in time period $t+1$, $\tilde{D}_0^{t+1}(x_0^{t+1}, y_0^{t+1})$, can be optimistically computed. Moreover, the first mixed period of measure, $\tilde{D}_0^t(x_0^{t+1}, y_0^{t+1})$, can be formulated as follows:

$$\tilde{D}_0^t(x_0^{t+1}, y_0^{t+1}) = \text{Min } \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i^{t+1} / x_{i0}^{t+1}$$

Subject to

$$\begin{aligned}
&1 = \frac{1}{s}\sum\nolimits_{r=1}^{s} \tilde{y}_r^{t+1} / y_{r0}^{t+1}, \\
&\tilde{x}_i^{t+1} \ge \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j x_{ij}^t, && i = 1,..,m \\
&\tilde{y}_r^{t+1} \le \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j y_{rj}^t, && r = 1,..,s \\
&\tilde{x}_i^{t+1} \ge q x_{i0}^{t+1}, \\
&\tilde{y}_r^{t+1} \le q y_{r0}^{t+1} \\
&\tilde{y}_r^{t+1} \ge 0, \quad \Lambda_j \ge 0 \quad q \ge 0
\end{aligned} \tag{49}$$

Likewise, the second mixed period of measure, $D_0^{t+1}(x_0^t, y_0^t)$, can be computed by substituting $(x_{i0}^t, \tilde{x}_i^t, x_{ij}^{t+1}, y_{r0}^t, \tilde{y}_r^t, y_{rj}^{t+1})$ with $(x_{i0}^{t+1}, \tilde{x}_i^{t+1}, x_{ij}^t, y_{r0}^{t+1}, \tilde{y}_r^{t+1}, y_{rj}^t)$ in model (49).

10.2 4.2. The pessimistic point of view

In the situation that $d_0^t(x_0^t, y_0^t) = 1$ which means that DMU_0 is efficient based on the data set belongs to time period t. Therefore, the super efficiency score, $\tilde{d}_0^t(x_0^t, y_0^t)$, is measured from the pessimistic point of view as follows:

$$\tilde{d}_0^t(x_0^t, y_0^t) = \text{max } \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i^t / x_{i0}^t$$

Subject to

$$\begin{aligned}
&1 = \frac{1}{s}\sum\nolimits_{r=1}^{s} \tilde{y}_r^t / y_{r0}^t, \\
&\tilde{x}_i^t \le \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j x_{ij}^t, && i = 1,..,m \\
&\tilde{y}_r^t \ge \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j y_{rj}^t, && r = 1,..,s \\
&\tilde{x}_i^t \le q x_{i0}^t, \\
&\tilde{y}_r^t \ge q y_{r0}^t \\
&\tilde{x}_i^t \ge 0, \quad \Lambda_j \ge 0 \quad q \ge 0
\end{aligned} \tag{50}$$

By substituting $(x_{i0}^{t+1}, \tilde{x}_i^{t+1}, x_{ij}^{t+1}, y_{r0}^{t+1}, \tilde{y}_r^{t+1}, y_{rj}^{t+1})$ with $(x_{i0}^t, \tilde{x}_i^t, x_{ij}^t, y_{r0}^t, \tilde{y}_r^t, y_{rj}^t)$ in model (50), the super efficiency in time period $t+1$, $\tilde{d}_0^{t+1}(x_0^{t+1}, y_0^{t+1})$ can be pessimistically computed. Moreover, the first mixed period of measure, $\tilde{d}_0^t(x_0^{t+1}, y_0^{t+1})$, can be formulated as follows:

$$\tilde{d}_0^t(x_0^{t+1}, y_0^{t+1}) = \max \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i^{t+1}/x_{i0}^{t+1}$$

$$\begin{aligned}
&\text{Subject to}\\
&1 = \frac{1}{s}\sum\nolimits_{r=1}^{s} \tilde{y}_r^{t+1}/y_{r0}^{t+1},\\
&\tilde{x}_i^{t+1} \leq \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j x_{ij}^t, \quad i = 1, .., m\\
&\tilde{y}_r^{t+1} \geq \sum\nolimits_{j=1\neq 0}^{n} \Lambda_j y_{rj}^t, \quad r = 1, .., s\\
&\tilde{x}_i^{t+1} \leq q x_{i0}^{t+1},\\
&\tilde{y}_r^{t+1} \geq q y_{r0}^{t+1}\\
&\tilde{x}_i^{t+1} \geq 0, \quad \Lambda_j \geq 0 \quad q \geq 0
\end{aligned} \tag{51}$$

Likewise, the second mixed period of measure, $d_0^{t+1}(x_0^t, y_0^t)$, can be computed by substituting $(x_{i0}^t, \tilde{x}_i^t, x_{ij}^{t+1}, y_{r0}^t, \tilde{y}_r^t, y_{rj}^{t+1})$ with $(x_{i0}^{t+1}, \tilde{x}_i^{t+1}, x_{ij}^t, y_{r0}^{t+1}, \tilde{y}_r^{t+1}, y_{rj}^t)$ in model (51).

Abbreviations

DEA : Data Envelopment Analysis; CCR : Charnes, Cooper and Rhodes; SBM : Slacks-Based Measure; DMU: Decision Making Unit; ER: Evidential Reasoning; DF-SBM- MPI: Double-Frontier SBM-based Malmquist Productivity Index; MPI: Malmquist Productivity Index; WHO: World Health Organization; DF-SBM-ER: Double-Frontier SBM aggregated by ER algorithm; BCC: Banker, Charnes and Cooper; DEA-RS : DEA-based Road Safety model; TOPSIS: Technique for Order Preference by Similarity to an Ideal Solution; PMPI : Pessimistic SBM-based MPI; OMPI: Optimistic SBM-based MPI; RMTO: Road Maintenance and Transportation Organization; PS: Police Station; RMD : Road Maintenance Depot; E&V: Equipment and vehicles; C: Camera; EMS : Emergency medical service; RLS: Road with lighting system

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Availability of data and materials

The required data were collected from the following website (in Persian) http://www.rmto.ir/Pages/SalnameAmari.aspx

Authors' contributions

Both authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

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