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An Alternative prioritization Method in the Presence of Contextual Variables: A case on Gas Companies

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Abstract
After assessing the efficiency of the units under evaluation, determining their ranking becomes a critical concern for decision-making. Ranking methodologies rely on specific unit inputs and outputs, but some variables affecting unit performance are not directly observable and are termed contextual variables. Thus, the primary objective of this research is to introduce a ranking methodology that incorporates these variables. To achieve this, a two-step approach is employed. Firstly, the Data Envelopment Analysis (DEA) technique calculates efficiency scores for each Decision-Making Unit (DMU), considering its unique inputs and outputs. Subsequently, the linear regression method is applied to assess the impact of contextual variables on efficiency. Finally, efficiency scores are modified by removing the impact of contextual variables, enabling unit ranking. To illustrate this proposed methodology, we conducted a performance evaluation of provincial gas companies in Iran. The evaluation covered four periods, from 2013 to 2016.
Keywords: *Data envelopment analysis, Regression, Contextual variable, Efficiency, Ranking*

Introduction

One crucial aspect of evaluating unit performance is determining the production function, which illustrates the maximum achievable output for any combination of inputs. The complexity of the production process, technological advancements, and the multifaceted nature of inputs make finding this function a challenge. Consequently, an approximate determination becomes necessary. In general, two methods are available for approximating the production function: parametric and non-parametric approaches. While parametric methods have been widely utilized in the past, they have encountered difficulties. Therefore, Farrell (1957) introduced a non-parametric approach, and subsequently, Charnes et al. (1978) proposed the non-parametric Data Envelopment Analysis (DEA) technique as a solution to overcome these challenges. This technique has been used in various industries in the past decades (Kaveh et al., 2020; Paidar et al., 2021; Darvish Motevalli and Ebrahimi, 2021; Latifiee and Shafiee, 2023; and Shirouyehzadeh et al., 2023).

Unlike parametric methods, DEA does not require a predefined production function; instead, it assesses efficiency solely based on specific inputs consumed by the system to generate outputs. In contrast, parametric methods necessitate the identification of a production function that accurately depicts the relationship between inputs and outputs. Consequently, an incorrect selection of a production function can introduce errors in the evaluation process. The absence of a production function requirement in DEA confers a significant advantage to this technique. Additionally, DEA enables the

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evaluation of decision-making units (DMUs) with multiple inputs and outputs, while alternative efficiency estimation methods typically consider only a single output. This feature further enhances the advantages of the non-parametric method. One fundamental assumption of DEA is variable returns to scale, signifying the rate of output increase corresponding to a unit increase in input. Models that incorporate this assumption are more reliable in terms of providing economic estimates, as they align with the fundamental principles of production theory, such as monotone increasing and concavity.

As mentioned earlier, classical models of DEA primarily assess unit performance based on specific inputs and outputs. However, in reality, there are hidden factors that may not be directly observable but still exert influence on performance. These influential factors are referred to as contextual variables. Identifying these contextual variables and estimating their impact on performance evaluation can provide valuable insights for managers in formulating effective strategies. Consequently, researchers have introduced various methods in recent years, including single-stage and two-stage approaches, to determine the effect of contextual variables. Single-stage methods and two-stage methods differ in their approach. Single-stage methods typically rely on parametric techniques, while two-stage methods involve a combination of both parametric and non-parametric approaches.

Ray (1988) pioneered the implementation of a two-stage approach, combining non-parametric techniques such as DEA with parametric regression analysis, to investigate the impact of contextual variables on efficiency. Subsequently, Wang and Schmidt (2002) noted that the one-step method yields better results when the sample size is limited, while the two-step method demonstrates superior performance for larger sample sizes. Furthermore, Simar and Wilson (2007) advocated for the adoption of a two-step method utilizing the Monte Carlo method to estimate the effect of contextual variables on efficiency. In a comprehensive study, Banker and Natarajan (2008, 2019) investigated various one-stage and two-stage methods for assessing the effect of contextual variables on efficiency. They concluded that the two-stage technique, which combines ordinary least squares (OLS) methods with DEA, provides more accurate approximations of the impact of contextual variables on efficiency. This approach involves initially calculating the efficiency value using DEA and subsequently employing the OLS method to estimate the influence of contextual variables on the efficiency value.

Our research aims to estimate relative efficiency in the presence of contextual variables and subsequently rank the DMUs. To achieve this, we begin by analyzing and evaluating the performance of each DMU through DEA, assessing their inputs and outputs. Next, we evaluate the influence of contextual variables on the efficiency score using linear regression. After removing the impact of contextual variables, units are ranked based on their modified efficiency. Finally, we apply our proposed approach to assess the performance of Iran's provincial gas companies.

The next section introduces the proposed approach. Subsequently, in the third section, we apply this approach to assess the performance and ranking of Iranian gas companies from 2013 to 2016. Finally, the fourth section presents the results obtained from the proposed method.

Methodology

Contextual variables are beyond the direct control of managers, yet they significantly impact efficiency levels, whether increasing or decreasing. Omitting the effects of contextual variables allows managers to achieve a certain level of efficiency, forming the foundation for a suitable analysis. Accordingly, in the initial phase, the performance of each unit is calculated using the DEA technique for assessment. Following this, the regression method is employed to estimate the influence of contextual variables.

- **Phase 1:** *Efficiency assessment*

Suppose we have a set of $j = 1,...,J$ DMUs and $t = 1,...,T$ time periods, where each $DMU_j^{(t)}$ includes of input vectors $x_j^{(t)} = (x_{1j}^{(t)},...,x_{Ij}^{(t)}) \geq \cdot$, output $y_j^{(t)} = (y_{1j}^{(t)},...,y_{Rj}^{(t)}) \geq \cdot$, and a vector of contextual variables $z_j^{(t)} = (z_{1j}^{(t)},...,z_{Sj}^{(t)}) \geq \cdot$, as illustrated in Figure 1.

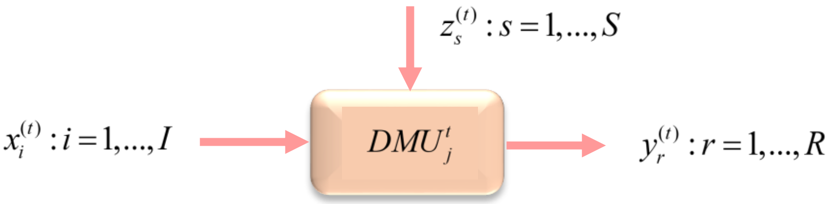

Figure 1. *Structure of* $DMU_j^{(t)} : t = 1,...,T, j = 1,..,J$

The performance of DMU_o is determined through the following model, which takes into account principles such as the inclusion of observation, free disposability for inputs and outputs, convexity, and minimum extrapolation (Banker et al., 1984).

$$
\begin{aligned}
& E_o = Min\ \delta \\
& s.t. \\
& \sum_{t=1}^{T}\sum_{j=1}^{J} \lambda_j^{(t)} x_{ij}^{(t)} \leq \delta x_{io}^{(t)},\ i = 1,...,I, \\
& \sum_{t=1}^{T}\sum_{j=1}^{J} \lambda_j^{(t)} y_{rj}^{(t)} \geq y_{ro}^{(t)},\ r = 1,...,R, \\
& \sum_{t=1}^{T}\sum_{j=1}^{J} \lambda_j^{(t)} = 1, \\
& \delta \text{ is free}, \\
& \lambda_j^{(t)} \geq 0,\ \forall t, j.
\end{aligned}
\tag{1}
$$

Model (1) is an input-oriented model that focuses on the reduction of inputs level. The objective function value in this model is bounded between zero and one $(0 < E_o \leq 1)$. The unit under evaluation is considered efficient if and only if $E_o = 1$; otherwise, it is deemed inefficient.

- **Phase 2:** *Estimating the effect of contextual variables*

After calculating the efficiency score of DMU_o in this phase, we utilize the following regression model to estimate the impact of the contextual variables:

$$Log_{10}(E_o) = \eta_0^{(t)} + \sum_{s=1}^{S} \beta_s^{(t)} z_{sj}^{(t)} + \varepsilon_j^{(t)},\quad \forall j,t,s. \tag{2}$$

In Model (2), we conduct a regression analysis by regressing the logarithm of the efficiency score on contextual variables. $\eta_0^{(t)}$ and $\varepsilon_j^{(t)}$ represent the intercept and the residual error, respectively, in the regression model. $\beta_s^{(t)}$ denotes the coefficients that estimate the impact of contextual variables on the efficiency score. These coefficients can take positive or negative values. A positive value indicates a direct effect on the efficiency score, while a negative value suggests an inverse effect.

Once the impact of contextual variables on the efficiency score has been estimated, the new efficiency score (E_{New}) is calculated. This new efficiency score allows for a meaningful comparison of DMUs' performance. Importantly, the new efficiency score is obtained by eliminating the influence of contextual variables on the efficiency score.

Application to Gas companies

The gas industry plays a crucial role in meeting the energy demands of modern society, providing a reliable and efficient source of fuel for various sectors. Gas companies are at the forefront of this industry, responsible for the extraction, processing, transportation, and distribution of natural gas. As key players in the energy sector, gas companies face a range of challenges and opportunities. They must navigate complex regulatory frameworks, address environmental concerns, and adapt to technological advancements that impact their operations. Additionally, gas companies must ensure the safe and secure delivery of gas to end-users, while also maintaining cost-effective operations and meeting the growing energy needs of the population. Achieving these objectives requires strategic planning, innovative solutions, and a keen understanding of market dynamics. Moreover, gas companies must actively engage with stakeholders, including government entities, environmental groups, and local communities, to foster sustainable practices and address societal expectations. By leveraging their expertise and embracing advancements in technology, gas companies can contribute to the energy transition and play a pivotal role in shaping the future of the energy landscape. The importance of this industry has led researchers to focus on this field in recent years. In the following section, we will refer to some of these studies that are based on the DEA technique.

Guncharuk (2008) utilized domestic and international benchmarking to evaluate the efficiency of the gas distribution industry in Ukraine. They considered material costs, the number of employees, amortization, and accounts payable as input variables, and operating revenues and trade account payable as outputs. Erbetta and Rappuoli (2008) employed DEA to determine the optimal scale for Italian gas distribution companies. They considered comprehensive costs as the input variable and the number of customers and delivered volumes as output variables. Zorić et al. (2009) conducted DEA benchmarking for gas distribution utilities in Slovenia, the Netherlands, and the UK. They utilized operating expenditures of gas distribution and supply activities, the number of customers, gas throughput supplied, peak demand, and JES network length as input and output variables across five different models. Ertürk and t-Aşik (2011) utilized DEA to assess the relative efficiency of natural gas distribution companies in Turkey. Sadjadi et al. (2011) proposed a robust super-efficiency DEA model to rank provincial gas companies in Iran. Their analysis included kilometers of the network and the number of employees as input variables, while delivered volumes, the number of customers, and the percentage of installed gas served as output variables. Tovar et al. (2015) analyzed the efficiency of the gas distribution industry in Brazil, considering factors such as capital, the cost of sales, operating costs, network, sales, density of customers, maximum demand, ownership, and the time trend. Yardımcı and Karan (2015) assessed the efficiency and service quality of natural gas distribution companies in Turkey. They considered the operational expenditures of ordinary customers as the input variable, and the total consumption of ordinary consumers, the number of ordinary consumers, the total length of the network, and environmental factors (climate) as output variables. Lo Storto (2018) conducted a multi-stage DEA study to measure the efficiency of the transmission segment in the US natural gas industry. Their analysis incorporated operating and maintenance expenses, gas volume transmitted, transmission system length, and compression stations as inputs and outputs across different stages. Fernández et al. (2018) employed the Malmquist technique to evaluate the energy efficiency of natural gas facilities. Kong et al. (2018) evaluated the risks associated with natural gas imports in China and explored optimal import strategies. In 2019, Ghazi and Hoseinzade Lotfi proposed a practical solution to organizational budget allocation using a restricted linear budget model based on data envelopment analysis. Their approach, applied to the Iranian gas industry, enhances efficiency by systematically reallocating budgets, offering a streamlined method for improved resource distribution. Wegener and Amin (2019) applied directional inverse DEA to evaluate gas and oil companies from 2011 to 2015. Bansal (2019) conducted an assessment of the performance of India's oil and gas sectors utilizing the DEA technique. Amirteimoori et al. (2020) employed DEA to evaluate the performance of gas companies in Iran. Their evaluation considered twelve variables, including five inputs (the number of employees, operational costs, fixed assets, allocated budgets, and delivered gas volume), four desirable outputs (total revenue, the number of subscribers, the network, and gas diffusion factor), two undesirable outputs (environmental pollution and overdue debts), and one nondiscretionary output (lost gases). Dia et al. (2021) investigated the performance of Canadian oil and gas companies from 2012 to 2015. In 2023, Borodin et al. employed DEA and logistic regression methods to assess the efficiency of oil and gas firms in Russia. Jarboui (2023) conducted a study on the environmental efficiency of several oil and gas companies in the U.S. from 2000 to 2018, with a focus on the critical role of renewable energy in environmental protection.

Considering the significant importance of the gas industry, we have decided to implement our proposed approach specifically for Iranian gas companies. In the following subsections, we will first introduce the variables used for evaluating performance and subsequently present the results obtained from our approach.

Description of variables

We have considered 29 provincial gas companies for our analysis, taking into account certain limitations. Each company in our study follows a structure illustrated in Figure 2.

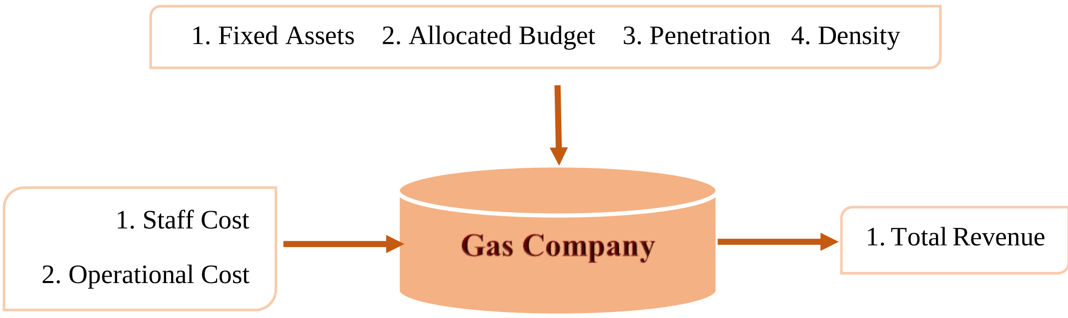

Figure 2. *Structure of Gas companies*

The indicators for inputs, desirable outputs, and contextual variables for each company are presented as follows:

- ❖ **Inputs:**
  - — *Staff Costs:* These expenses arise from employing full-time staff members actively contributing to the operations of each provincial company, distinct from operational costs.
  - — *Operational Costs:* Encompassing expenditures directly associated with the day-to-day functioning of a business, as well as those incurred in maintaining and operating various devices, components, equipment, or facilities.
- ❖ **Output:**
  - — *Total Revenue:* The overall income derived from the sale of gas or related products and services.
- ❖ **Contextual Variables:**
  - — *Fixed Assets:* Tangible properties owned by a company to generate income, of a long-term nature, and utilized in the company's regular operations.
  - — *Allocated Budget:* In the context of our analysis, this represents a portion

of the predefined budget allocated and acquired by each company.

- *Penetration:* Obtained by dividing the number of households in a particular province by the total population, this metric yields a value ranging from zero to one and helps assess market coverage or reach.
- *Density:* A measure determined by the ratio of the number of households to the length of gas lines within each province, aiding in evaluating the concentration of gas infrastructure relative to the number of households served.

Description of data

The values for the defined indicators were collected over four time periods (2013-2016), and a statistical summary is presented in Table 1.

Table 1.
Statistical summary of data for 29 Iranian Gas companies (2013-2016)

Variables	Min	Median	Max	Mean	Std.	Q1	Q3
Staff Costs	524.08	2215.08	16069.3	3742.20	3328.30	1613.85	4053.94
Operational Costs	1847.27	914270	9039931	1435380.31	1522331.23	541847	1678840.25
Total Revenue	171430	2252677	20960420	4085677.16	5043699.82	952802.5	4727519.5
Log of Fixed Assets	5.47	6.66	7.46	6.69	0.34	6.44	6.94
Log of Allocated budget	5.23	5.87	6.97	5.91	0.32	5.68	6.10
Penetration	0.014	0.84	1	0.80	0.19	0.72	0.91
Density	**7.77**	**49.12**	**560.79**	**74.64**	**88.62**	**36.01**	**76.81**

Efficiency assessment results and analysis of contextual variables

In this subsection, we analyze the performance of 29 gas companies over four years (116 observations) using our proposed approach, focusing on reducing inputs such as staff costs and operating costs. The method, as mentioned earlier, was implemented in two steps: first, we conducted the calculation of technical efficiency, followed by adjusting efficiency scores by removing the influence of contextual variables. Subsequently, the companies were ranked based on the revised efficiency scores.

The results obtained from our proposed approach are presented in Table 2. Results illustrate how contextual variables influence efficiency, resulting in either an increase or decrease in the technical efficiency scores. It is noteworthy that the efficiency value increased for 59% of companies after removing the effect of contextual variables. Among the four periods, the second period witnessed the largest share of this increase. Figure 3 illustrates changes in efficiency values, encompassing both increases and decreases.

In general, among the 116 companies, Hormozgan, Tehran-Alborz gas companies secured the highest and lowest ranks, respectively. When considering the four periods separately, Ilam, Khorasan Jonoubi, Qom and Kohkiloyeh and Boyar Ahmad gas companies were assigned the 2nd to 8th ranks, while Tehran-Alborz, and Mazandaran companies claimed the 29th and 28th ranks.

The modified efficiency results across four periods reveal that some companies consistently increased or decreased in all periods, while others exhibited a mix of increases and decreases. For instance, gas companies in Azarbaijan Sharghi, Ardabil, Khorasan Razavi, Zanjan, Kordestan, Kerman, Golestan, Guilan, and Hormozgan demonstrated efficiency increases in all four periods. Conversely, companies in Ilam, Boushehr, Khorasan Jonoubi, Fars, and Mazandaran consistently decreased in efficiency. Additionally, other companies showed a combination of increases and decreases in different periods.

According to Table 2, it is evident that Hormozgan Company was efficient in 2017 and 2018 but inefficient in 2019 and 2020. The modified efficiency value increased after removing the effect of contextual variables from the technical efficiency value, resulting in the company being assigned the highest rank in all four periods. In contrast, Ilam Company was efficient in the first period but inefficient in subsequent periods. Unlike Hormozgan Company, Ilam Company's technical efficiency decreased over all four periods. Notably, despite this decline, Ilam Company secured the second and third ranks. Tehran-Alborz Company consistently exhibited the lowest efficiency in all four periods. Even after removing the effect of contextual variables, the technical efficiency value increased in the first, second, and fourth periods, but the company still retained the lowest rank. The technical efficiency of Azerbaijan Sharghi and Fars Companies displayed a decreasing trend. However, after removing the impact of contextual variables, the efficiency of Azerbaijan Sharghi increased, while Fars Company's efficiency decreased in all four periods. These changes correspondingly affected the ranking, with an upward trend observed for Azerbaijan Sharghi and a downward trend for Fars Company.

Table 2
Efficiency and ranking results

Gas Company	2013		2014		2015		2016	
	E_o	E_{New}	E_o	E_{New}	E_o	E_{New}	E_o	E_{New}
Azarbaijan Sharghi	0.1922	0.3700 (24)	0.1122	0.5142 (8)	0.11	0.4520 (7)	0.1023	0.4977 (3)
Azarbaijan Gharbi	0.4352	0.3079 (27)	0.3641	0.4415 (19)	0.3156	0.3471 (20)	0.2654	0.2995 (22)
Ardebil	0.2535	0.4921 (13)	0.3783	0.4512 (16)	0.3128	0.4208 (10)	0.2844	0.3579 (14)
Esfehan	0.1128	0.4174 (22)	0.0931	0.3867 (25)	0.2273	0.1396 (28)	0.1669	0.1018 (29)
Ilam	1	0.8066 (2)	0.7348	0.6582 (2)	0.5794	0.5252 (3)	0.9346	0.5954 (2)
Boushehr	0.7429	0.5314 (6)	1	0.5949 (5)	0.6639	0.3427 (21)	1	0.4645 (5)
Tehran-Alborz	0.0787	0.1366 (29)	0.0885	0.1028 (29)	0.0927	0.0776 (29)	0.1002	0.1820 (27)
Chaharmahal Bakhtiari	0.4912	0.4481 (17)	0.4501	0.4747 (13)	0.3242	0.4231 (9)	0.3087	0.4065 (9)
Khorasan Jonoubi	0.8387	0.7162 (4)	0.6831	0.6204 (4)	0.68	0.5764 (2)	0.55	0.4833 (4)
Khorasan Razavi	0.1724	0.4173 (23)	0.165	0.4154 (23)	0.1579	0.3720 (17)	0.1533	0.3364 (19)
Khorasan Shomali	0.653	0.5257 (7)	0.5417	0.4315 (21)	0.53	0.3870 (15)	0.4958	0.3298 (20)
Khozestan	0.1924	0.3627 (25)	0.2878	0.3261 (27)	0.2237	0.2756 (26)	0.1991	0.2565 (26)
Zanjan	0.5564	0.5020 (10)	0.41	0.4597 (14)	0.6603	0.4408 (8)	0.5349	0.3827 (12)
Semnan	0.3523	0.5022 (9)	0.4172	0.5130 (9)	0.4742	0.5090 (5)	0.448	0.4469 (7)
Fars	1	0.4877 (15)	0.9346	0.4503 (17)	0.7459	0.2894 (25)	0.7219	0.1574 (28)
Ghazvin	0.5524	0.4222 (21)	0.4695	0.3821 (26)	0.3769	0.4017 (12)	0.367	0.3866 (11)
Qom	0.9664	0.6212 (5)	0.7914	0.5502 (6)	0.6268	0.4735 (6)	0.6356	0.4089 (8)
Kordestan	0.4641	0.5010 (11)	0.3672	0.4791 (11)	0.3789	0.3950 (13)	0.3451	0.3526 (16)
Kermanshah	0.4684	0.4900 (14)	0.3923	0.4181 (22)	0.3994	0.3657 (19)	0.3428	0.3505 (17)
Kerman	0.3008	0.4854 (16)	0.276	0.5488 (7)	0.2775	0.4038 (11)	0.2441	0.3964 (10)
Kohkiloyeh and Boyer Ahmad	0.8098	0.7326 (3)	0.573	0.6207 (3)	0.5419	0.5093 (4)	0.4284	0.4587 (6)
Golestan	0.3279	0.4286 (20)	0.2682	0.4434 (18)	0.2872	0.3665 (18)	0.2443	0.3571 (15)
Guilan	0.232	0.4446 (18)	0.179	0.4875 (10)	0.2408	0.3370 (22)	0.1965	0.2972 (23)

Lorestan	0.5332	0.5237 (8)	0.3961	0.4758 (12)	0.4186	0.3889 (14)	0.3364	0.3469 (18)
Mazandaran	0.2805	0.2424 (28)	0.3021	0.2236 (28)	0.2578	0.2008 (27)	0.1963	0.2959 (24)
Markazi	0.7202	0.4358 (19)	0.3997	0.4589 (15)	0.3789	0.3329 (23)	0.4072	0.3112 (21)
Hormozgan	1	1.0817 (1)	1	1.1036 (1)	0.8238	1.0966 (1)	0.8977	0.9227 (1)
Hamedan	0.3289	0.3179 (26)	0.274	0.4111 (24)	0.2375	0.3744 (16)	0.2373	0.3707 (13)
Yazd	0.481	0.4988 (12)	0.3661	0.4324 (20)	0.4153	0.3243 (24)	0.3481	0.2756 (25)

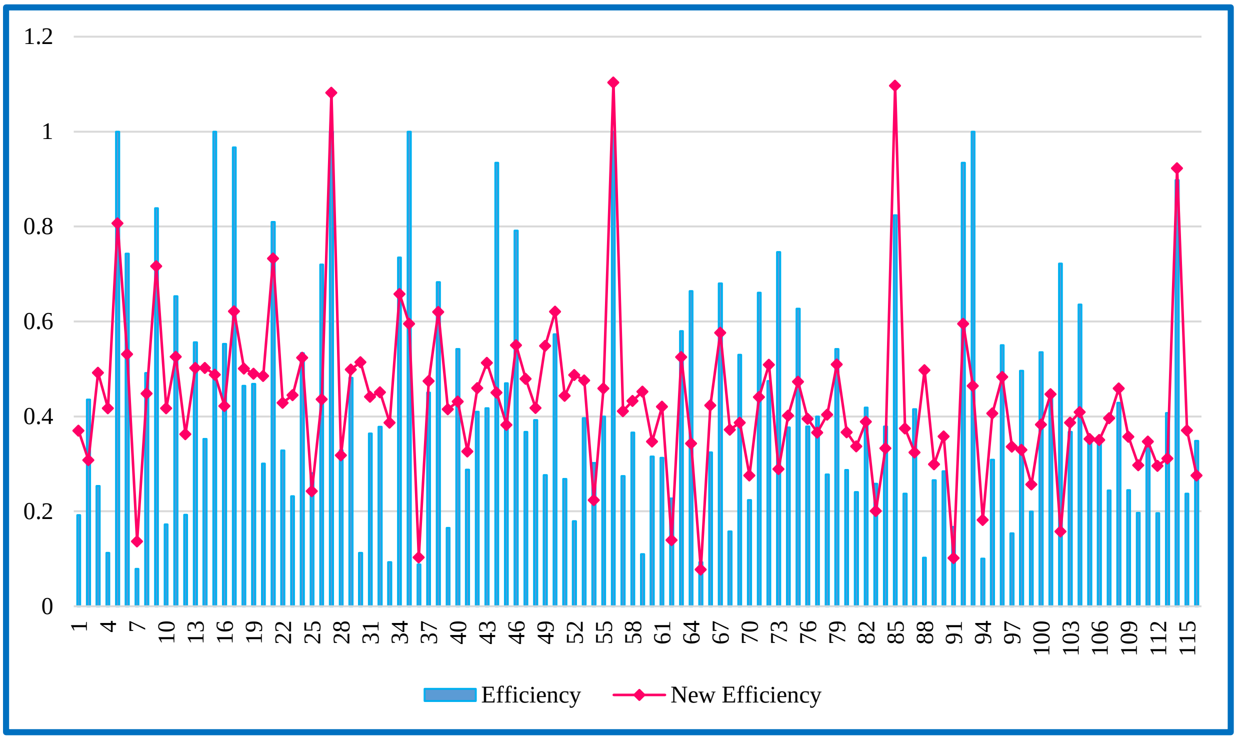

Figure 3. *Impact of contextual variables on efficiency scores*

Our proposed approach offers several distinct advantages compared to traditional ranking methods. Firstly, it can rank all units without excluding efficient units or establishing new boundaries. This ensures a comprehensive ranking, including non-extreme efficient units. Another advantage of our method is its ability to address the issue of infeasibility for efficient units, providing a more robust and reliable ranking process.

The regression analysis has revealed an inverse relationship between contextual variables and efficiency. Among these variables, penetration has the most significant impact, while density has the least effect. The regression model exhibits a high R-squared value, signifying a strong correlation between contextual variables and efficiency.

Conclusion

DEA is a non-parametric method used to assess the efficiency of homogeneous DMUs with multiple inputs and outputs. It's essential to note that factors beyond a manager's control, such as contextual variables, can influence the performance and productivity of these units. In this research, we employed two techniques, DEA and linear regression, to explore the relationship between DMU efficiency and contextual variables' impact. In the following section, we investigated the performance of Iranian gas companies over a four-year period using our proposed approach. The results highlight several advantages associated with it. Firstly, it allows for the simultaneous comparison and ranking of all units, without the need to exclude extremely efficient units or establish new boundaries. Secondly, this approach effectively solves the infeasibility of efficient units during the ranking procedure. Another advantage is its ability to quantify the impact of contextual variables on efficiency.

Availability of data

All data used in this paper are available per request.

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