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ORIGINAL RESEARCH

Diagnosing Critical Performance Drivers in the Iranian Gas Industry under Uncertainty: A Hybrid Fuzzy DEA–EFQM Approach

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Abstract

The gas industry exhibits considerable sensitivity to variations in specific determinants that substantially influence organizational efficiency, commonly termed as critical factors. The European Foundation for Quality Management (EFQM) has introduced a broadly applied framework for assessing organizational performance against nine criteria, each of which can affect efficiency if changed. Data Envelopment Analysis (DEA) is a robust nonparametric tool for evaluating Decision-Making Units (DMU) performance based on multiple inputs and outputs. However, classical DEA models usually assume precise data and deterministic conditions. In practice, especially in large-scale industries such as the gas sector, performance data are frequently ambiguous, imprecise, and uncertain, making it difficult to identify the critical factors. Previous studies have either treated inputs/outputs as certain or applied EFQM and DEA separately, leaving a notable gap in the literature regarding the integration of fuzzy environments with organizational excellence frameworks to identify critical factors.

In order to bridge this gap, we present a new hybrid approach that integrates Fuzzy DEA (FDEA) with the EFQM model. Our model is non-radial and is expressed as a deterministic linear programming (LP) problem that enables the identification of critical factors under uncertainty. Using the Fuzzy Analytic Hierarchy Process (FAHP), we evaluated nine EFQM criteria in 15 Iranian gas companies and applied the proposed model to identify the most influential critical factors. The results show that only a limited number of companies achieved full efficiency, while the majority benefited from identifying critical factors

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to improve their performance. This study emphasizes the practical value of combining FDEA and EFQM for managers seeking robust tools to improve efficiency in an uncertain environment.

Keywords: Gas industry; Fuzzy Data Envelopment Analysis (FDEA); EFQM; Critical Factors; Fuzzy AHP

1-Introduction

The endeavor to sustain competitiveness in the global energy market has increasingly challenged the competitive viability of numerous contemporary organizations. While there are many performance improvement strategies that organizations can implement, it remains unclear which strategies, or combinations thereof, are most effective in enhancing organizational performance. Energy, as one of the most critical drivers of any economic process, has a strategic position in developing and developed economies and is regarded as one of the fundamental factors for development. In other words, energy, like other production factors, is a key factor contributing to economic growth.

Natural gas stands out as one of the most significant energy carriers of the 21st century, which plays a very important role in world trade as it is an important fuel. Iran, endowed with vast proven reserves, exploits this resource both for domestic consumption and for export to numerous countries. Furthermore, as the second-largest holder of proven natural gas reserves globally and due to its excellent geographical conditions, Iran occupies an indispensable position in global gas markets.

However, in the context of Iran's gas industry, where billions of dollars are invested annually and operational inefficiencies directly affect both domestic energy security and international competitiveness, overlooking the influence of critical performance factors may result in substantial financial and strategic losses.

Systematic identification of organizational challenges from both internal and external perspectives facilitates the discovery of core strengths and weaknesses, as well as emerging opportunities and potential threats. In the contemporary industrial landscape, most sectors — including the gas industry — confront critical challenges such as inadequate management practices, suboptimal resource allocation, and insufficient recruitment of skilled personnel.

To address these challenges, recent advances in management thinking and the rise of quality management as a key driver of competitiveness convey a clear message: management in the twenty-first century constitutes a highly specialized and intellectually demanding profession, comparable in rigor and complexity to the medical profession. Accordingly, managers must not only possess a thorough understanding of their operating environment and its inherent complexities, but also master the principles of management science and apply appropriate tools and techniques to guide their organizations effectively. In this sense, excellence models are a suitable method for evaluating the performance of organizations. Through the application of these models, organizations are able to benchmark their performance against domestic and international competitors. These models demonstrate that organizational excellence is not merely a theoretical construct, but rather the attainment of empirically grounded, measurable outcomes. Within the scope of contemporary management concepts that have taken a significant place across many countries worldwide, organizational excellence strengthens the movement for improvement and progress in organizations by

creating a competitive environment. The European Foundation for Quality Management developed the EFQM model as a comprehensive instrument for assessing the degree of organizational growth and excellence, and for delineating the trajectory toward sustained organizational advancement [1].

When applied rigorously, the EFQM model provides a powerful mechanism for embedding excellence-oriented concepts within institutions, facilitating the formulation and implementation of strategic plans and supporting continuous organizational improvement. It further enables the identification of best-practice processes and facilitates the rationalization of human resource utilization. To date, a relatively large amount of research has been conducted in the field of organizational performance measurement; see for example: Sharma and Talwar [2], Eskildsen et al. [3], Mavroidis et al. [4], Calvo-Mora et al. [5], Zárrega-Rodríguez and Álvarez [6], Calvo-Mora et al. [7].

In the pursuit of financial and operational improvement, the attainment of optimal outcomes has consistently remained a focal concern for both researchers and practitioners. Among the most appropriate criteria for evaluating performance units is the rigorous measurement of efficiency. Numerous methodological approaches have been proposed for the purpose of relative organizational evaluation. Among the most widely adopted techniques for evaluating the performance and comparative efficiency of decision-making units is Data Envelopment Analysis (DEA). DEA provides a nonparametric analytical framework for measuring the relative performance of homogeneous systems operating across multiple inputs and outputs. In DEA, each system is modeled as a Decision-Making Unit (DMU), and its relative efficiency is computed through the solution of a corresponding set of linear programming (LP) problems.

Data Envelopment Analysis (DEA) is primarily based on two classical models: the CCR model proposed by Charnes, Cooper, and Rhodes [8], which assumes Constant Returns to Scale (CRS), and the BCC model developed by Banker, Charnes, and Cooper [9], which extends the approach to Variable Returns to Scale (VRS).

These foundational models represent the cornerstone of DEA methodology, and subsequent decades have witnessed remarkable advances in DEA model development across diverse industries and scientific disciplines. While traditional DEA models presuppose the availability of precise and deterministic data, real-world applications frequently involve uncertain, imprecise, and ambiguous information. To address this limitation, a range of Fuzzy DEA (FDEA) methodologies have been developed to explicitly accommodate imprecision and ambiguity within the DEA framework. The fuzzy sets proposed by Zadeh [10] have been used to determine the efficiency of DMUs in situations where data are imprecise.

Recently, studies have been developed and conducted in this area; see, for example, Ahmadvand and Pishvaei [11], Saati et al. [12], Esfandiari and Saati [13], Hatami-Marbini et al. [14], Moreno and Lozano [15], Saati et al. [16], Lozano [17].

Broadly speaking, fuzzy DEA models may be classified into four principal categories according to their methodological foundations: the tolerance approach (Sengupta [18]; Kahraman and Tolga [19]), the α -cut-based approach (Maeda et al. [20], Kao and Liu [21], Hatami-Marbini and Saati [22]), the fuzzy-based ranking approach (Guo and Tanaka [23]), the possibility approach (Dubois and Prade [24], Lertworasirikul [25], Lertworasirikul et al. [26]).

An additional significant feature of DEA is its managerial perspective, which offers multiple analytical viewpoints for examining the effects of inputs and outputs on DMU performance. This is attributable to the fact that managers seek to sustain optimal performance in efficient DMUs through appropriate adjustments to inputs and outputs, while inefficient units may attain the efficiency frontier through corresponding modifications to their input-output configurations. Furthermore, changes in certain factors — inputs or outputs — may exert a disproportionately greater impact on efficiency relative to others. Identifying these factors can be useful for the study of DMUs. Factors for which marginal variations induce measurable changes in efficiency are designated as critical factors. Zhu [27] was the first to consider all inputs and outputs as potentially critical and systematically measured the effects of input and output perturbations on each efficient unit. Subsequently, Zhu [27] proposed an extended CCR DEA model to identify the efficiency frontier projections of DMUs in input and output directions and generate cones containing the remaining DMUs. Necessary and sufficient conditions were established to determine the circumstances under which an extreme DMU retains its efficiency classification despite increases in inputs and decreases in outputs.

Owing to inherent structural limitations, Zhu's models yielded inconclusive results, manifesting as infeasibility under certain conditions. Subsequently, Thrall [28] classified DMUs into four categories and assessed their stability simultaneously with input and output variations using LP-based DEA models. Boljuncic [29] subsequently examined and rectified the deficiencies of Thrall's models, particularly those arising in the context of the dominant hyperplane, and proposed an improved LP formulation. Daneshvar et al. [30] introduced a novel methodology grounded in the generalized CCR framework for identifying critical performance measures. Chen and Zhu [31] demonstrated that inputs and outputs are critical when appropriate modifications to these variables enable the transformation of inefficient DMUs to their corresponding projections on the efficiency frontier — thereby establishing efficiency targets — while simultaneously preserving the efficiency status of units already on the frontier. Furthermore, Chen and Zhu [31] employed statistical and regression techniques to evaluate the performance of a set of DMUs. After obtaining the performance coefficient in the DMUs, they determined efficiency values using the fractional scheduling model, which is equivalent to the BCC model in terms of output. Critical thresholds were subsequently computed based on the hyperplane defining the efficiency frontier. Wu and Liang [32], building upon the super-efficiency model of Andersen and Petersen [33], developed a methodology for calculating critical measures across input-output combinations. Unfortunately, evaluating the efficiency score using the defined set of m inputs and the set of s outputs requires solving the nonlinear model for the evaluated DMU. To address this challenge, a first-order Taylor series expansion was employed to approximate the nonlinear constraints in the optimization model; the resulting linearized model was substituted for the original nonlinear formulation, enabling the computation of allowable changes in input-output combinations. Nevertheless, the approach of Wu and Liang [32] is subject to approximation errors inherent in the truncation of the Taylor series after the first-order term, compromising the accuracy and precision of the results.

Based on previous studies, the EFQM Model for Excellence was introduced as the primary framework for assessing and improving organizations. The DEA is also known as an efficient tool for evaluating organizational processes. Although the EFQM model is extensively applied as a benchmark for

organizational excellence and DEA/FDEA is employed to measure efficiency, their integrated application for the identification of critical factors under conditions of uncertainty has not yet been systematically investigated. This integration is of particular importance for strategically significant sectors such as the Iranian gas industry, where decision-making under conditions of uncertainty is the norm rather than the exception.

Accordingly, DEA and the EFQM excellence model have been employed in combination for organizational efficiency assessment. For example, Donnelly [34] proposed a system for evaluating public sector operations that combines the DEA method with the EFQM model of excellence. Tomažević et al. [35] used DEA and EFQM models to measure police performance. Their findings revealed a strong and statistically significant correspondence between DEA efficiency scores and the resulting rankings of police stations.

By contrast, in prior studies within this domain, critical factors have been treated as deterministic and precisely known, whereas real-world data are characteristically imprecise and subject to uncertainty. Specifically, input and output data may not always be precisely quantifiable and may exhibit substantial vagueness. Such imprecision or vagueness typically arises from indeterminate and incomplete information.

Another topic of significant managerial relevance concerns the ranking of DMUs according to their relative performance. Many studies have been conducted in this area. For example, Mehrabian et al. [36] proposed an LP model in the presence of zero data, called the MAJ model. However, the MAJ model exhibits infeasibility under certain conditions, as formally established by a theorem presented in [36]. Saati et al. [37] subsequently enhanced the MAJ model, demonstrating that the modified formulation maintains feasibility under all conditions while simultaneously accommodating both input- and output-oriented perspectives. Management decisions are frequently characterized by multiple conflicting criteria, inherent uncertainty, and the subjective judgments of diverse stakeholders. To address these challenges, methodologies such as the Fuzzy Analytic Hierarchy Process (FAHP) have been developed, specifically designed for the resolution of multi-criteria decision problems under uncertainty and for ranking DMUs according to managerial priorities.

As previously noted, the determination of critical factors plays a pivotal role in enhancing DMU performance; however, this issue has received insufficient attention in the extant literature.

To the best of the authors' knowledge, this paper is the first to systematically identify and analyze critical factors while explicitly accounting for the inherent fuzziness of input and output data. To this end, the model proposed by Saati et al. [37] was extended to incorporate fuzzy inputs and outputs. Through the application of this approach, the possibilistic programming formulation is transformed into an equivalent deterministic model. Furthermore, a systematic procedure is provided for improving DMU performance through the identification of critical factors. The proposed model is non-radial in nature, enabling the detection of minimal perturbations in inputs and outputs. Given the pivotal role of industrial development in national economic progress, considerable research effort has been directed in recent years toward identifying the critical factors that govern industrial efficiency. Accordingly, in this paper, a novel deterministic LP model is applied to evaluate the performance of 15 gas refineries (DMUs) in Iran. To this end, questionnaires grounded in the EFQM model were constructed, and the relative importance

of the EFQM criteria was determined through the application of the FAHP method. Finally, critical factors were identified for the Iranian gas refineries among the top five ranked EFQM criteria — designated as inputs or outputs — through the application of the proposed model, from which targeted improvement plans for DMU performance were derived.

The structure of the remaining sections is outlined below:

Some essential preliminary remarks and basic definitions are given in Section 2. Section 3 presents a novel linear method based on the modified model of Saati et al. [37]. Section 4 presents the proposed model based on a real case study. Finally, Section 5 presents the concluding remarks and highlights the important findings of the research.

2- Preliminaries

2-1 DEA models

Suppose that there are n DMUs ($DMU_j, j = 1, \dots, n$) such that each DMU_j consumes multiple non-negative m inputs x_{ij} ($i = 1, \dots, m$) to produce multiple non-negative outputs y_{rj} ($r = 1, \dots, s$). It is supposed that $\mathbf{x}_j = (x_{1j}, \dots, x_{mj})^T \neq \mathbf{0}_m$ and $\mathbf{y}_j = (y_{1j}, \dots, y_{sj})^T \neq \mathbf{0}_s$ for each j . Moreover, assume that $D_j = (\mathbf{x}_j, \mathbf{y}_j)^T$ expresses input and output vectors of each $DMU_j, j \in J = \{1, \dots, n\}$. The model presumes the absence of duplicate DMUs.

Banker et al. [9] proposed a LP model named BCC model under VRS assumption to analyze and quantify the efficiency of DMU_p , DMU under evaluation as below:

$$\begin{aligned} \theta^* &= \min \theta & (1) \\ \text{s.t. } & \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{ip} \quad \forall i \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq y_{rp} \quad \forall r \\ & \sum_{j=1}^n \lambda_j = 1 \\ & \lambda_j \geq 0 \quad \forall j \end{aligned}$$

Definition 2-1: DMU_p is BCC efficient if and only if $\theta^* = 1$ and else it is inefficient.

Saati et al. [37] suggested a non-radial DEA model with VRS consumption to measure the efficiency of units as follows:

$$\varphi^* = \min \varphi = w_p + 1 \quad (2)$$

$$\begin{aligned} s.t \quad & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{ip} + w_p \quad \forall i \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq y_{rp} - w_p \quad \forall r \\ & \sum_{j=1}^n \lambda_j = 1 \\ & \lambda_j \geq 0 \quad \forall j; \\ & w_p : URS \end{aligned}$$

Given that the input and output data are categorized by different measurement scales, and the objective function of Model (2) depends on their measurement units, normalization is applied to obtain comparable efficiency values.

One of the things that lead to the improvement and promotion of the performance of organizations is their ranking and comparison with each other. In this vein, Saati et al. [37] modified the MAJ model [36] and based on Model (2) presented the following LP Model (3) to rank DMUs:

$$\varphi^* = \min \varphi = w_p + 1 \quad (3)$$

$$\begin{aligned} s.t \quad & \sum_{\substack{j=1 \\ j \neq p}}^n \lambda_j x_{ij} \leq x_{ip} + w_p \quad \forall i \\ & \sum_{\substack{j=1 \\ j \neq p}}^n \lambda_j y_{rj} \geq y_{rp} - w_p \quad \forall r \\ & \sum_{\substack{j=1 \\ j \neq p}}^n \lambda_j = 1 \\ & \lambda_j \geq 0 \quad \forall j, \quad j \neq p; \\ & w_p : URS \end{aligned}$$

Theorem 2-1: The Model (3) is always feasible and the optimal values are bounded.

Proof : see [37].

2-2 Fuzzy numbers

Fuzzy set theory, introduced by Zadeh [10], provides a formal framework for the representation and manipulation of uncertainty and imprecision in data that reflect human perception and reasoning. In what follows, several foundational definitions pertaining to fuzzy set theory are reviewed (see; Dubois and Prade [24]; Zimmermann [38]).

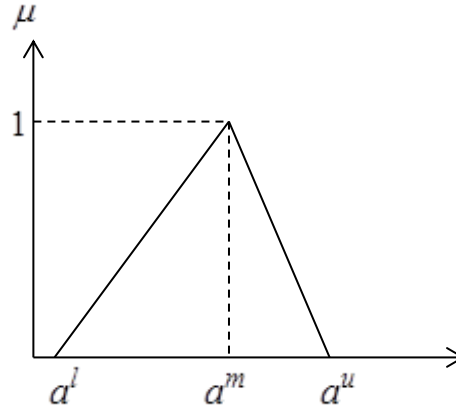


Fig 1. Triangular fuzzy number

Definition 2-2: (Fuzzy sets) Suppose X is a non-empty set. The fuzzy set \tilde{A} in X is specified as $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\}$ where $\mu_{\tilde{A}}(x) : X \rightarrow [0, 1]$ is named the degree of membership of element x belongs to fuzzy set \tilde{A} for each $x \in X$.

Definition 2-3: (α -cut) An α -cut set of the fuzzy set \tilde{A} is a crisp set established by A_α and is defined as follows:

$$A_\alpha = \{x \in X \mid \mu_{\tilde{A}}(x) \geq \alpha\}$$

Definition 2-4: (Fuzzy number) A fuzzy set \tilde{A} is named a fuzzy number if the following assumptions hold true:

- i) $\mu_{\tilde{A}}(x)$ is continuous.
- ii) There exists at least one $x \in X$ that $\mu_{\tilde{A}}(x) = 1$.
- iii) \tilde{A} must be convex.

Definition 2-5: (Triangular fuzzy number) A fuzzy number $\tilde{A} = (a^l, a^m, a^u)$ is named a triangular fuzzy number for which membership function $\mu_{\tilde{A}}$ is defined as (see Fig. 1.):

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & x < a^l \\ \frac{x - a^l}{a^m - a^l} & a^l \leq x \leq a^m \\ \frac{a^u - x}{a^u - a^m} & a^m \leq x \leq a^u \\ 0 & x > a^u \end{cases}$$

In this study, and without limiting generality, all fuzzy numbers are represented using triangular membership functions.

2-3 Critical input-output combinations

Critical factors refer to the set of interrelated inputs and outputs whose variations cause measurable changes in the efficiency performance of a system.

Model (4), proposed by Wu and Liang [32], serves to identify the specific combinations of inputs and outputs that critically influence efficiency.

$$\begin{aligned}
 & \min \phi_M^Q & (4) \\
 & s.t \quad \sum_{j=1, j \neq p}^n \lambda_j x_{ij} \leq \phi_M^Q x_{ip} \quad i \in M \\
 & \quad \sum_{j=1, j \neq p}^n \lambda_j x_{ij} \leq x_{ip} \quad i \notin M \\
 & \quad \sum_{j=1, j \neq p}^n \lambda_j y_{rj} \geq \frac{1}{\phi_M^Q} y_{rp} \quad r \in Q \\
 & \quad \sum_{j=1, j \neq p}^n \lambda_j y_{rj} \geq y_{rp} \quad r \notin Q \\
 & \quad \sum_{j=1, j \neq p}^n \lambda_j = 1, \lambda_j \geq 0 \quad j = 1, \dots, n \\
 & \quad \lambda_j \geq 0 \quad \forall j
 \end{aligned}$$

The model assumes that the DMU under consideration is omitted from the reference set, and only its input set M and output set Q are subject to modification, while all other data remain unchanged. According to Wu and Liang [32], four cases may be observed.

i) $\phi_M^{Q*} < 1$

ii) $\phi_M^{Q*} = 1$

iii) $\phi_M^{Q*} > 1$

iv) Model (4) is infeasible

Model (4) is a non-linear programming problem. Wu and Liang [32] used the first order expansion of the Taylor series and provided an approximation for the non-linear constraint. In order to solve a nonlinear programming problem, they have used a very poor approximation for the expressions in the constraints. This approximation introduces an error in addition to the problems of the nonlinear programming problem.

When DMU_{*p*} is inefficient, $\max \{ \phi_M^{Q*} \}$ is used to detect the most critical input-output amalgamations

and when DMU_{*p*} is efficient, $\min \{ \phi_M^{Q*} \}$ is used to explore the most critical input-output combinations.

Infeasibility associated with the Model (4) indicates the non-critical input and output combinations.

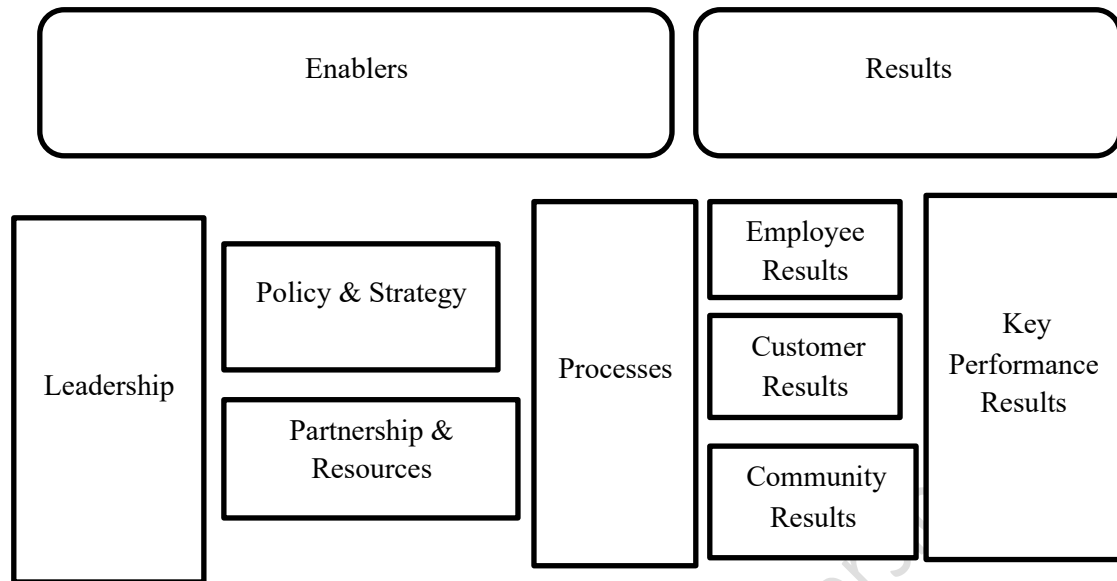


Fig 2. EFQM excellence model

2-4 The EFQM Excellence Model

Designed as a flexible and non-prescriptive approach, the EFQM Excellence Model includes nine central criteria that underpin the assessment of organizational excellence.

The EFQM model contains nine criteria, five of which are associated with the approaches that build the organizational capabilities referred to as enablers. The other four areas relate to the examination of the results of the use of enablers in organizations, known as outcomes.

The Leadership domain has four sub-criteria and each area of policy, employees, resources and processes have five sub-criteria. The areas of customer outcomes, employee outcomes, community outcomes and business outcomes each have two sub-criteria: as shown in Fig. 2.

Below is a detailed explanation of the EFQM Model criteria:

Leadership

We find the element of leadership when you free your employees from the constraints of current rules and participate in the creation of new conditions and rules. Outstanding organizations are led by individuals who anticipate and realize future goals, serving as ethical exemplars and fostering a culture of trust and integrity.

Strategy

Organizations that excel strategically align their mission and vision with stakeholder needs, establishing and implementing policies, objectives, and processes that translate strategy into measurable action.

Employees

Outstanding organizations recognize employees as key enablers of success, building a culture that harmonizes personal growth with organizational achievement. They strengthen workforce capabilities and ensure equal opportunities for all.

Partnerships and resources

Organizations recognized for excellence manage resources and partnerships holistically, integrating suppliers and stakeholders to reinforce process efficiency and policy execution.

Processes, products and services

Organizations committed to excellence design, manage, and continuously improve their processes, products, and services to create value for both customers and stakeholders.

Customer results

Excellent organizations identify and agree upon key performance measures and output indicators derived from customer expectations, enabling them to assess how effectively strategies and related actions are implemented.

Employee results

Leading organizations design employee-focused performance indicators and related outcomes to determine the degree of success in implementing strategies and supporting programs.

Community results

High-performing organizations establish performance indicators and related outcomes aligned with the expectations of external stakeholders to evaluate how effectively their strategies and supporting actions address societal and environmental responsibilities.

Key performance results

Excellent organizations identify and agree upon key financial and non-financial performance outcomes based on the needs and expectations of their key stakeholders to determine the successful strategic implementation.

3- Detecting critical factor with fuzzy data via non-radial model

This section proposes a novel Fuzzy DEA approach for the systematic investigation of critical determinants in environments characterized by data uncertainty. Formally, suppose there are n DMUs, $DMU_j = (\tilde{\mathbf{x}}_j, \tilde{\mathbf{y}}_j)$; $j \in J = \{1, \dots, n\}$ with imprecise data can be represented by $\tilde{x}_{ij} = (x_{ij}^l, x_{ij}^m, x_{ij}^u)$ and $\tilde{y}_{rj} = (y_{rj}^l, y_{rj}^m, y_{rj}^u)$ are triangular fuzzy numbers. The number of inputs and final outputs of DMU be denoted by m and r , respectively. As an initial step, the efficiency levels of decision-making units are assessed using fuzzy-valued inputs and outputs. To accomplish this, Model (2) is reformulated with triangular fuzzy numbers as follows:

$$\begin{aligned}
 \min \quad & \varphi = w_p + 1 & (5) \\
 \text{s.t.} \quad & \sum_{j=1}^n \lambda_j \tilde{x}_{ij} \leq \tilde{x}_{ip} + w_p \quad \forall i \\
 & \sum_{j=1}^n \lambda_j \tilde{y}_{rj} \geq \tilde{y}_{rp} - w_p \quad \forall r \\
 & \sum_{j=1}^n \lambda_j = 1 \\
 & \lambda_j \geq 0 \quad \forall j \\
 & w_p : URS
 \end{aligned}$$

Model (5) constitutes a possibilistic programming formulation, which is subsequently transformed into the following non-radial LP model through the application of Lai and Hwang's method [39]:

$$\begin{aligned}
 \min \quad & \varphi = w_p + 1 & (6) \\
 \text{s.t.} \quad & \sum_{j=1}^n \lambda_j x_{ij}^l \leq x_{ip}^l + w_p \quad \forall i \\
 & \sum_{j=1}^n \lambda_j x_{ij}^m \leq x_{ip}^m + w_p \quad \forall i \\
 & \sum_{j=1}^n \lambda_j x_{ij}^u \leq x_{ip}^u + w_p \quad \forall i \\
 & \sum_{j=1}^n \lambda_j y_{rj}^l \geq y_{rp}^l - w_p \quad \forall r \\
 & \sum_{j=1}^n \lambda_j y_{rj}^m \geq y_{rp}^m - w_p \quad \forall r \\
 & \sum_{j=1}^n \lambda_j y_{rj}^u \geq y_{rp}^u - w_p \quad \forall r \\
 & \sum_{j=1}^n \lambda_j = 1 \\
 & \lambda_j \geq 0 \quad \forall j \\
 & w_p : URS
 \end{aligned}$$

Theorem 3-1: Model (6) is always feasible, and the optimal value is in $(0,1]$.

Proof: $\lambda_j = 0 (j = 1, \dots, n, j \neq p)$, $\lambda_p = 1$ and $w_p = 0$ is a feasible solution of Model (6). According to the status of objective function, this feasible solution implies that $\varphi^* \leq 1$ which φ^* is an optimal solution of Model (6). On the contrary, assume that $w_p \leq -1$ then $x_{ip}^l + w_p \leq 0$, since the data,

inputs and outputs are normalized. This is a contradiction because $\sum_{j=1}^n \lambda_j x_{ij}^l \leq x_{ip}^l + w_p \leq 0 \quad \forall i$.

Therefore, $w_p > -1$ and $0 < \varphi^* \leq 1$ and the proof is complete. ■

Since partial modifications to certain inputs, outputs, or both can improve the efficiency and performance of DMUs, the analysis proceeds to identify the corresponding critical factors. Accordingly, for the identification of critical determinants, it is assumed that multiple inputs and/or outputs may require concurrent adjustment, and the corresponding measures are examined in combination. Thus, as in the non-linear Model (4), it is assumed that DMU_p , the DMU to be evaluated, is removed from the reference sets and only the inputs M and the outputs Q may be changed, while the remaining inputs and outputs are maintained at their present levels. According to these assumptions, Model (6) can be written as Model (7). In contrast to the nonlinear Model (4), the linear Model (2) has been modified to yield a novel non-radial LP model for the determination of critical factors.

$$\varphi^* = \min \quad \varphi = w_p + 1 \quad (7)$$

$$\begin{aligned}
 \text{s.t} \quad & \sum_{j=1, j \neq p}^n \lambda_j x_{ij}^l \leq x_{ip}^l + w_p \quad \forall i \in M \\
 & \sum_{j=1, j \neq p}^n \lambda_j x_{ij}^m \leq x_{ip}^m + w_p \quad \forall i \in M \\
 & \sum_{j=1, j \neq p}^n \lambda_j x_{ij}^u \leq x_{ip}^u + w_p \quad \forall i \in M \\
 & \sum_{j=1, j \neq p}^n \lambda_j x_{ij}^l \leq x_{ip}^l \quad \forall i \notin M \\
 & \sum_{j=1, j \neq p}^n \lambda_j x_{ij}^m \leq x_{ip}^m \quad \forall i \notin M \\
 & \sum_{j=1, j \neq p}^n \lambda_j x_{ij}^u \leq x_{ip}^u \quad \forall i \notin M \\
 & \sum_{j=1, j \neq p}^n \lambda_j y_{rj}^l \geq y_{rp}^l - w_p \quad \forall r \in Q \\
 & \sum_{j=1, j \neq p}^n \lambda_j y_{rj}^m \geq y_{rp}^m - w_p \quad \forall r \in Q \\
 & \sum_{j=1, j \neq p}^n \lambda_j y_{rj}^u \geq y_{rp}^u - w_p \quad \forall r \in Q \\
 & \sum_{j=1, j \neq p}^n \lambda_j y_{rj}^l \geq y_{rp}^l \quad \forall r \notin Q \\
 & \sum_{j=1, j \neq p}^n \lambda_j y_{rj}^m \geq y_{rp}^m \quad \forall r \notin Q \\
 & \sum_{j=1, j \neq p}^n \lambda_j y_{rj}^u \geq y_{rp}^u \quad \forall r \notin Q \\
 & \sum_{j=1, j \neq p}^n \lambda_j = 1 \\
 & \lambda_j \geq 0 \quad \forall j, j \neq p
 \end{aligned}$$

According to Model (7), four possible cases may occur:

- i) $\varphi^* < 1$
- ii) $\varphi^* = 1$
- iii) $\varphi^* > 1$
- iv) Model (7) is infeasible.

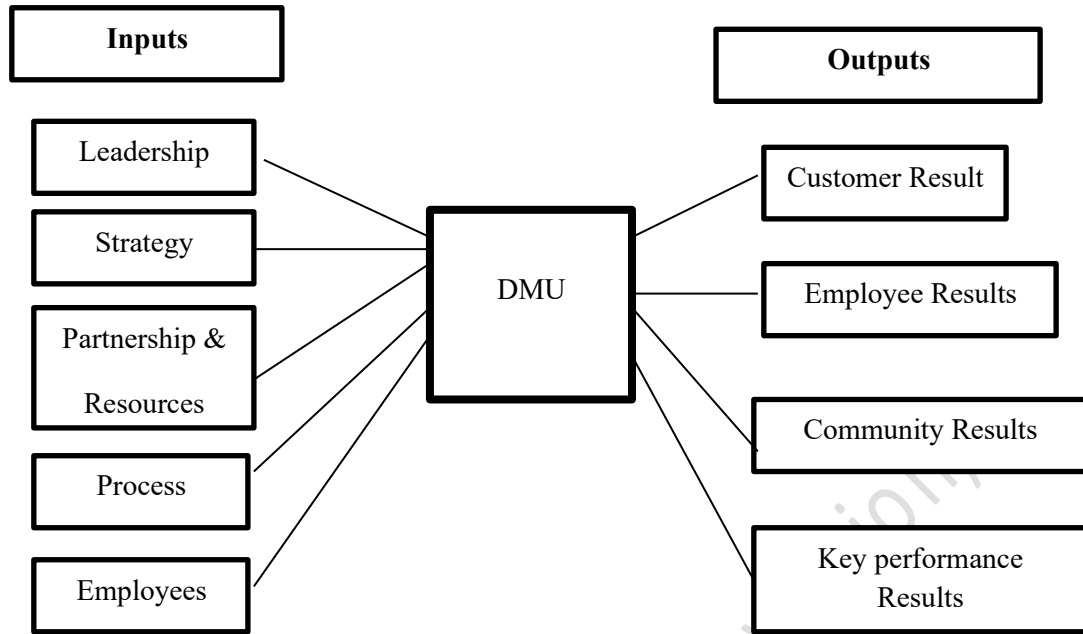


Fig 3. The schematic of DEA-EFQM model

$\varphi^* < 1$ suggests the presence of inefficiencies in DMU_p's inputs M and outputs Q , since DMU_p requires a reduction in input M to $x_{ip}^l - w_p, x_{ip}^m - w_p, x_{ip}^u - w_p$ and increase its outputs Q to $y_{ip}^l + w_p, y_{ip}^m + w_p, y_{ip}^u + w_p$ in order to reach the efficient frontier. For inefficient DMUs, we select $Max \{ \varphi^* \}$ to explore the most critical input and output measures.

Case *ii* to *iv* indicate that no inefficiencies exist in DMU_p's inputs M and outputs Q .

4- Case Study

Contemporary organizations in Iran are undergoing a fundamental transition in their operating environment — from a predominantly supportive setting toward an increasingly competitive landscape. Within such an environment, organizations must manage their resources with prudence and strategic foresight in order to sustain competitive viability and achieve long-term success. At the global level, the natural gas industry represents one of the most strategically critical and economically influential sectors underpinning industrial development. The natural gas industry constitutes one of the most strategically vital and economically significant sectors within Iran's national economic architecture.

The National Iranian Gas Company (NIGC) ranks among the ten largest gas supply companies in the Middle East and is one of the four principal entities under the Ministry of Petroleum, bearing responsibility for supplying more than 61% of the country's fuel requirements. The Iran National Gas Company was founded in 1965. Natural gas constitutes one of the most critical resources for the provision

Table 1: The collective fuzzy data of EFQM model

DMU	I_1	I_2	I_3	I_4	I_5	O_1	O_2	O_3	O_4
1	(7,5,3)	(5,3,1)	(2,0,0)	(7,5,3)	(9,7,5)	(1,3,5)	(5,7,9)	(8,9,10)	(1,3,5)
2	(9,7,5)	(9,7,5)	(9,7,5)	(7,5,3)	(10,9,8)	(1,3,5)	(1,3,5)	(3,5,7)	(1,3,5)
3	(9,7,5)	(7,5,3)	(5,3,1)	(5,3,1)	(7,5,3)	(0,0,2)	(1,3,5)	(5,7,9)	(3,5,7)
4	(9,7,5)	(7,5,3)	(7,5,3)	(9,7,5)	(5,3,1)	(0,0,2)	(3,5,7)	(5,7,9)	(1,3,5)
5	(9,7,5)	(7,5,3)	(5,3,1)	(5,3,1)	(10,9,8)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)
6	(7,5,3)	(5,3,1)	(5,3,1)	(5,3,1)	(7,5,3)	(1,3,5)	(3,5,7)	(8,9,10)	(3,5,7)
7	(9,7,5)	(5,3,1)	(5,3,1)	(7,5,3)	(9,7,5)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)
8	(9,7,5)	(7,5,3)	(7,5,3)	(5,3,1)	(7,5,3)	(0,0,2)	(5,7,9)	(3,5,7)	(8,9,10)
9	(9,7,5)	(7,5,3)	(5,3,1)	(5,3,1)	(10,9,8)	(3,5,7)	(8,9,10)	(5,7,9)	(8,9,10)
10	(7,5,3)	(5,3,1)	(5,3,1)	(2,0,0)	(7,5,3)	(1,3,5)	(8,9,10)	(8,9,10)	(3,5,7)
11	(7,5,3)	(5,3,1)	(2,0,0)	(2,0,0)	(9,7,5)	(1,3,5)	(3,5,7)	(8,9,10)	(3,5,7)
12	(7,5,3)	(5,3,1)	(2,0,0)	(2,0,0)	(9,7,5)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)
13	(9,7,5)	(5,3,1)	(7,5,3)	(7,5,3)	(9,7,5)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)
14	(7,5,3)	(5,3,1)	(5,3,1)	(5,3,1)	(9,7,5)	(0,0,2)	(3,5,7)	(5,7,9)	(1,3,5)
15	(7,5,3)	(2,0,0)	(5,3,1)	(5,3,1)	(7,5,3)	(1,3,5)	(3,5,7)	(3,5,7)	(0,0,2)

of fuel and electricity generation and has played an integral role in the country's economic and social development through the deployment of diverse facilities, skilled and efficient human resources, and a wide array of advanced technological equipment. Given the NIGC's strategic importance both domestically and internationally, it is imperative to identify the critical factors governing the performance of gas companies in order to enhance their operational efficiency.

As previously discussed, the EFQM model evaluates organizational performance along two principal dimensions: enabling processes and measurable outcomes. The results derived from this evaluation delineate the relative strengths of the assessed companies.

In this study, the requisite data were collected from 15 companies, designated as DMUs, using a structured questionnaire based on the standard EFQM model. These 15 gas companies operate in the Iranian gas industry. The questionnaire was administered to personnel of the National Iranian Gas Company, encompassing managers, deputies, senior specialists, and statistical analysts. The computed Cronbach's alpha coefficient of 0.981 confirmed the exceptional reliability and internal consistency of the survey instrument. The data obtained from the questionnaire includes five enabling criteria as inputs and four outcome criteria as outputs: as shown in Fig. 2. Based on Figure 3, the inputs are Leadership (I_1), Strategy (I_2), Partnership & Resources (I_3), Process (I_4), Employees (I_5) and outputs are Customer Result (O_1), Employee Results (O_2), Community Results (O_3), Key Performance Results (O_4).

Upon completion of the questionnaires, scores for each criterion of the EFQM Excellence Model were assigned to each company in the form of triangular fuzzy numbers. The corresponding fuzzy data are shown in Table 1.

The FAHP method was employed to evaluate organizational excellence across each of the EFQM criteria. As a first step, the relative importance (weights) of the excellence criteria were determined through the application of FAHP. This approach operates hierarchically, proceeding from pairwise comparisons of the most granular sub-factors within each criterion to comparisons of the excellence criteria at a higher level of aggregation. The evaluators responsible for the

Table 2: The weight of nine criteria of EFQM model

Criteria	Weight	Rank
Leadership	0.18	2
Strategy	0.25	1
Employees	0.08	6
Partnerships and Resources	0.11	4
Processes, Products and Services	0.06	7
Customer Results	0.16	3
Employee Results	0.09	5
Community Results	0.04	8
Key Results	0.03	9

pairwise comparisons possessed the requisite technical expertise and practical experience. They were also thoroughly familiar with the organization's strategic objectives and operational priorities. The final weighting of the EFQM criteria is shown in Table 2.

Based on the results obtained, the criteria of strategy, leadership, customer results, partnerships and resources, and employee results received the highest weighted scores, in descending order of priority. Based on the analysis, the criteria of strategy, leadership, customer results, partnerships and resources, and employee results received the highest priority scores, respectively. The following analysis examines how the top five criteria influence the performance of the 15 gas companies under study. Specifically, the critical factors among these six criteria — those exerting the greatest influence on company efficiency — are systematically identified. As an initial step, Model (6) was applied to the 15 gas refineries in the Iranian gas industry to derive their respective efficiency scores. The efficiency scores yielded by Model (6) are presented in Table 3. It is obvious that only DMUs 1, 10, 11 and 15 are efficient while the others are inefficient. Notably, only 26.7% of the refineries under consideration achieved an efficiency score of unity.

Table 3: Efficient and inefficient DMUs via Model (6)

DMU	Efficiency score
1	1
2	0.513
3	0.635
4	0.501
5	0.761
6	0.921
7	0.546
8	0.480
9	0.641
10	1
11	1
12	0.704
13	0.582
14	0.671
15	1

Table 4: The result of Model (7)

DMU	$\left\{ \begin{matrix} x_1, \\ y_1 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_1, \\ y_2 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_2, \\ y_1 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_2, \\ y_2 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_4, \\ y_1 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_4, \\ y_2 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_1, x_2, \\ x_4, y_1 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_1, x_2, \\ x_4, y_2 \end{matrix} \right\}$	$\left\{ \begin{matrix} x_1, x_2, x_4, \\ y_1, y_2 \end{matrix} \right\}$
1	1	Inf.	1.12	1.32	1	Inf.	Inf.	1.41	1.45
2	0.532	0.680	0.589	0.582	0.591	0.721	0.762	0.760	0.785
3	0.802	0.603	0.652	0.735	0.730	0.802	0.810	0.821	0.836
4	0.521	0.505	0.526	0.604	0.605	0.501	0.625	0.645	0.762
5	0.761	0.670	0.803	0.697	0.802	0.823	0.948	0.961	0.965
6	0.910	0.800	0.829	0.956	0.907	0.921	0.991	0.999	1
7	0.632	0.609	0.573	0.583	0.632	0.612	0.832	0.825	0.841
8	0.670	0.502	0.526	0.602	0.460	0.624	0.865	0.862	0.870
9	0.812	0.742	0.812	0.685	0.812	0.798	0.845	0.861	0.912
10	1	1.058	1.143	1	1.36	1.25	1.52	1.46	1.61
11	1	1	Inf.	1.21	1.41	1.32	Inf.	1	Inf.
12	0.815	0.698	0.803	0.802	0.702	0.836	0.921	0.975	1
13	0.608	0.640	0.617	0.742	0.751	0.742	0.753	0.762	0.832
14	0.704	0.673	0.702	0.732	0.699	0.740	0.975	0.977	0.999
15	1.08	1.02	1	Inf.	1	1.34	1.51	1.43	1.56

DMU 8 recorded the lowest efficiency score among all evaluated units. This result indicates that the operational performance of this refinery is substantially below acceptable standards. This underscores the critical importance of identifying the factors that have the greatest potential to enhance DMU performance. When analyzing the critical input-output combinations, different input–output configurations are evaluated individually. Based on the weights reported in Table 2, the criteria of strategy, leadership, customer results, partnerships and resources, employee results, and processes were ranked first through sixth, respectively. Given their assessed importance by the domain experts, these six criteria were incorporated as inputs and outputs in the determination of critical factors. According to Model (7), strategy, leadership, partnerships and resources and employees belong to M and customer outcomes and employee outcomes belong to Q . The deterministic LP Model (7) is subsequently applied to identify the critical input-output combinations. The outcomes of the Model (7) are shown in columns 2–10 of Table 4. Table 4 presents the outcomes for critical combinations involving one input–one output, three inputs–one output, and three inputs–two outputs.

The results demonstrate that efficient DMUs retain their efficiency status, while the efficiency scores of inefficient DMUs improve progressively as the number of input-output combinations under consideration increases. According to Table 5, combination of one input and one output, most of the inefficient Gas refineries have one critical combination, while only two inefficient DMUs (DMU₃ and DMU₇) have two critical combinations and DMU₉ has three critical combinations.

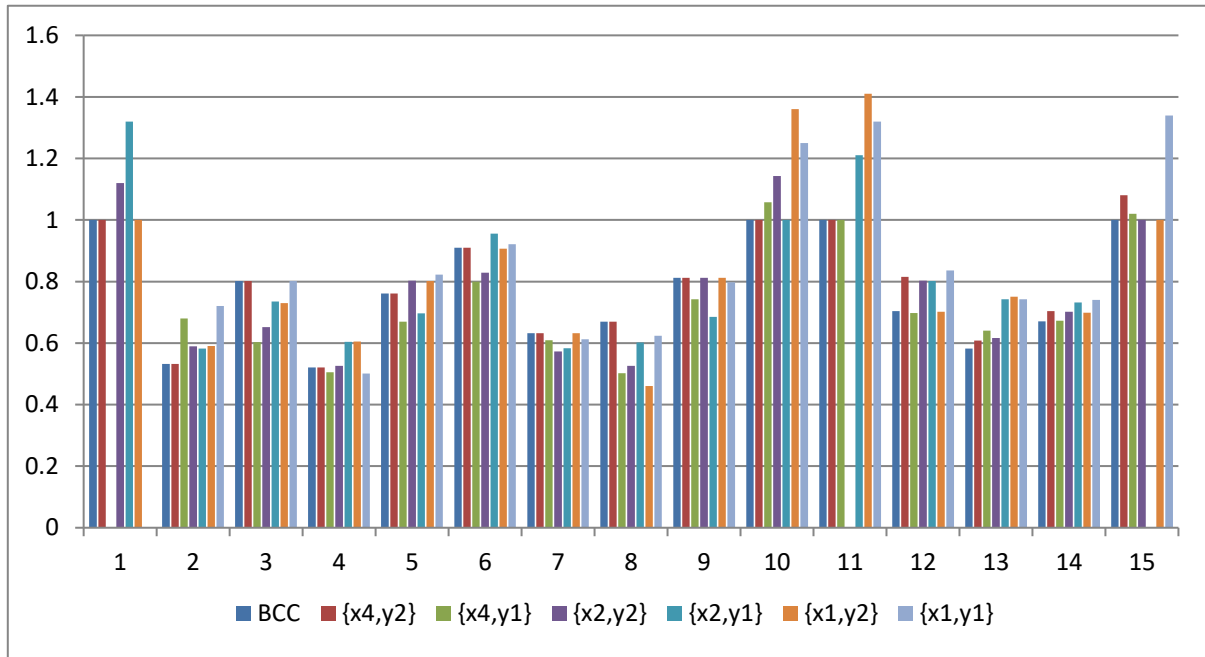


Fig 4: The efficiency scores of 15 Gas refineries under different combinations of critical factors

The efficiency score equals or exceeds one for efficient units, whereas infeasibility may arise for some input–output combinations. For instance, Model (7) is infeasible for DMU₁ with combinations $\{x_1, y_2\}$, $\{x_4, y_2\}$ and $\{x_1, x_2, x_4, y_1\}$. For the remaining combinations, the efficiency score is greater than or equal to unity. It can be inferred that these inputs and outputs have no significant effect on DMU₁'s efficiency performance. Also, DMU₂, by reducing its input x_4 to $x_4 - 0.0551$ ($x_4 - w$) and increasing its output y_2 to $y_2 + 0.0551$ ($y_2 + w$), the efficiency score is increased from 0.513 to 0.721. Additionally, Figure 4 provides a comparative visualization of the efficiency scores from Table 3 alongside the critical-factor analysis results from Table 5. Figure 4 illustrates the efficiency scores of each DMU across different critical-factor combinations. The results clearly demonstrate that the identification of

Table 5: The critical combinations (1 input-1 output)

DMU	$\begin{Bmatrix} x_1, \\ y_1 \end{Bmatrix}$	$\begin{Bmatrix} x_1, \\ y_2 \end{Bmatrix}$	$\begin{Bmatrix} x_2, \\ y_1 \end{Bmatrix}$	$\begin{Bmatrix} x_2, \\ y_2 \end{Bmatrix}$	$\begin{Bmatrix} x_4, \\ y_1 \end{Bmatrix}$	$\begin{Bmatrix} x_4, \\ y_2 \end{Bmatrix}$	Critical input-output combination
1	1	Inf.	1.12	1.32	1	Inf.	-
2	0.532	0.680	0.589	0.582	0.591	0.721	$\{x_4, y_2\}$
3	0.802	0.603	0.652	0.735	0.730	0.802	$\{x_1, y_1\}, \{x_4, y_2\}$
4	0.521	0.505	0.526	0.604	0.605	0.501	$\{x_4, y_1\}$
5	0.761	0.670	0.803	0.697	0.802	0.823	$\{x_4, y_2\}$
6	0.910	0.800	0.829	0.956	0.907	0.921	$\{x_4, y_2\}$
7	0.632	0.609	0.573	0.583	0.632	0.612	$\{x_1, y_1\}, \{x_4, y_1\}$
8	0.670	0.502	0.526	0.602	0.460	0.624	$\{x_1, y_1\}$
9	0.812	0.742	0.812	0.685	0.812	0.798	$\{x_1, y_1\}, \{x_2, y_1\}, \{x_4, y_1\}$
10	1	1.058	1.143	1	1.36	1.25	-
11	1	1	Inf.	1.21	1.41	1.32	-
12	0.815	0.698	0.803	0.802	0.702	0.836	$\{x_4, y_2\}$
13	0.608	0.640	0.617	0.742	0.751	0.742	$\{x_4, y_1\}$
14	0.704	0.673	0.702	0.732	0.699	0.740	$\{x_4, y_2\}$
15	1.08	1.02	1	Inf.	1	1.34	-

critical factors for inefficient DMUs leads to measurable improvements in their efficiency scores.

Based on the findings summarized in Table 5, the following key deficiencies may be identified:

- No systematic program exists within the Iranian gas companies for capturing the needs and expectations of stakeholders and incorporating them into the development and revision of organizational strategies and policies.
- Regarding partnerships and resources, the Iranian gas companies have not established sustainable, trust-based relationships with their strategic partners. Furthermore, certain operational activities have been identified as detrimental to societal and environmental welfare, and human resource management practices remain inadequate.
- The results show weaknesses in this criterion, indicating that creativity in designing and developing new services together with customers, partners, and other stakeholders is not sufficiently utilized. Business models are not properly defined in terms of organizational capabilities, processes, partnerships, and value creation.
- The companies also fail to adequately identify and segment their customer base, and demonstrate insufficient capacity to effectively respond to, anticipate, and address the diverse needs and expectations of different customer groups.

5- Conclusion

The systematic evaluation of Decision-Making Units (DMUs) with respect to efficiency and performance constitutes a fundamental element of evidence-based managerial decision-making in real-world organizations. The DEA methodology offers a powerful analytical framework for evaluating and comparing the relative efficiency of decision-making units operating within comparable environments. Classical DEA models compute efficiency values on the basis of accurate and deterministic data. In practice, however, data seldom possess complete precision, as they may be subject to vagueness, estimation errors, or informational incompleteness. To address this limitation, the Fuzzy DEA (FDEA) method was introduced. Numerous studies have been carried out to assess the overall efficiency of the system and its sub-processes based on FDEA modelling.

Certain inputs and outputs are characterized by the property that marginal changes in their values induce measurable shifts in the efficiency score of a DMU; these are designated as critical factors. The identification of these critical factors provides managers with actionable insights for targeted performance improvement. In the industrial domain, the rigorous evaluation of organizational performance is of paramount importance. Numerous methodological frameworks have been proposed for measuring organizational efficiency. Organizational excellence models have succeeded in establishing a robust framework for managing organizations in competitive environments, drawing upon the benchmarking of globally successful enterprises. Among these, the European Foundation for Quality Management (EFQM) model has been widely adopted — particularly across Europe — as a comprehensive and operationally effective framework for organizational management. The EFQM Organizational Excellence Model functions as a voluntary self-assessment instrument comprising nine interrelated criteria. Five of these criteria pertain to organizational enablers, while four address measurable outcomes. The enabler criteria relate to organizational processes and approaches, whereas the outcome criteria reflect the results and achievements of the organization.

This paper presents, for the first time, an integrated application of the FDEA model and the EFQM framework for the identification of critical factors in the evaluation of 15 Iranian gas companies. To this end, a novel deterministic linear programming model was developed for the identification of critical factors under fuzzy data conditions. Structured questionnaires grounded in the EFQM model were subsequently designed, and data were collected from domain experts in the gas industry. The nine EFQM criteria were then ranked according to their relative importance using the FAHP method. The proposed model was subsequently solved for the top six criteria, in which strategy, leadership, partnerships and resources, and employees served as inputs, and customer results and employee results were designated as outputs. The results reveal that among the 15 major Iranian gas refineries evaluated, only four were classified as fully efficient, while the remaining eleven were determined to be inefficient. Through the application of the proposed model, the critical factors whose improvement would enhance the efficiency of the inefficient DMUs were systematically identified. For efficient DMUs, the proposed model yielded solutions greater than or equal to unity or was infeasible in certain configurations. This finding confirms that the corresponding inputs and outputs exert no significant influence on the efficiency level of the respective DMUs. The overall results indicate that the majority of the evaluated refineries are operating at suboptimal efficiency levels. The systematic identification of

these critical factors provides a structured basis for targeted efficiency improvements. The leadership criterion was identified as particularly deficient across the evaluated units. To address this deficiency, managers should actively foster a culture of excellence within their organizations. Investment in staff development programs is also strongly recommended. Customer relationship management practices require systematic enhancement. Organizations should leverage information systems and advanced technologies to support more effective and data-driven decision-making processes.

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