

Research Article

Evaluating the Performance of Oil and Gas Companies by an Extended Balanced Scorecard and the Hesitant Fuzzy Best-Worst Method

Amir Karbassi Yazdi ¹, Amir Mehdiabadi ², Thomas Hanne ³,
 Amir Homayoun Sarfaraz ⁴, and Fatemeh Tabatabaei Yazdian ⁵

¹School of Engineering, Universidad Católica Del Norte, Coquimbo, Chile

²Department of Industrial Management, Mahan Business School, Tehran 156917314, Iran

³Institute for Information Systems, University of Applied Sciences and Arts Northwestern Switzerland, Olten, Switzerland

⁴Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

⁵Amir Kabir University, Tehran, Iran

Correspondence should be addressed to Thomas Hanne; thomas.hanne@fhnw.ch

Received 10 August 2022; Revised 25 October 2022; Accepted 27 October 2022; Published 17 November 2022

Academic Editor: Hasan Dinçer

Copyright © 2022 Amir Karbassi Yazdi et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The aim of this research is to find and prioritize a multicriteria performance measurement based on the balanced scorecard (BSC) for oil and gas (O & G) companies in an uncertain environment using the hesitant fuzzy best-worst method (HFBWM). The O & G industry has a key role in the economies of many countries. Hence, the evaluation of the performance of the O & G industry plays an important role. We utilize BSC for this purpose, which usually considers the financial, customer-oriented, internal, learning-oriented, and growth perspectives. In our research, the social responsibility perspective will be added. After finding multiple performance measurements, many companies cannot implement all of them because of limited resources. Therefore, multicriteria decision-making (MCDM) methods can be applied for prioritizing and selecting the most important measurement criteria. One of the MCDM methods is the best-worst method (BWM). This approach has several advantages compared to other MCDM methods. Due to uncertainties in decision-making, a suitable method for decision-making in an uncertain environment is necessary. Hesitant fuzzy approaches are applied as one such uncertainty-based method in this research. Our results indicate that among the five perspectives of BSC that we considered, the customer and internal process perspectives are the most important ones, and the cost of the R & D indicator is the most important subcriterion among these.

1. Introduction

One of the main concerns of organizations is achieving a comprehensive, reliable, and flexible performance appraisal method to help them obtain accurate and sufficient information about their position and learn from past mistakes by looking to the future [1]. New approaches to organization and management (customer orientation, quality orientation, virtualization, etc.) also emphasize the double necessity of the concept and subject of evaluation. Accurate, comprehensive, and purposeful monitoring and evaluation are

considered one of the most important facilitators of growth, dynamism, and excellence in the field of management [2]. Evaluating the performance of organizations has always been one of the main concerns of managers and their officials. Performance calculation helps organizations become more transparent [3]. In fact, a performance measurement system includes a diverse set of performance appraisal indicators that relate to organizational strategies and provide information about all components of the supply chain ([4], 398; [5], 5). One of the most popular and effective performance appraisal systems is the balanced scorecard (BSC).

BSC is a comprehensive, complete, and accurate performance appraisal system for planning and monitoring an organization's progress toward achieving its goals ([6], 138; [7], 360; [8], 73).

Over the years of research on performance appraisal, researchers have presented numerous papers on BSC methods and hybrid models. Hegazy et al. [9] provide a detailed framework for supporting audit firms with BSC. The results show that the development and application of the proposed BSC measures improve the performance of audit firms. Auditing firms have a better understanding of the various performance factors and strategies and thus create a competitive advantage. Aujrrapongpan et al. [10] evaluated the performance of social hospitals in Thailand with the BSC approach. The results of this study are presented as a five-year comparison of performance evaluation indicators. Laury et al. [11] analyze the strategic planning and strategic performance of companies with BSC in a review article. Nazari-Shirkouhi et al. [12] evaluated the performance of an educational institution with an integrated IPA-BSC approach. Tuan [13] addressed the impact of BSC on performance in Vietnamese bank branches. Akbarei et al. [14] used a combined approach AHP-TOPSIS-BSC to evaluate the performance of bank branches and provide ways to improve it. Karbassi Yazdi et al. [15] have developed performance criteria for export agencies with the DEA approach. Karbassi Yazdi et al. [16] also developed an analytical vision of performance for the company using a combination of fuzzy clustering and DEA.

In the past, the most crucial performance measurement was based on financial indicators [17, 18]. However, Kaplan and Norton [19] pointed out that these indicators were not solely responsible for the performance and that various further factors had an influence on it. Consequently, the BSC was suggested. This model consists of four perspectives: finance, customers, internal processes, and learning and growth. In order to get to know the situation of their company better and to find out its strengths and weaknesses, managers may use BSC, which introduces a comprehensive model for evaluating the company according to the mentioned four perspectives and relevant indicators [20, 21]. As mentioned above, traditional BSC has four perspectives, but Kaplan and Norton [22, 23] and Kaplan et al. [24] suggested that companies could add other perspectives to BSC or remove some of the suggested ones. To create new perspectives, the most crucial performance measurement should be considered. One of the most important obligations of oil and gas companies is to pay more attention to social responsibility performance measurement, such as the protection of the environment.

After having extracted performance measurement indicators, companies should implement measures for improving these indicators. However, frequently, companies do not have a sufficient budget, time, or staff to implement these measures. Therefore, these performance measurement indicators should be prioritized in order to focus on the most important ones. There are many methods for prioritizing items that are characterized by multiple criteria, especially multiple criteria decision-making (MCDM) methods. These methods can be classified into different categories. Methods

based on a finite set of alternatives (or a decision matrix) are usually denoted as multiple attribute decision-making (MADM) [25]. Suitable methods usually involve either a direct evaluation of alternatives (for instance, based on assessing a utility function or some other scalarizing function) or making use of a pairwise comparison of alternatives (such as the analytical hierarchy process (AHP) and the family of outranking methods [26]).

In this paper, the best-worst method (BWM) is applied, which belongs to the pairwise comparison methods. This method has some benefits compared to other methods. In particular, it needs less data for comparison, and the result is more reliable than others [27, 28]. In our permanently changing world, decision-makers (DMs) cannot accurately judge. Based on this fact, DMs need a tool that helps them identify their preferences. Fuzzy sets are an approach for considering uncertainty. Methods using fuzzy sets can better support decisions in an uncertain environment. Hesitant fuzzy sets (HFS) (and hesitant fuzzy numbers, HFN) are one of the respective approaches. In this paper, we suggest using a modification of BWM based on HFS that can be used for MADM problems under uncertainty and to help make a decision. The respective approach is denoted as the hesitant fuzzy best-worst method (HFBWM). The oil and gas industry are the most important industry in Iran, and most of the budget of Iran depends on the revenues from the sale of oil. By increasing the number of oil sales, a country can create more job opportunities, decrease the Gini coefficient (for obtaining an equal income or wealth distribution in society), increase financial investments in the infrastructure, and so on, and therefore this industry plays an important role. For these reasons, evaluating the performance of the oil and gas industry helps managers make better decisions for improving the performance indicators.

The research questions of this research are about the indicators of BSC in the oil and gas industry and which perspectives and indicators have the highest priority. The contribution of this paper is to prioritize the performance measurement of oil and gas companies by HFBWM. As this method is rather new, only a few papers have been published about it so far, in terms of BSC and extended versions of BSC. Another contribution of this study is applying a combination of BWM and BSC to the oil and gas industry. Also, a social responsibility perspective is added to the other aspects considered in this model. The final contribution is using real data for this research and data gathering based on questionnaires filled in by experts in this industry.

Performance management is one of the crucial issues among companies, especially in the O & G industry, due to its strong impact on various fields such as economics, healthcare, education, or infrastructure. Therefore, performance management is essential for O & G companies to design road maps to realize their vision.

This paper consists of the following sections: After the introductory section, a literature review of BSC is presented in Section 2. In Section 3, the best-worst method is pointed out. Section 4 deals with the research methodology. Data analysis and results are illustrated in Section 5. The final section reveals the conclusions.

2. Literature Review

2.1. Balanced Scorecard (BSC) and Multiattribute Decision-Making (MADM). BSC is a tool for translating the strategy of organizations into a common language, which can be understood by the staff of a company. This model helps managers and staff to find out where their company stands, how far it deviates from the predetermined indicators (benchmark values), why they do not achieve them, and how to improve them. This method can be used to evaluate all aspects of companies and uses cause-and-effect relationships for the considered performance measurement. After the introduction of this model, various directions of research were investigated. In the following, we discuss research based on a combination of BSC and MADM methods.

Yazdi et al. [25] evaluated the performance of Colombian bank branches using a combined approach of BSC, SWARA, and WASPAS. Heydariyeh et al. [29] combined the BSC model and the fuzzy DEMATEL (DEcision MAKing Trial and Evaluation Laboratory) to present a new approach to integrated strategy map analysis. Ajripour et al. [30] developed a model for managing the performance of organizations using BSC, PROMETHEE, ELECTRE, and TOPSIS methods. Ozdogan et al. [31] provide a model for evaluating the performance of municipal services with a combined approach of multiple decision methods. Var-mazyar et al. [32] developed a novel hybrid MCDM model for the performance evaluation of research and technology organizations based on the BSC approach.

Dinçer et al. [33] illustrated a model of BSC in the European energy industry using a combination of fuzzy MCDM methods. They combined the quality function deployment (QFD) technique with fuzzy DEMATEL, fuzzy AHP, and the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The result indicates which policy should be selected and which policies should be changed accordingly. Deng et al. [34] studied the combination of DEMATEL, the analytic network process (ANP), a modified VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) approach, and BSC for evaluating Taiwanese companies. The result pointed out that the customer perspective is the most important one and that these companies should focus on customer-oriented performance measurement. Lu et al. [35] combined DEMATEL, ANP, and modified VIKOR in the context of a sustainability-oriented BSC for evaluating international airports. First, the relationship between key performance indicators is determined by DEMATEL. Then, DEMATEL-ANP is used for finding weights. Finally, the gap between the current situation and the ideal situation is found by the modified VIKOR method. The result demonstrated that the airport's image is the most important factor among others. Also, the best airport is found. Dinçer et al. [36] revealed a combination of the BSC model with fuzzy DEMATEL, fuzzy ANP, and the MOORA (Multiobjective Optimization Method by Ratio Analysis) method. Fuzzy DEMATEL and fuzzy ANP are used to find weights, and then nine airline companies are prioritized by the MOORA method. The result showed which airline company has a proper performance. Zhao and Li [37] implemented BSC,

fuzzy Delphi, ANP, and fuzzy TOPSIS for thermal power enterprises. First, performance measurements of BSC are determined by fuzzy Delphi. Then, weights for the model are obtained by ANP, and companies are ranked by fuzzy TOPSIS and performance measurements. The result depicted a model for the evaluation of companies using hybrid methods. Meena and Thakkar [38] illustrated a model based on the combination of ISM and ANP for improving the BSC method for finding performance measurements. Then, by using the ISM method, relationships among them are shown. ANP was applied for the purpose of finding priorities for these performance measurements. Quezada and López-Ospina [39] depicted a method for drawing a strategy map of BSC by using an MCDM method (AHP) and linear programming (LP). The aim of using AHP and LP methods is to minimize the number of selected relationships while maximizing their total importance in selecting relationships. The result shows the trade-off between these aspects and designing a strategy map of BSC. Rabbani et al. [40] investigated sustainability using BSC and MCDM methods, considering linguistic variables in the oil and gas industry. They considered five perspectives such as economics, environment, social, internal process and growth, and the learning perspective. In this research, the criteria and subcriteria of BSC are defined first. Then, weights for them were obtained by the ANP method. Fuzzy COPRAS (COMplex PROportional ASsessment of alternatives) is used for finding the best strategy. Shafiee et al. [41] designed a model for evaluating SCM performance by data envelopment analysis (DEA), DEMATEL, and BSC. First, based on four BSC perspectives, performance indicators were created. Then, the relationship among the performance measurements was determined by DEMATEL. Finally, Iranian food companies were evaluated in a case study using the network DEA and BSC methods.

Rezaei et al. [42] measured the port performance using the best-worst method. They stated that costs and times of transportation in the supply chain are the most important factors. Galankashi et al. [43] discussed a hybrid model of BSC and fuzzy AHP for supplier selection in the automobile industry. First, for each supplier, a BSC model was designed, and after that, the performance measurements of each supplier were ranked by fuzzy AHP to find the best supplier. Lin [44] studied the implementation of BSC and a closed-loop ANP together with a fuzzy Delphi method in the higher education sector. They used fuzzy Delphi and ANP to find relationships in the closed-loop structure. Abo-Hamad and Arisha [45] illustrated a model of BSC with the analytical hierarchy process (AHP) and a simulation for measuring the performance of emergency departments. The result indicated how one could improve the efficiency of the processes by using these methods. Bhattacharya et al. [46] measured the performance of a green supply chain by using fuzzy-ANP and a balanced scorecard. Fuzzy-ANP was used to rank the BSC perspectives and performance measurements. The result showed how a supplier's performance could be aligned with industry standards. Khairalla et al. [47] depicted a model for an outsourcing strategy based on ANP and BSC. In this research, after finding performance measurements, these were ranked by ANP for identifying the best strategies.

After that, sensitivity analysis is used for increasing the robustness of the model. Hsu et al. [48] implemented fuzzy Delphi, ANP, and sustainable BSC for the semiconductor industry. They used a revised BSC with sustainability, stakeholders, internal business processes, and learning and growth perspectives. Then, performance measurements were extracted by fuzzy Delphi. Finally, perspectives and performance measurements were ranked by ANP. The result indicated that the sustainability perspective and some performance measurements had high priority.

Bazrkar et al. [49] depicted a model for customer satisfaction with a combination of BSC and Lean Six Sigma (LSS). First, BSC perspectives and indicators are extracted. Then, data envelopment analysis (DEA) is implemented for selecting indicators. Finally, the Define, Measure, Analyze, Improve, and Control (DMAIC) cycle is applied for improving the quality of the process. The results pointed out that sigma levels increased and the time of processes decreased. Wang and Chien [50] illustrated a hybrid model of BSC and DEA for Taiwanese companies. First, the performance measurement of the BSC model is set as the inputs and outputs of the model. Then, companies' performances are determined by DEA. Wu and Liao [51] used BSC and DEA for evaluating airline companies. They extracted inputs and outputs from the model based on BSC, and then 38 airline companies were evaluated by the DEA method.

Tizroo et al. [52] designed a model of BSC and Interpretive Structural Modeling (ISM) in the steel industry. They found a relationship between the criteria and subcriteria of BSC. The results indicated how strategies for this industry can be formulated based on the results of the ISM and BSC. The result showed how this approach helps the stakeholders to make better decisions. Linet al. [53] used hierarchical BSC with fuzzy linguistics in hospitals. After determining performance measurements of BSC, fuzzy linguistics is applied for developing the model. The result indicated how management might use a new approach for the design and implementation of a new strategy in their organizations.

Kaviani et al. [54] used gray numbers while considering hybrid MADM methods for ranking suppliers in the O & G industry. Yazdi et al. [55] used hybrid MADM methods using Z-numbers for evaluating suppliers in the O & G industry.

2.2. Hesitant Fuzzy Sets (HFSs) and MADM. Various studies show the importance and reliability of HFS for decision-making under uncertainty and considering the complexity of organizations. Alcantud et al. [56] have introduced hesitant fuzzy sets as a new method. Tüysüz and Şimşek [57] used an AHP method based on hesitant fuzzy sets to evaluate the performance of a shipping company in Turkey. Divsalar et al. [58] developed the DANP technique using interval-valued hesitant fuzzy elements (IVHFEs). Zhai [59] has proposed the hesitant fuzzy linguistic preference relations (HLPRs) method for the performance evaluation of wireless sensor networks. The research findings shed new light on the selection, performance selection, and promotion of wireless sensor networks. Pérez-Domínguez et al. [60] focused on performance appraisal in a manufacturing company using a

combination of TOPSIS and hesitant fuzzy linguistic term set (HFLTS) models. Using this method, they presented a model for lean manufacturing (LM). Liao et al. [61] used the hesitant fuzzy linguistic BWM method to evaluate the performance of hospitals. They state that the proposed method is more effective than the hesitant fuzzy AHP method. Liu et al. [62] used a combination of probabilistic hesitant fuzzy elements (PHFE) and MADM methods for the selection of venture capital investment projects. Candan [63] focuses on the efficiency and performance of economic research in 15 OECD countries using bibliographic elements for the period 2010–2017. There are seven criteria that are thought to affect the efficiency and performance of economic research. In this study, he used the hesitant fuzzy AHP and the OCRA method. Gong et al. [64] presented a new integrated approach using LHF-TODIM and BWM for E-learning website evaluation and selection. The results show that the proposed method is more effective. Meng et al. [65] introduced a new model using a combination of dual hesitant fuzzy preference relations (DHFPRs) and provided a new group decision-making method. Lin et al. [66] used a combination of probabilistic hesitant fuzzy best-worst (PHFBW) and MULTIMOORA for prioritizing distributed stream processing frameworks for IoT applications.

2.3. Our Proposed Method. Based on categorizing the previous research, methods for this subject can be divided into hybrid MADM methods, pairwise comparison methods, DEA methods, and soft computing methods. Some of these methods are based on fuzzy numbers. In one of the previous studies [42], they used BWM for BSC. In some other research, authors used fuzzy numbers in their research.

However, in this paper, the first traditional BSC method is transferred in to revised BSC method. Then, BWM is combined with hesitant fuzzy sets. These changes are not apparent in the previous research. Table 1 summarizes the methods used in previous studies.

According to Table 1 and the abovementioned review, many papers have been published about BSC, and it is the most popular topic among researchers. In this research, we suggest using a new MADM method based on HFS in combination with BSC, which helps to design a road map for supporting decision-makers and improves some weaknesses of previous studies.

3. Multicriteria Decision-Making in an Uncertain Environment

3.1. The Best-Worst Method. Many MCDM methods help decision-makers in making better decisions. One of the new approaches in the area of MCDM methods is the Best-Worst Method (BWM). This model belongs to the methods based on a finite set of alternatives (also denoted as multiple attribute decision-making, or MADM) and uses pairwise comparisons for finding weights of alternatives. Rezaei [27] introduced this model. The method compares vectors representing the criteria values of alternatives on a pairwise basis for the purpose of finding out which of these vectors is

TABLE 1: Previous studies on BSC and other methods.

Indicator	Researcher																						
	Dinçer et al. [33]	Rezaei et al. [42]	Deng et al. [34]	Lu et al. [35]	Dinçer et al. [36]	Bazkar et al. [49]	Tizroo et al. [52]	Galanekashi et al. [43]	Lin [44]	Wang and Chien [50]	Zhao & Li [37]	Abo-Hamad and Arisha [45]	Bhattacharya et al. [46]	Meena and Thakkar [38]	Quezada and López-Ospina [39]	Rabbani et al. [40]	Khairalla et al. [47]	Wu and Liao [51]	Shafiee et al. [41]	Lin et al. [53]	Hsu et al. [48]		
Fuzzy linguistics																							
Fuzzy COPRAS																*							
LP																							
AHP												*											
Fuzzy Delphi																							*
ISM																							
DEA																							
LSS																							
MOORA																							
Fuzzy ANP																							*
WIKOR																							
ANP																							
DEMATEL																							
BWM																							
Fuzzy TOPSIS	*																						
Fuzzy AHP	*																						
Fuzzy DEMATEL	*																						
QFD	*																						

most beneficial (or the best vector). This model is based on the nonlinear minimax model for computing the maximum absolute difference in weight ratios and minimizing the corresponding comparison. For finding weights of alternatives by BWM, the following steps are needed:

Step 1. Criteria and alternatives of the model are assumed to be specified. Criteria are denoted as $C = \{c_1, c_2, \dots, c_n\}$.

Step 2. The type of criteria is determined. The criteria can be best or worst criteria (criteria to be maximized or minimized).

Step 3. Determine the relative preferences of the best criterion (denoted as B) in comparison to all other criteria based on a 1–9 scale. The preferences for the best criterion B are indicated as $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$. It is obvious that $a_{BB} = 1$.

Step 4. Determine the relative preferences of the worst criterion (denoted as W) in comparison to all other criteria based on a 1–9 scale. The preferences of worst criterion W are indicated as $A_w = (a_{w1}, a_{w2}, \dots, a_{wn})$. It is obvious that $a_{ww} = 1$.

Step 5. Final weights are obtained based on the following approach. These weights are shown as $(w_1^*, w_2^*, \dots, w_n^*)$.

The maximum absolute differences $|w_B/w_j - a_{Bj}|$ and $|w_j/w_w - a_{wj}|$ will be minimized for all j , such that the ratio of weights best corresponds to the relative preferences. The following equation shows this computation:

$$\begin{aligned} & \min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_w} - a_{wj} \right| \right\} \\ & \text{s.t.} \\ & \sum_j w_j = 1 \\ & w_j \geq 0, \text{ for all } j. \end{aligned} \quad (1)$$

This model can be rewritten as follows:

$$\begin{aligned} & \min \xi \\ & \text{s.t.} \\ & \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \text{ for all } j \end{aligned}$$

$$\left| \frac{w_j}{w_w} - a_{wj} \right| \leq \xi, \text{ for all } j$$

$$\sum_j w_j = 1$$

$$w_j \geq 0, \text{ for all } j. \quad (2)$$

3.2. Hesitant Fuzzy Sets. Let X represent a reference set. A hesitant fuzzy set of X is defined by a function h on X that returns a subset of $[0, 1]$.

We usually consider cases where $h(x)$ is a finite set [67]. Special cases of $h(x)$ are as follows:

$$\begin{aligned} & \text{empty set: } h(x) = \{0\} \text{ for all } x \in X, \\ & \text{full set: } h(x) = \{1\} \text{ for all } x \in X, \end{aligned} \quad (3)$$

$$\text{complete ignorance: } x \in X, h(x) = [0, 1],$$

$$\text{nonsense set: } h(x) = \emptyset.$$

$\mu(x) = 1$ and $\mu(x) = 0$ point out the empty and full sets, which should not be confused with nonsense situations or complete ignorance.

For a fuzzy set with membership function μ on the reference set $[0, 1]$, we can use hesitant fuzzy sets to represent the inverse function of μ , i.e., the hesitant fuzzy set $h(x)$ is defined by $h(x) = \mu^{-1}(x)$ or, respectively,

$$h(x) = \{\alpha \mid \alpha \in X, \mu(\alpha) = x\}. \quad (4)$$

Hesitant fuzzy sets can also be constructed from several fuzzy sets: considering a set of N membership functions, $M = \{\mu_1, \dots, \mu_N\}$. The hesitant fuzzy set of M , h_M , is then defined as

$$h_M(x) = \cup_{\mu \in M} \{\mu(x)\}. \quad (5)$$

This concept can be used in group decision-making when experts or DMs are evaluating a set of alternatives. In this case, M represents the preferences or opinions of the DMs for each of the alternatives, and then h_M represents the opinions of all of them.

Assume h_1 , h_2 , and h_2 are HFS. Typical operations on HFS are as follows:

$$\begin{aligned}
 &\text{lower bound : } h^-(x) = \min h(x), \\
 &\text{upper bound : } h^+(x) = \max h(x), \\
 &\alpha - \text{upper bound : } h_\alpha^+(x) = \{h \in h(x) | h \geq \alpha\}, \\
 &\alpha - \text{lower bound : } h_\alpha^-(x) = \{h \in h(x) | h \leq \alpha\}, \\
 &\text{complement : } h^c(x) = \cup_{\gamma \in h(x)} \{1 - \gamma\}, \\
 &\text{union : } (h_1 \cup h_2)(x) = \{h \in (h_1(x) \cup h_2(x)) | h \geq \max(h_1^-, h_2^-)\}, \\
 &\text{or, equivalently } (h_1 \cup h_2)(x) = h_1(x) \cup h_2(x)_\alpha^+ \text{ for } \alpha = \max(h_1^-, h_2^-), \\
 &\text{intersection : } (h_1 \cap h_2)(x) = \{h \in (h_1(x) \cap h_2(x)) | h \leq \min(h_1^-, h_2^-)\}, \\
 &\text{or, equivalently } (h_1 \cap h_2)(x) = h_1(x) \cap h_2(x)_\alpha^+ \text{ for } \alpha = \min(h_1^-, h_2^-).
 \end{aligned} \tag{6}$$

The idea behind this definition is as follows: whenever we have two hesitant fuzzy sets, if a hesitant fuzzy set is a possible set of alternatives, for all x , the lower bound of $h_1 \cup h_2$ is the largest of the two h_1^-, h_2^- . The definition of an intersection follows a similar consideration.

Assume that $h_1, h_2,$ and h_2 are HFS. According to Torra and Narukawa [67] some properties are as follows:

$$\text{complement: } (h^c)^c = h. \tag{7}$$

HFS is a kind of fuzzy type 2 approach [67]. For a HFS h , a corresponding fuzzy type 2 set can be defined as follows (note the type in Torra and Narukawa [67]):

$$\mu^2(x)(y) = \begin{cases} 1, & \text{if } y \in h(x), \\ 0, & \text{if } y \notin h(x). \end{cases} \tag{8}$$

There are various methods for transferring an HFS number to a crisp number.

In this paper, equations (9) and (10) are used for obtaining crisp number.

a : lower bound

b : middle value

c : upper bound

When we have three numbers, the formula is

$$\text{crisp number} = \frac{a + b + c}{3}, \tag{9}$$

and when there are a and c only,

$$\text{crisp number} = \frac{a + c}{2}. \tag{10}$$

4. Research Methodology

4.1. Social Responsibility Perspective. After the introduction of BSC, many papers were published about it based on the four traditional perspectives. However, rapid changes in the environment caused changes to this model. One of the new perspectives of BSC is social responsibility [68–70]. The oil and gas industry in Iran should focus on general aspects of society, e.g., preventing environmental pollution, etc. Therefore, social responsibility plays a crucial role in society.

4.2. Research Procedure. The research procedure is shown in Figure 1.

Figure 1 shows that this research starts with the design of the strategic plan. After that, based on strategic planning, performance measurements are extracted. In the next step, the questionnaires based on these performance measurements and BWM are created. Then, the questionnaires are distributed among experts in the oil and gas industry in Iran. After gathering those, the responses are prioritized by HFBWM with related software, which ranks these performance measurements. The results indicate which of these performance measurements and perspectives have high and which have low priority. The important point is that the present study is not a cause-and-effect relationship that goes through a statistical process and requires hypothesizing for analysis. Rather, the research approach is to use a combination of multicriteria decision-making methods and a new concept for prioritizing performance criteria in the oil and gas industry, which can be well adopted in the strategic planning approach.

4.3. The Reasons for Choosing HFBWM. As mentioned, there are many methods for MCDM, and numerous related papers are being published [71]. Each of these methods has its strengths and weaknesses. BWM has some strengths in comparison to other methods, especially other pairwise comparison methods. First, it requires fewer comparisons compared to other methods. Second, it provides a more consistent comparison compared to other methods [27, 28].

Hesitant fuzzy sets with the ability to model inaccurate information can be used widely and efficiently in decision-making. In general, in decision-making situations, there are several alternatives, and the goal is to evaluate these options by considering different criteria and then finally select and use the best alternative for the desired purpose. Therefore, the evaluation aspect of these alternatives and the information that is collected about them are important. Basically, several criteria are determined, and a number of experts are asked to comment on each of the alternatives regarding the chosen criteria. Any expert may hesitate to determine the extent to which an alternative satisfies each of the criteria. Instead of a membership value as for a traditional fuzzy set, experts possibly prefer to determine nonmembership



FIGURE 1: Research methodology.

(intuitionistic fuzzy set) or a set of membership values. This may be due to the expert's skepticism about collecting information and selecting the most appropriate alternative based on that information.

Thus, today there are many methods based on uncertainty that help managers to make accurate decisions. One of them that is suitable for MADM methods is HFS. The difference between HFS and other fuzzy methods is that DMs can tell the degree of uncertainty by the hesitant fuzzy situation. It helps DMs describe the degree of their uncertainty and ultimately leads to a better-founded decision. The combination of HFS and BWM, demonstrates that by using BWM the computation is reasonable despite the increase in accuracy. In addition, FHBWM better supports dealing with uncertain data, which is a common situation when dealing with real decision-makers.

4.4. Software of BWM. For finding weights using BWM, the related software LINGO is used. This software solves the linear programming model related to BWM.

4.5. Data Gathering. After defining performance measurements for these companies (e.g., based on suggestions in the literature and company-specific suggestions), questionnaires based on these performance measurements and BWM were designed. Then, these questionnaires were distributed among twelve top and middle managers of the respective companies. After gathering the data, the number that has the highest frequency among DMs preferences (the mode value) is selected as the final response. Table 2 shows the information about the DMs.

4.6. Hesitant Fuzzy Numbers. In this section, the DMs' opinions on their preferences based on hesitant fuzzy numbers are shown in Table 3. The table shows how the crisp preferences of DMs are transferred into hesitant fuzzy sets.

4.7. Information about the Sample Population. The companies considered in this research are large companies, i.e., companies with more than 1500 employees. There are quite a few companies that can be categorized as large, but unfortunately, only seven companies provided the information to us. Most locations of O & G sites are in the south of Iran; however, their headquarters are in Tehran. In addition, they were required to keep their names confidential.

5. Data Analysis and Results

First, performance measurement indicators from all five perspectives are extracted. Table 4 shows these performance

measurements. Note that actual measurements of these indicators are not required at this point in our analysis.

The weights, the preferences of the DMs for all perspectives of the model, and the results are shown in Tables 5–7. First, according to Table 3, the DMs specified their preferences related to the variables. Based on equation (2), the linear model of BWM is then created. The HFS numbers are transferred to crisp numbers according to equations (9)–(10). The respective optimization model is shown in Appendix (A.1).

Table 5 presents the best perspective of the BSC model compared with the other perspectives based on the DM's preferences.

In Table 6, the worst perspective of the BSC model is compared with the other perspectives based on the DM's preferences. In Table 7, the final weights and the ranks of the perspectives are shown.

This means that among the five perspectives, the internal processes and learning and the customer perspectives have the highest priority. Thus, by improving processes and focusing on supply chain aspects, the performance of the organization will be enhanced. Besides, customers have a high impact on the performance of oil and gas companies. The second most important perspective is the financial perspective. It shows that financial issues have strong effects on oil and gas companies. The learning and growth perspective is the third most important perspective. This result indicates that oil and gas companies may focus somewhat less on this issue. The least important perspective is social responsibility, but companies still adhere to environmental and social principles. The weights and preferences of DMs for financial performance measurement of the model, as well as the results, are shown in Tables 8–10. The respective optimization model is shown in Appendix (A.2).

In Table 8, the best performance measurement from the financial perspective is compared with the other performance measurements based on the DM's preferences. In Table 9, the worst performance measurement from the financial perspective is compared with the other performance measurements based on the DM's preferences. Table 10 shows the final weights and the ranks of the perspectives C11–C14.

In the financial perspective, total assets are the first and most important performance measurement. The second most important performance measurement is income; thus, oil and gas companies look forward to increasing it. The next performance measurement is debt that means companies are attempting to decrease it. The least important performance measurement is the total cost. It indicates oil and gas companies are not very concerned with total costs. The weights and the preferences of the DMs for customer performance measurements of the model, as well as the result,

TABLE 2: Information about DMs.

DM	1	2	3	4	5	6	7	8	9	10	11	12
Experience	26	28	29	31	28	29	30	34	33	26	27	29
Education	PhD	MSc	BSc	BSc	MSc	PhD	MSc	BSc	PhD	MSc	PhD	PhD

TABLE 3: Linguistic variables [72].

Crisp number	1	2	3	4	5	6	7	8	9
HF number	(0.1, 0.1, 0.2)	(0.1, 0.2, 0.3)	(0.2, 0.3, 0.4)	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)	(0.9, 0.9, 1)
Linguistic variables	Very very low	Very low	Low	Moderate	Fair-moderate	Fair good	Good	Very good	Very very good

TABLE 4: Perspectives and performance measurements of the model.

Perspective	Performance measurements
Finance (C1)	Total assets (C11), total costs (C12), income (C13), debt (C14)
Customer (C2)	Responsibility rate (C21), customer satisfaction rate (C22), sales volume (C23), number of participations in trade fairs (C24)
Internal process (C3)	Cost of R & D (C31), number of improvement processes (C32), improvement of the supply chain (C33)
Learning and growth (C4)	Motivation (C41), rate of absence (C42), training hours (C43), number of staff suggestions (C44)
Social responsibility (C5)	Number of accepted international standards (C51), budget allocated for the protection of environment (C52), budget for improving social aspects in society (C53)

TABLE 5: The preferences of the DMs for the best perspectives.

Criteria	C1	C2	C3	C4
C5	4	6	7	5
HFN	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)

TABLE 6: The preferences of the DMs for worst perspectives.

	C2	HFN
C1	7	(0.6, 0.7, 0.8)
C3	3	(0.2, 0.3, 0.3)
C4	5	(0.4, 0.5, 0.6)
C5	8	(0.7, 0.8, 0.9)

TABLE 7: Final weights and ranks of the perspectives.

	C1	C2	C3	C4	C5
Weights	0.224	0.276	0.276	0.196	0.148
Rank	2	1	1	3	4

TABLE 8: The preferences of the DMs for the best financial performance measurement.

Criteria	C11	C13	C14
C12	8	4	5
HFN	(0.7, 0.8, 0.9)	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)

are shown in Tables 11–13. The respective optimization model is presented in Appendix (A.3).

In Table 11, the best performance measurement from the customer’s perspective is compared with the other performance measurements based on the DM’s preferences. In

TABLE 9: The preferences of the DMs for the worst financial performance measurement.

	C11	HFN
C12	8	(0.7, 0.8, 0.9)
C13	7	(0.6, 0.7, 0.8)
C14	7	(0.6, 0.7, 0.8)

TABLE 10: Final weights and ranks of financial performance measurement.

	C11	C12	C13	C14
Weights	0.3	0.177	0.284	0.244
Rank	1	4	2	3

TABLE 11: The preferences of the DMs for the best customer performance measurement.

Criteria	C22	C23	C24
C21	5	7	9
HFN	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)	(0.9, 0.9, 1)

Table 12, the worst performance measurement from the customer perspective is compared with the others based on the DM’s preferences. Table 13 shows the final weights and the ranks of the perspectives C21–C24.

TABLE 12: The preferences of the DMs for the worst customer performance measurement.

	C24	HFN
C21	9	(0.9, 0.9, 1)
C22	8	(0.7, 0.8, 0.9)
C23	7	(0.6, 0.7, 0.8)

TABLE 13: Final weights and ranks of customer performance measurement.

	C21	C22	C23	C24
Weights	0.21	0.261	0.209	0.32
Rank	3	4	2	1

Participation in trade fairs is the most important factor. It means that attending these fairs is particularly important for oil and gas companies. The second most important performance measurement is sales volume. If oil and gas companies want to increase the export rates of their products, smaller amounts of their products should be sold in their home country. Therefore, decreasing home sales not only helps to increase the export of products but also supports the protection of the environment. The third performance measurement is the responsibility indicator, which shows that oil and gas companies should address customer needs better and faster. The least important performance measurement is customer satisfaction. It means that customer satisfaction with oil and gas companies does not need to be significantly improved. The weights and the preferences of DMs for internal process performance measurements of the model, as well as the result, are shown in Tables 14–16. The respective optimization model is shown in Appendix (A.4).

In Table 14, the best performance measurement from the internal process perspective is compared with the other performance measurements based on the DM's preferences. In Table 15, the worst performance measurement from the internal process perspective is compared with the others based on the DM's preferences. Table 16 shows the final weights and the ranks of perspectives C31–C33.

The most important performance measurement of the internal process perspective is the cost of *R & D*. This priority points out that these companies need to spend more money on *R & D* in order to create new products, services, etc. The improvement of the supply chain is the second most important performance measurement. It means that this performance measurement is very important because any interruption in the supply chain may cause various problems, such as interruptions in public or private transportation, problems in production, and subsequently problems in social conditions. It is also of predominant importance for the economic success of a company. The least important performance measurement is the improvement of the supply chain. The weights and the preferences of the DMs for learning and growth performance measurements of the model and results are shown in Tables 17–19. Appendix (A.5) presents the respective optimization model.

In Table 17, the best performance measurement from the learning and growth process perspective is compared with the remaining criteria based on the DMs' preferences. Table 18 shows the respective comparison results of the worst

performance measurement of learning and growth compared with the other performance indicators based on the DM's preferences. The final weights and ranks of perspectives C41–C44 are presented in Table 19.

The number of employee suggestions is the first performance measurement of the learning and growth perspective. It shows that these companies should pay sufficient attention to the suggestions of their employees. Motivation is the second most important performance measurement. This indicates that the focus of the oil and gas companies should also be on motivation. The rate of absence is the third performance measurement. It means that oil and gas companies should analyze the reasons and factors for their employees' absences and then develop appropriate improvement programs for them. Training hours are the least important performance measurement. This means that for these companies, it is not important to pay more attention to the training and further education of their employees. The weights, the preferences of DMs for social responsibility performance measurements of the model, and the results are shown in Tables 20–22. The respective optimization model is shown in Appendix (A.6).

In Table 20, the best performance measurement from the social responsibility process perspective is compared with the other performance measurements based on the DM's preferences. In Table 21, the worst performance measurement of the social responsibility process perspective is compared with the others based on the DMs' preferences.

In Table 22, the worst performance measurement from the social responsibility process perspective is compared with the other performance measurements based on the DMs' preferences.

The number of accepted international standards is the most important performance measurement. It shows that standards relating to management, quality, and environmental aspects are very important for these companies and that they must focus on that. The second performance measurement is the budget for the protection of the environment. It shows that it is of great importance for oil and gas companies to allocate budgets for environmental protection and that these should possibly be increased. The budget for improving social aspects of society is the final and least important performance measurement. It illustrates that oil and gas companies do not need to care much about their respective budgets (e.g., the support of football teams). The final weights of the model are shown in Table 23.

TABLE 14: The preferences of DMs for the best internal process performance measurement.

Criteria	C31	C33
C32	2	7
HFN	(0.1, 0.2, 0.3)	(0.6, 0.7, 0.8)

TABLE 15: The preferences of the DMs for the worst internal process performance measurement.

	C33	HFN
C31	8	(0.7, 0.8, 0.9)
C32	7	(0.6, 0.7, 0.8)

TABLE 16: Final weights and ranks of the internal process performance measurement.

	C31	C32	C33
Weights	0.414	0.184	0.402
Rank	1	3	2

TABLE 17: The preferences of the DMs for the best learning and growth performance measurement.

Criteria	C41	C42	C44
C43	5	8	3
HFN	(0.4, 0.5, 0.6)	(0.7, 0.8, 0.9)	(0.2, 0.3, 0.4)

TABLE 18: The preferences of DMs for the worst learning and growth performance measurement.

	C44	HFN
C41	9	(0.9, 0.9, 1)
C42	8	(0.7, 0.8, 0.9)
C43	8	(0.7, 0.8, 0.9)

TABLE 19: Final weights and ranks of learning and growth performance measurement.

	C41	C42	C43	C44
Weights	0.287	0.229	0.172	0.312
Rank	2	3	4	1

TABLE 20: The preferences of the DMs for the best social responsibility performance measurement.

Criteria	C51	C53
C52	8	7
HFN	(0.1, 0.2, 0.3)	(0.6, 0.7, 0.8)

TABLE 21: The preferences of the DMs for worst social responsibility performance measurement.

	C51	HFN
C52	8	(0.7, 0.8, 0.9)
C53	5	(0.4, 0.5, 0.6)

TABLE 22: Final weights and ranks of the social responsibility performance measurement.

	C51	C52	C53
Weights	0.4	0.271	0.329
Rank	1	3	2

TABLE 23: Final weights of performance measurement.

Perspectives	Perspective weights	Performance measurements	Relative weights	Final weights	Ranking
C1	0.224	C11	0.3	0.067	5
		C12	0.177	0.040	16
		C13	0.284	0.064	6
		C14	0.244	0.055	12
C2	0.276	C21	0.210	0.058	9
		C22	0.261	0.072	4
		C23	0.209	0.058	10
		C24	0.320	0.088	3
C3	0.276	C31	0.414	0.114	1
		C32	0.184	0.051	13
		C33	0.402	0.111	2
C4	0.196	C41	0.287	0.056	11
		C42	0.229	0.045	15
		C43	0.172	0.034	18
		C44	0.312	0.061	7
C5	0.148	C51	0.400	0.059	8
		C52	0.271	0.040	17
		C53	0.329	0.049	14

6. Conclusions

Today, many companies need to measure their performance because of the increasing importance of efficiency due to strong competition. For managers, it would be ideal to supervise performance measurement through a dashboard, like in an airplane, which shows all relevant aspects of the plane such as speed, altitude, fuel, and so on. Performance measurement should transparently show where a company stands and what its strengths and weaknesses are. There are many methods for measuring the performance of companies. One of the well-known methods is balanced scorecards. This method points out all relevant aspects for the evaluation of an organization according to performance criteria related to, e.g., finance, customers, internal processes, and learning and growth perspectives. By further developing companies, new concepts are added to the BSC's perspectives. One of them is social responsibility. After the introduction of BSC, many companies are attempting its implementation in their organizations. However, in many cases, they fail in implementation. One reason is that they need to prioritize the perspectives and performance measurements of BSC. Many methods are available for prioritization. One of these methods is the Best-Worst Method (BWM), which belongs to the family of pairwise comparison methods. This model has some advantages compared to other pairwise comparison methods, such as fewer comparisons and better consistency. In our paper, we suggested using this method in a fuzzy form, the hesitant fuzzy best-worst method (HFBWM), to consider uncertainties.

The oil and gas industry are the first and most important industry of Iran. Most of the budget in Iran depends on oil and gas, and many people use the products of these companies. Also, the oil and gas industry play a key role in the production of electricity for both houses and factories. For these reasons, it is particularly important for these companies to focus on their performance. The result of this

research is based on DMs' judgment. As pointed out in Section 4.5, we need to elicit the preferences of DMs as required by BWM. The research and results are completely based on the viewpoints of DMs, which were obtained from questionnaires. For filling in these questionnaires, 12 DMs were selected. The definition of DM in this research is that they should have much knowledge about the oil and gas industry and should be top persons in this field. Also, they need to have more than 25 years of experience in this field. This selection helps ensure that DMs can reliably specify their preferences based on their experiences. As a consequence, the results of BWM can also be considered reliable. In this paper, a combination of BWM and BSC is applied to design a new and accurate model for BSC. First, performance measurements are extracted from the strategic planning of oil and gas companies. These are then prioritized based on BWM. Finally, the ranking shows which performance indicators are important and which are less important. The result indicates that, among the five perspectives, customers and internal processes are the most important ones. Customers of the oil and gas industry are divided into internal and external customers. When sufficient focus and facilities are provided for them, the number of external customers may increase significantly, along with the respective revenues, which will help the progress of the country. Although this industry is governmental and does not have many competitors, insufficient attention to internal customers leads to problems such as transfers, the provision of food, and other basic human needs. Another highly important perspective is internal processes. In this perspective, whenever companies focus on improving their performance, the result indicates that the cost will decrease, while the speed of providing and serving the customers, and the revenues increase dramatically. In prioritizing BSC performance measurement, *R & D* performance measurement cost is the most important among the 18 performance measures. It shows that oil and gas companies must focus on

increasing their cost of R & D for the development and implementation of new customer services. The least important performance measurement is the number of training hours. It means that oil and gas companies already pay sufficient attention to this aspect and understand its importance. However, investing in training may decrease their costs and lead to increased effectiveness. Therefore, they may already consider this aspect to a sufficient extent. Let us note that the results of Varmazyar et al. [32], contradict our research. In Varmazyar et al. [32] the financial perspective is the most important, but in our research, it has the second highest priority. In addition, internal processes are the least important in Varmazyar et al. [32]. However, this perspective is the most important in our findings. Singh et al. [73] demonstrate that the customer perspective is the most important in their research. This is directly related to the outcome of our research. Besides, in these studies, the learning and growth perspective has the lowest priority. Lu et al. [35] illustrate that social responsibility has the highest priority but is the least important in our research. Internal processes are the least important in Lu et al. [35], but they are the most important perspective in our study.

6.1. Limitations and Future Research. A limitation of this study is the number of indicators that can be analyzed. An

increased number would require a higher effort for ranking them by BMW. In particular, the effort of the DMs to respond to the questionnaires would lead to difficulties. As DMs are working in different cities across the country, accessing them has proven difficult. In addition, repeated discussions were needed to familiarize them with the used concepts and to fill in the questionnaires. For future research, other methods based on uncertainty should be used for prioritizing perspectives and indicators of BSC and designing a road map for allocating limited resources to high-priority perspectives and indicators. Moreover, for the implementation of this method in an uncertain environment, some other fuzzy numbers, such as Z -numbers or D -numbers, could be used.

Appendix

Linear Programming Models for the Different Perspectives

- (1) The linear programming model of the main perspective is as follows:

$$\text{Min } k^*$$

$$-k * u_1 \leq i_5 - 0.3 * u_1 \leq k * u_1,$$

$$-k * m_1 \leq m_5 - 0.4 * m_1 \leq k * m_1,$$

$$-k * i_1 \leq u_5 - 0.5 * i_1 \leq k * i_1,$$

$$-k * u_2 \leq i_5 - 0.5 * u_2 \leq k * u_2,$$

$$-k * m_2 \leq m_5 - 0.6 * m_2 \leq k * m_2,$$

$$-k * u_2 \leq i_5 - 0.7 * u_2 \leq k * u_2,$$

$$-k * u_3 \leq i_5 - 0.6 * u_3 \leq k * u_3,$$

$$-k * m_3 \leq m_5 - 0.7 * m_3 \leq k * m_3,$$

$$-k * i_3 \leq u_5 - 0.8 * i_3 \leq k * i_3,$$

$$-k * u_4 \leq i_5 - 0.4 * u_4 \leq k * u_4,$$

$$-k * m_4 \leq m_5 - 0.5 * m_4 \leq k * m_4,$$

$$-k * i_4 \leq u_5 - 0.6 * i_4 \leq k * i_4,$$

$$-k * u_2 \leq i_1 - 0.6 * u_2 \leq k * u_2,$$

$$-k * m_2 \leq m_1 - 0.7 * m_2 \leq k * m_2,$$

$$-k * i_2 \leq u_1 - 0.8 * i_2 \leq k * i_2,$$

$$-k * u_2 \leq i_2 - 0.2 * u_2 \leq k * u_2,$$

$$-k * m_2 \leq m_2 - 0.3 * m_2 \leq k * m_2,$$

$$\begin{aligned}
& -k * i_2 \leq u_2 - 0.4 * i_2 \leq k * i_2, \\
& -k * u_2 \leq i_1 - 0.4 * u_2 \leq k * u_2, \\
& -k * m_2 \leq m_1 - 0.5 * m_2 \leq k * m_2, \\
& -k * i_2 \leq u_1 - 0.6 * i_2 \leq k * i_2, \\
& -k * u_2 \leq i_1 - 0.7 * u_2 \leq k * u_2, \\
& -k * m_2 \leq m_1 - 0.8 * m_2 \leq k * m_2, \\
& -k * i_2 \leq u_1 - 0.9 * i_2 \leq k * i_2, \\
& \frac{1}{3}i_1 + \frac{1}{3}m_1 + \frac{1}{3}u_1 + \frac{1}{3}i_2 + \frac{1}{3}m_2 + \frac{1}{3}u_2 + \frac{1}{3}i_3 + \frac{1}{3}m_3 + \frac{1}{3}u_3 + \frac{1}{3}i_4 + \frac{1}{3}m_4 + \frac{1}{3}u_4 + \frac{1}{3}i_5 + \frac{1}{3}m_5 + \frac{1}{3}u_5 = 1, \\
& i_1 \leq m_1 \leq u_1, \\
& i_2 \leq m_2 \leq u_2, \\
& i_3 \leq m_3 \leq u_3, \\
& i_4 \leq m_4 \leq u_4, \\
& i_5 \leq m_5 \leq u_5, \\
& i_1, i_2, i_3, i_4, i_5 > 0, \\
& k \geq 0.
\end{aligned} \tag{A.1}$$

(2) The linear programming model of the financial perspective is as follows:

Min k^*

$$\begin{aligned}
& -k * u_1 \leq i_2 - 0.7 * u_1 \leq k * u_1, \\
& -k * m_1 \leq m_2 - 0.8 * m_1 \leq k * m_1, \\
& -k * i_1 \leq u_2 - 0.9 * i_1 \leq k * i_1, \\
& -k * u_3 \leq i_2 - 0.3 * u_3 \leq k * u_3, \\
& -k * m_3 \leq m_2 - 0.4 * m_3 \leq k * m_3, \\
& -k * i_3 \leq i_2 - 0.5 * i_3 \leq k * i_3, \\
& -k * u_4 \leq i_2 - 0.4 * u_4 \leq k * u_4, \\
& -k * m_4 \leq m_2 - 0.5 * m_4 \leq k * m_4, \\
& -k * i_4 \leq u_2 - 0.6 * i_4 \leq k * i_4,
\end{aligned}$$

$$\begin{aligned}
 & -k * u_2 \leq i_2 - 0.7 * u_1 \leq k * u_2, \\
 & -k * m_2 \leq m_2 - 0.8 * m_1 \leq k * m_2, \\
 & -k * i_2 \leq u_2 - 0.9 * i_1 \leq k * i_2, \\
 & -k * u_3 \leq i_3 - 0.6 * u_1 \leq k * u_3, \\
 & -k * m_3 \leq m_3 - 0.7 * m_1 \leq k * m_3, \\
 & -k * i_3 \leq u_3 - 0.8 * i_1 \leq k * i_3, \\
 & -k * u_4 \leq i_4 - 0.6 * u_1 \leq k * u_4, \\
 & -k * m_4 \leq m_4 - 0.7 * m_1 \leq k * m_4, \\
 & -k * i_4 \leq u_4 - 0.8 * i_1 \leq k * i_4, \\
 & \frac{1}{3}i_1 + \frac{1}{3}m_1 + \frac{1}{3}u_1 + \frac{1}{3}i_2 + \frac{1}{3}m_2 + \frac{1}{3}u_2 + \frac{1}{3}i_3 + \frac{1}{3}m_3 + \frac{1}{3}u_3 + \frac{1}{3}i_4 + \frac{1}{3}m_4 + \frac{1}{3}u_4 = 1 \\
 & i_1 \leq m_1 \leq u_1, \\
 & i_2 \leq m_2 \leq u_2, \\
 & i_3 \leq m_3 \leq u_3, \\
 & i_4 \leq m_4 \leq u_4, \\
 & i_1, i_2, i_3, i_4 > 0, \\
 & k \geq 0.
 \end{aligned} \tag{A.2}$$

(3) The linear programming model of the customer perspective is as follows:

Min k^*

$$\begin{aligned}
 & -k * u_2 \leq i_1 - 0.4 * u_2 \leq k * u_2, \\
 & -k * m_2 \leq m_1 - 0.5 * m_2 \leq k * m_2, \\
 & -k * i_2 \leq u_1 - 0.6 * i_2 \leq k * i_2, \\
 & -k * u_3 \leq i_1 - 0.6 * u_3 \leq k * u_3, \\
 & -k * m_3 \leq m_1 - 0.7 * m_3 \leq k * m_3, \\
 & -k * i_3 \leq i_1 - 0.8 * i_3 \leq k * i_3, \\
 & -k * u_4 \leq i_1 - 0.9 * u_4 \leq k * u_4, \\
 & -k * m_4 \leq m_1 - 0.9 * m_4 \leq k * m_4, \\
 & -k * i_4 \leq u_1 - 0.1 * i_4 \leq k * i_4,
 \end{aligned}$$

$$\begin{aligned}
& -k * u_1 \leq i_1 - 0.9 * u_4 \leq k * u_1, \\
& -k * m_1 \leq m_1 - 0.9 * m_4 \leq k * m_1, \\
& -k * i_1 \leq u_1 - 0.1 * i_4 \leq k * i_1, \\
& -k * u_2 \leq i_2 - 0.7 * u_4 \leq k * u_2, \\
& -k * m_2 \leq m_2 - 0.8 * m_4 \leq k * m_2, \\
& -k * i_2 \leq u_2 - 0.9 * i_4 \leq k * i_2, \\
& -k * u_3 \leq i_3 - 0.6 * u_4 \leq k * u_3, \\
& -k * m_3 \leq m_3 - 0.7 * m_4 \leq k * m_3, \\
& -k * i_3 \leq u_3 - 0.8 * i_4 \leq k * i_3, \\
& \frac{1}{3}i_1 + \frac{1}{3}m_1 + \frac{1}{3}u_1 + \frac{1}{3}i_2 + \frac{1}{3}m_2 + \frac{1}{3}u_2 + \frac{1}{3}i_3 + \frac{1}{3}m_3 + \frac{1}{3}u_3 + \frac{1}{3}i_4 + \frac{1}{3}m_4 + \frac{1}{3}u_4 = 1, \\
& i_1 \leq m_1 \leq u_1, \\
& i_2 \leq m_2 \leq u_2, \\
& i_3 \leq m_3 \leq u_3, \\
& i_4 \leq m_4 \leq u_4, \\
& i_1, i_2, i_3, i_4 > 0, \\
& k \geq 0.
\end{aligned} \tag{A.3}$$

(4) The linear programming model of the internal perspective is as follows:

Min k^*

$$\begin{aligned}
& -k * u_1 \leq i_2 - 0.1 * u_1 \leq k * u_1, \\
& -k * m_1 \leq m_2 - 0.2 * m_1 \leq k * m_1, \\
& -k * i_1 \leq u_2 - 0.3 * i_1 \leq k * i_1, \\
& -k * u_3 \leq i_2 - 0.6 * u_2 \leq k * u_3, \\
& -k * m_3 \leq m_2 - 0.7 * m_2 \leq k * m_3, \\
& -k * i_3 \leq u_2 - 0.8 * i_2 \leq k * i_3, \\
& -k * u_1 \leq i_1 - 0.7 * u_3 \leq k * u_1, \\
& -k * m_1 \leq m_1 - 0.8 * m_3 \leq k * m_1, \\
& -k * i_1 \leq u_1 - 0.9 * i_3 \leq k * i_1,
\end{aligned}$$

$$\begin{aligned}
 & -k * u_2 \leq i_2 - 0.6 * u_3 \leq k * u_2, \\
 & -k * m_2 \leq m_2 - 0.7 * m_3 \leq k * m_2, \\
 & -k * i_2 \leq u_2 - 0.8 * i_3 \leq k * i_2, \\
 & \frac{1}{3}i_1 + \frac{1}{3}m_1 + \frac{1}{3}u_1 + \frac{1}{3}i_2 + \frac{1}{3}m_2 + \frac{1}{3}u_2 + \frac{1}{3}i_3 + \frac{1}{3}m_3 + \frac{1}{3}u_3 = 1, \\
 & i_1 \leq m_1 \leq u_1, \\
 & i_2 \leq m_2 \leq u_2, \\
 & i_3 \leq m_3 \leq u_3, \\
 & i_1, i_2, i_3 > 0, \\
 & k \geq 0.
 \end{aligned} \tag{A.4}$$

(5) The linear programming model of the learning perspective is as follows:

Min k^*

$$\begin{aligned}
 & -k * u_1 \leq i_3 - 0.4 * u_1 \leq k * u_1, \\
 & -k * m_1 \leq m_3 - 0.5 * m_1 \leq k * m_1, \\
 & -k * i_1 \leq u_3 - 0.6 * i_1 \leq k * i_1, \\
 & -k * u_2 \leq i_3 - 0.7 * u_2 \leq k * u_2, \\
 & -k * m_2 \leq m_3 - 0.8 * m_2 \leq k * m_2, \\
 & -k * i_2 \leq u_3 - 0.9 * i_2 \leq k * i_2, \\
 & -k * u_4 \leq i_3 - 0.2 * u_4 \leq k * u_4, \\
 & -k * m_4 \leq m_3 - 0.3 * m_4 \leq k * m_4, \\
 & -k * i_4 \leq u_3 - 0.4 * i_4 \leq k * i_4, \\
 & -k * u_1 \leq i_1 - 0.9 * u_4 \leq k * u_1, \\
 & -k * m_1 \leq m_1 - 0.9 * m_4 \leq k * m_1,
 \end{aligned}$$

$$\begin{aligned}
& -k * i_1 \leq u_1 - 0.1 * i_4 \leq k * i_1, \\
& -k * u_2 \leq i_2 - 0.7 * u_4 \leq k * u_2, \\
& -k * m_2 \leq m_2 - 0.8 * m_4 \leq k * m_2, \\
& -k * i_2 \leq u_2 - 0.9 * i_4 \leq k * i_2, \\
& -k * u_3 \leq i_3 - 0.7 * u_4 \leq k * u_3, \\
& -k * m_3 \leq m_3 - 0.8 * m_4 \leq k * m_3, \\
& -k * i_3 \leq u_3 - 0.9 * i_4 \leq k * i_3, \\
& \frac{1}{3}i_1 + \frac{1}{3}m_1 + \frac{1}{3}u_1 + \frac{1}{3}i_2 + \frac{1}{3}m_2 + \frac{1}{3}u_2 + \frac{1}{3}i_3 + \frac{1}{3}m_3 + \frac{1}{3}u_3 + \frac{1}{3}i_4 + \frac{1}{3}m_4 + \frac{1}{3}u_4 = 1, \\
& i_1 \leq m_1 \leq u_1, \\
& i_2 \leq m_2 \leq u_2, \\
& i_3 \leq m_3 \leq u_3, \\
& i_4 \leq m_4 \leq u_4, \\
& i_1, i_2, i_3, i_4 > 0, \\
& k \geq 0.
\end{aligned} \tag{A.5}$$

(6) The linear programming model of the social responsibility perspective is as follows:

Min k^*

$$\begin{aligned}
& -k * u_1 \leq i_2 - 0.1 * u_1 \leq k * u_1, \\
& -k * m_1 \leq m_2 - 0.2 * m_1 \leq k * m_1, \\
& -k * i_1 \leq u_2 - 0.3 * i_1 \leq k * i_1, \\
& -k * u_3 \leq i_2 - 0.6 * u_2 \leq k * u_3, \\
& -k * m_3 \leq m_2 - 0.7 * m_2 \leq k * m_3, \\
& -k * i_3 \leq u_2 - 0.8 * i_2 \leq k * i_3, \\
& -k * u_2 \leq i_2 - 0.7 * u_1 \leq k * u_2, \\
& -k * m_2 \leq m_2 - 0.8 * m_1 \leq k * m_2, \\
& -k * i_2 \leq u_2 - 0.9 * i_1 \leq k * i_2,
\end{aligned}$$

$$\begin{aligned}
 & -k * u_3 \leq i_2 - 0.6 * u_1 \leq k * u_3, \\
 & -k * m_3 \leq m_2 - 0.7 * m_1 \leq k * m_3, \\
 & -k * i_3 \leq u_2 - 0.8 * i_1 \leq k * i_3, \\
 & \frac{1}{3}i_1 + \frac{1}{3}m_1 + \frac{1}{3}u_1 + \frac{1}{3}i_2 + \frac{1}{3}m_2 + \frac{1}{3}u_2 + \frac{1}{3}i_3 + \frac{1}{3}m_3 + \frac{1}{3}u_3 = 1, \\
 & i_1 \leq m_1 \leq u_1, \\
 & i_2 \leq m_2 \leq u_2, \\
 & i_3 \leq m_3 \leq u_3, \\
 & i_1, i_2, i_3 > 0, \\
 & k \geq 0.
 \end{aligned} \tag{A.6}$$

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request. Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] R. Dabbagh and S. Ahmadi, "Evaluation of water and wastewater company performance by using balanced scorecard model; case study: west Azarbayjan water and wastewater company," *Journal of Water and Wastewater*, vol. 30, no. 1, pp. 50–63, 2018, (In Persian).
- [2] M. Mehregan and Z. Moradi, "Using the multi-stage of integrating approaches data envelopment analysis (DEA) and balanced scorecard (BSC) for enhanced performance assessment," *Journal of Industrial Management Perspective*, vol. 10, no. 1, pp. 143–165, 2020.
- [3] C. Propper and D. Wilson, "The use and usefulness of performance measures in the public sector," *Oxford Review of Economic Policy*, vol. 19, no. 2, pp. 250–267, 2003.
- [4] R. H. Chenhall, "Integrative strategic performance measurement systems, strategic alignment of manufacturing, I earning and strategic outcomes: an exploratory study," *Accounting, Organizations and Society*, vol. 30, pp. 395–422, 2005.
- [5] A. J. Nanni, J. R. Dixon, and T. E. Vollman, "Integrated performance measurement: management accounting to support new manufacturing realities," *Journal of Management Accounting Research*, vol. 4, pp. 1–19, 1992.
- [6] S. Davis and T. Albright, "An investigation of the effect of Balanced Scorecard implication on financial performance," *Management Accounting Research*, vol. 15, pp. 135–153, 2004.
- [7] G. Lawrie, I. Cobbold, and J. Marshall, "Corporate performance management system in a developed UK Governmental organization: a case study," *International Journal of Productivity and Performance Management*, vol. 53, no. 4, pp. 353–370, 2004.
- [8] C. J. Pinero, "The balanced card: an incremental approach model to health care management," *Journal of Health Care Finance*, vol. 28, no. 4, pp. 69–80, 2002.
- [9] M. Hegazy, K. Hegazy, and M. Eldeeb, "The balanced scorecard: Measures that drive performance evaluation in auditing firms," *Journal of Accounting, Auditing & Finance*, vol. 37, no. 4, pp. 902–927, 2022.
- [10] S. Aujirapongpan, K. Meesook, P. Theinsathid, and C. Maneechot, "Performance evaluation of community hospitals in Thailand: an analysis based on the balanced scorecard concept," *Iranian Journal of Public Health*, vol. 49, no. 5, pp. 906–913, 2020.
- [11] H. A. Laury, N. Matondang, and M. T. Sembiring, "Balanced scorecard in the integration of corporate strategic planning and performance: a literature review," in *IOP Conference Series: materials Science and Engineering* vol. 801, no. 1, IOP Publishing, Article ID 12135, 2020.
- [12] S. Nazari-Shirkouhi, S. Mousakhani, M. Tavakoli, M. R. Dalvand, J. Šaparauskas, and J. Antuchevičienė, "Importance-performance analysis based balanced scorecard for performance evaluation in higher education institutions: an integrated fuzzy approach," *Journal of Business Economics and Management*, vol. 21, no. 3, pp. 647–678, 2020.
- [13] T. T. Tuan, "The impact of balanced scorecard on performance: the case of Vietnamese commercial banks," *The Journal of Asian Finance, Economics and Business*, vol. 7, no. 1, pp. 71–79, 2020.
- [14] N. Akbari, M. V. Monfard, and E. Sarfi, "The performance evaluation of banks using balanced scorecard, fuzzy AHP and fuzzy TOPSIS techniques and the offering of solutions to performance improvement of banks," *International Journal of Business Information Systems*, vol. 35, no. 2, pp. 204–224, 2020.
- [15] A. Karbassi Yazdi, Y. J. Wang, and M. M. Kahorin, "Performance benchmarking on export credit agencies: a data envelopment analysis," *International Journal of Productivity and Quality Management*, vol. 28, no. 3, pp. 340–359, 2019.
- [16] A. Karbassi Yazdi, Y. J. Wang, and A. Alirezai, "Analytical insights into firm performance: a fuzzy clustering approach for data envelopment analysis classification," *International Journal of Operational Research*, vol. 33, no. 3, pp. 413–429, 2018.

- [17] R. S. Kaplan and D. P. Norton, "Putting the balanced scorecard," *Performance Measurement, Management, and Appraisal Sourcebook*, vol. 66, 1995.
- [18] R. S. Kaplan and D. P. Norton, "Transforming the balanced scorecard from performance measurement to strategic management: Part II," *Accounting Horizons*, vol. 15, no. 2, pp. 147–160, 2001.
- [19] R. S. Kaplan and D. P. Norton, "The balanced scorecard - measures that drive performance," *Harvard Business Review*, vol. 70, no. 1, pp. 71–79, 1992.
- [20] R. S. Kaplan, "Conceptual foundations of the balanced scorecard," *Handbooks of Management Accounting Research*, Elsevier, , vol. 3, pp. 1253–1269, 2009.
- [21] R. S. Kaplan and D. P. Norton, *Building a Strategy-Focused Organization*, Harvard Business School Publishing, Boston, MA, USA, 1999.
- [22] R. S. Kaplan and D. P. Norton, *Alignment: Using the Balanced Scorecard to Create Corporate Synergies*, Harvard Business Press, Boston, MA, USA, 2006.
- [23] R. S. Kaplan and D. P. Norton, "Using the balanced scorecard as a strategic management system," *Harvard Business Review*, vol. 85, no. 7/8, p. 150, 2007.
- [24] R. S. Kaplan, D. P. Norton, and B. Rugelsjoen, "Managing alliances with the balanced scorecard," *Harvard Business Review*, vol. 88, no. 1, pp. 114–120, 2010.
- [25] A. K. Yazdi, A. R. Komijan, P. F. Wanke, and S. Sardar, "Oil project selection in Iran: a hybrid MADM approach in an uncertain environment," *Applied Soft Computing*, vol. 88, Article ID 106066, 2020.
- [26] A. Karbassi Yazdi, A. Rashidi Komijan, S. Raissi, and M. Modiri, "A robust model for supplying LNG from different contracts considering overall and incremental discount options," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 43, no. 15, pp. 1805–1824, 2021.
- [27] J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega*, vol. 53, pp. 49–57, 2015.
- [28] J. Rezaei, "Best-worst multi-criteria decision-making method: some properties and a linear model," *Omega*, vol. 64, pp. 126–130, 2016.
- [29] S. Heydariyeh, M. Javidnia, and A. Mehdiabadi, "A new approach to analyze strategy map using an integrated BSC and FUZZY DEMATEL," *Management Science Letters*, vol. 2, no. 1, pp. 161–170, 2012.
- [30] I. Ajripour, M. Asadpour, and L. Tabatabaie, "A model for organization performance management applying MCDM and BSC: a case study," *Journal of Applied Research on Industrial Engineering*, vol. 6, no. 1, pp. 52–70, 2019.
- [31] S. Ozdogan, A. Yildizbasi, and B. D. Rouyendegh, "Performance evaluation of municipal services with fuzzy multi-criteria decision making approaches: a case study from Turkey," *SN Applied Sciences*, vol. 2, no. 6, pp. 1–12, 2020.
- [32] M. Varmazyar, M. Dehghanbaghi, and M. Afkhami, "A novel hybrid MCDM model for performance evaluation of research and technology organizations based on BSC approach," *Evaluation and Program Planning*, vol. 58, pp. 125–140, 2016.
- [33] H. Dinçer, S. Yüksel, and L. Martínez, "Balanced scorecard-based analysis about European energy investment policies: a hybrid hesitant fuzzy decision-making approach with quality function deployment," *Expert Systems with Applications*, vol. 115, pp. 152–171, 2019.
- [34] D. Deng, S. Wen, F.-H. Chen, and S.-L. Lin, "A hybrid multiple criteria decision making model of sustainability performance evaluation for Taiwanese Certified Public Accountant firms," *Journal of Cleaner Production*, vol. 180, pp. 603–616, 2018.
- [35] M.-T. Lu, C.-C. Hsu, J. J. H. Liou, and H.-W. Lo, "A hybrid MCDM and sustainability-balanced scorecard model to establish sustainable performance evaluation for international airports," *Journal of Air Transport Management*, vol. 71, pp. 9–19, 2018.
- [36] H. Dinçer, U. Hacıoglu, and S. Yüksel, "Balanced scorecard based performance measurement of European airlines using a hybrid multicriteria decision making approach under the fuzzy environment," *Journal of Air Transport Management*, vol. 63, pp. 17–33, 2017.
- [37] H. Zhao and N. Li, "Evaluating the performance of thermal power enterprises using sustainability balanced scorecard, fuzzy Delphic and hybrid multi-criteria decision making approaches for sustainability," *Journal of Cleaner Production*, vol. 108, pp. 569–582, 2015.
- [38] K. Meena and J. Thakkar, "Development of balanced scorecard for healthcare using interpretive structural modeling and analytic network process," *Journal of Advances in Management Research*, vol. 11, no. 3, pp. 232–256, 2014.
- [39] L. E. Quezada and H. A. López-Ospina, "A method for designing a strategy map using AHP and linear programming," *International Journal of Production Economics*, vol. 158, pp. 244–255, 2014.
- [40] A. Rabbani, M. Zamani, A. Yazdani-Chamzini, and E. K. Zavadskas, "Proposing a new integrated model based on sustainability balanced scorecard (SBSC) and MCDM approaches by using linguistic variables for the performance evaluation of oil producing companies," *Expert Systems with Applications*, vol. 41, no. 16, pp. 7316–7327, 2014.
- [41] M. Shafiee, F. H. Lotfi, and H. Saleh, "Supply chain performance evaluation with data envelopment analysis and balanced scorecard approach," *Applied Mathematical Modelling*, vol. 38, no. 21–22, pp. 5092–5112, 2014.
- [42] J. Rezaei, L. van Wulfften Palthe, L. Tavasszy, B. Wiegman, and F. van der Laan, "Port Performance Measurement in the Context of Port Choice: An MCDA Approach," *Management Decision*, vol. 57, 2018.
- [43] M. R. Galankashi, S. A. Helmi, and P. Hashemzahi, "Supplier selection in automobile industry: a mixed balanced scorecard-fuzzy AHP approach," *Alexandria Engineering Journal*, vol. 55, no. 1, pp. 93–100, 2016.
- [44] S. Lin, "Identifying the critical success factors and an optimal solution for mobile technology adoption in travel agencies," *International Journal of Tourism Research*, vol. 19, 2016.
- [45] W. Abo-Hamad and A. Arisha, "Multi-criteria approach using simulation-based balanced scorecard for supporting decisions in health-care facilities: an emergency department case study," *Health Systems*, vol. 3, no. 1, pp. 43–59, 2014.
- [46] A. Bhattacharya, P. Mohapatra, V. Kumar et al., "Green supply chain performance measurement using fuzzy ANP-based balanced scorecard: a collaborative decision-making approach," *Production Planning & Control*, vol. 25, no. 8, pp. 698–714, 2014.
- [47] M. Khairalla, M. F. Rahmat, N. Abdul Wahab, I. T. Thuku, T. Tajdari, and A. A. Yusuf, "Particles flow identification in pipeline using adaptive network-based fuzzy inference system and electrodynamic sensors [JOUR]," *Sensor Review*, vol. 34, no. 2, pp. 201–208, 2014.
- [48] C.-W. Hsu, A. H. Hu, C.-Y. Chiou, and T.-C. Chen, "Using the FDM and ANP to construct a sustainability balanced scorecard for the semiconductor industry," *Expert Systems with Applications*, vol. 38, no. 10, Article ID 12891, 2011.

- [49] A. Bazrkar, S. Iranzadeh, and N. Feghhi Farahmand, "Total quality model for aligning organization strategy, improving performance, and improving customer satisfaction by using an approach based on combination of balanced scorecard and lean six sigma," *Cogent Business & Management*, vol. 4, no. 1, Article ID 1390818, 2017.
- [50] C.-H. Wang and Y.-W. Chien, "Combining balanced scorecard with data envelopment analysis to conduct performance diagnosis for Taiwanese LED manufacturers," *International Journal of Production Research*, vol. 54, no. 17, pp. 5169–5181, 2016.
- [51] W.-Y. Wu and Y.-K. Liao, "A balanced scorecard envelopment approach to assess airlines' performance," *Industrial Management & Data Systems*, vol. 114, no. 1, pp. 123–143, 2014.
- [52] A. Tizroo, A. Esmaeili, E. Khaksar, J. Šaparauskas, and M. M. Mozaffari, "Proposing an agile strategy for a steel industry supply chain through the integration of balance scorecard and Interpretive Structural Modeling," *Journal of Business Economics and Management*, vol. 18, no. 2, pp. 288–308, 2017.
- [53] Q.-L. Lin, L. Liu, H.-C. Liu, and D.-J. Wang, "Integrating hierarchical balanced scorecard with fuzzy linguistic for evaluating operating room performance in hospitals," *Expert Systems with Applications*, vol. 40, no. 6, pp. 1917–1924, 2013.
- [54] M. A. Kaviani, A. K. Yazdi, L. Ocampo, and S. Kusi-Sarpong, "An Integrated Grey-Based Multi-Criteria Decision-Making Approach for Supplier Evaluation and Selection in the Oil and Gas Industry," *Kybernetes*, vol. 49, 2019.
- [55] A. K. Yazdi, P. F. Wanke, T. Hanne, F. Abdi, and A. H. Sarfaraz, "Supplier selection in the oil & gas industry: a comprehensive approach for Multi-Criteria Decision Analysis," *Socio-Economic Planning Sciences*, vol. 79, Article ID 101142, 2022.
- [56] J. C. R. Alcantud, R. de Andrés Calle, and M. J. M. Torrecillas, "Hesitant Fuzzy Worth: an innovative ranking methodology for hesitant fuzzy subsets," *Applied Soft Computing*, vol. 38, pp. 232–243, 2016.
- [57] F. Tüysüz and B. Şimşek, "A hesitant fuzzy linguistic term sets-based AHP approach for analyzing the performance evaluation factors: an application to cargo sector," *Complex & Intelligent Systems*, vol. 3, no. 3, pp. 167–175, 2017.
- [58] M. Divsalar, A. Safaei Ghadikolaei, and M. Madhoushi, "Extension of the DANP decision making method based on interval-valued hesitant fuzzy sets," *Modern Research in Decision Making*, vol. 2, no. 3, pp. 123–145, 2017.
- [59] W. Zhai, "Performance evaluation of wireless sensor networks based on hesitant fuzzy linguistic preference relations," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 14, no. 5, pp. 233–240, 2018.
- [60] L. Pérez-Domínguez, D. Luviano-Cruz, D. Valles-Rosales, J. I. Hernández Hernández, and M. I. Rodríguez Borbón, "Hesitant fuzzy linguistic term and TOPSIS to assess lean performance," *Applied Sciences*, vol. 9, no. 5, p. 873, 2019.
- [61] H. Liao, X. Mi, Q. Yu, and L. Luo, "Hospital performance evaluation by a hesitant fuzzy linguistic best worst method with inconsistency repairing," *Journal of Cleaner Production*, vol. 232, pp. 657–671, 2019.
- [62] X. Liu, Z. Wang, S. Zhang, and J. Liu, "Probabilistic hesitant fuzzy multiple attribute decision-making based on regret theory for the evaluation of venture capital projects," *Economic Research-Ekonomska Istraživanja*, vol. 33, no. 1, pp. 672–697, 2020.
- [63] G. Candan, "Efficiency and performance analysis of economics research using hesitant fuzzy AHP and OCRA methods," *Scientometrics*, vol. 124, pp. 2645–2659, 2020.
- [64] J.-W. Gong, H.-C. Liu, X.-Y. You, and L. Yin, "An integrated multi-criteria decision-making approach with linguistic hesitant fuzzy sets for E-learning website evaluation and selection," *Applied Soft Computing*, vol. 102, Article ID 107118, 2021.
- [65] F. Meng, J. Tang, and W. Pedrycz, "Dual hesitant fuzzy decision making in optimization models," *Computers & Industrial Engineering*, vol. 154, Article ID 107103, 2021.
- [66] Z. Lin, C. Huang, and M. Lin, "Probabilistic Hesitant Fuzzy Methods for Prioritizing Distributed Stream Processing Frameworks for IoT Applications," *Mathematical Problems in Engineering*, vol. 2021, Article ID 6655477, 12 pages, 2021.
- [67] V. Torra and Y. Narukawa, "On hesitant fuzzy sets and decision," in *Proceedings of the 2009 IEEE International Conference on Fuzzy Systems*, pp. 1378–1382, Jeju, Republic of Korea, August 2009.
- [68] P. K. Humphreys, Y. K. Wong, and F. T. S. Chan, "Integrating environmental criteria into the supplier selection process," *Journal of Materials Processing Technology*, vol. 138, no. 1–3, pp. 349–356, 2003.
- [69] P. Humphreys, R. McIvor, and F. Chan, "Using case-based reasoning to evaluate supplier environmental management performance," *Expert Systems with Applications*, vol. 25, no. 2, pp. 141–153, 2003.
- [70] G. Noci, "Designing 'green' vendor rating systems for the assessment of a supplier's environmental performance," *European Journal of Purchasing & Supply Management*, vol. 3, no. 2, pp. 103–114, 1997.
- [71] T. Hanne, *Intelligent strategies for meta multiple criteria decision making Reprint*, Springer, Singapore, 2012.
- [72] A. K. Yazdi and M. Haddadi, "Integration of balanced scorecard and Fuzzy FMEA for designing road map," *Australian Journal of Basic and Applied Sciences*, vol. 5, no. 9, 2011.
- [73] S. Singh, E. U. Olugu, S. N. Musa, and A. B. Mahat, "Fuzzy-based sustainability evaluation method for manufacturing SMEs using balanced scorecard framework," *Journal of Intelligent Manufacturing*, vol. 29, pp. 1–18, 2015.