Sustainable Production and Consumption 27 (2021) 905–920

Contents lists available at ScienceDirect

Sustainable Production and Consumption

journal homepage: www.elsevier.com/locate/spc

A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy

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ARTICLE INFO

Article history:
Received 9 December 2020
Revised 5 February 2021
Accepted 9 February 2021
Available online 12 February 2021

Keywords:
Sustainable circular supplier selection
decision support system
best-worst method
fuzzy inference system
machine learning

ABSTRACT

Supplier selection is an important and challenging problem in sustainable supply chain management. We propose a dynamic decision support system (DSS) for sustainable supplier selection in circular supply chains. Unlike the linear take-make-waste-dispose production systems, circular supply chains are nonlinear make-waste-recycle production systems with zero-waste vision. The proposed DSS allows users to customize and weight their economic, social, and circular criteria with a fuzzy best-worst method (BWM) and select the most suitable supplier with the fuzzy inference system (FIS). Machine learning is used to maintain and synthesize the criteria scores for the suppliers after each supplier selection engagement. We present a case study at a petrochemical holding company with a controlling interest over several subsidiary companies to demonstrate the applicability of the proposed approach.

1. Introduction

The increasing awareness of customers and stockholders towards environmental concerns and sustainability coupled with competitive advantage have forced organizations to adopt green and sustainable business practices (Mardan et al., 2019; Ghayebloo et al., 2015). The first step in designing a sustainable supply chain is to collaborate with sustainable suppliers positioned in the upstream chain, impacting the downstream chain (Yu et al., 2019). Sustainable supplier selection requires a triple bottom line (i.e., economic, environmental, and social) consideration (Govindan et al., 2013). In addition to enhancing supply chain sustainability, selecting the right sustainable supplier has a significant impact on cost reduction, quality enhancement, and supply chain efficiency (Kannan et al., 2020).

Fallahpour et al. (2017) have argued the selection of suitable suppliers in supply chain management is a complex task requiring a comprehensive evaluation process, often under uncertain conditions. A large number of studies have proposed stand-alone or hybrid models for sustainability assessment and supplier selection. Despite these efforts, little attention has been paid to the development of a comprehensive framework for circular supplier evaluation and selection. Accordingly, the following research questions remain unanswered:

a) Which economic, social, and circular criteria are most suitable for supplier selection in a circular supply chain?
b) Which approach is most suitable for a comprehensive and inclusive evaluation of sustainable suppliers in a circular supply chain?

Before the availability of new digital technologies such as cloud computing, machine learning, and the internet of things, an analysis of a vast amount of data was difficult, often producing limited and unpersuasive results (Liu et al., 2018). The advent of new technologies and digital systems such as machine learning has provided decision-makers with ready access to information anytime and anywhere (Cavalcante et al., 2019). In this study, machine learning, the best-worst method (BWM), and fuzzy inference system (FIS) are effectively integrated within a dynamic decision support system (DSS) for sustainable supplier selection in circular supply chains. The users select relevant criteria from a database of economic, social, and circular criteria. The importance weight of criteria is determined with the fuzzy BWM, and the final score of the suppliers is calculated with the FIS method. The decision model is composed of a hierarchical structure to present the economic, social, and circularity aspects of the problem and the rele-

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https://doi.org/10.1016/j.spc.2021.02.015
2352-5509/

Nomenclature

w_b	The weight of the best criterion
w_w	The weight of the worst criterion
w_j	The weight of the criterion j
w_{bj}	The best-to-others vector
w_{jw}	The others-to-worst vector
γ^*	Auxiliary variable
(w_b^l, w_b^m, w_b^u)	The fuzzy weights of the best criterion
(w_w^l, w_w^m, w_w^u)	The fuzzy weights of the worst criterion
$(w_{bj}^l, w_{bj}^m, w_{bj}^u)$	The fuzzy best-to-others vector
$(w_{jw}^l, w_{jw}^m, w_{jw}^u)$	The fuzzy others-to-worst vector
CI	Consistency index
CR	Consistency ratio

vant evaluation criteria and alternative suppliers. The analytic hierarchy process (AHP) is a common pairwise comparison method for determining the criteria weights in multi-criteria decision making (MCDM). The BWM, similarly, uses pairwise comparisons to determine the criteria weights in MCDM. This study uses BWM, which requires fewer pairwise comparisons and produces more consistent results (Rezaei, 2015, 2016). Thus, BWM calculates the criteria weights and the suppliers' economic, circular, and social scores. Other methods used for developing criteria weights are a direct estimation. However, a direct estimation of criteria weights is arbitrary and often subject to random and subjective decision-makers' valuation. A nonlinear relationship is dominant between the criteria and the final scores; therefore, rule-based methods such as FIS are a suitable method for obtaining the suppliers' final scores in this study (Jain et al., 2020). There are two methods for designing FIS: the Mamdani approach (Mamdani and Assilian, 1975) and Sugeno approach (Sugeno, 1985). Mamdani's approach utilizes knowledge modeling in DSSs, but Sugeno's approach is grounded in mathematical modeling. In addition, the output of a Mamdani FIS is derived from nonlinear functions, but the output of a Sugeno FIS is produced from a constant or a linear function. In Sugeno FIS, unlike Mamdani FIS, it is not possible to define the membership functions for the output variables. Hence, In this paper, we use a Mamdani FIS to design our DSS. The reason we use FIS in this study is fivefold: (i) mathematical concepts within FIS reasoning are simple, (ii) FIS is flexible, (iii) it is easy to modify a FIS just by adding or deleting rules, (iv) FIS is built on expertise and relies on the know-how of the ones who understand the system, and (v) FIS can be blended with other systems such a machine learning embedded in the proposed DSS to update and synthesize historical data.

We (i) propose a practical and user-friendly DSS with customization capabilities for sustainable supplier selection in circular supply chains; (ii) apply a dynamic DSS for sustainable supplier selection using the fuzzy BWM and FIS methods in an integrated framework; (iii) use machine learning to maintain supplier information synthesize historical data, and (iv) validate the proposed DSS through implementation in a petrochemical holding company with a controlling interest over 18 other companies. The remainder of this paper is organized as follows. In section 2, we present the relevant literature on supplier selection criteria and methods. Section 3 presents the proposed framework. In Section 4, we present a case study to demonstrate the applicability of the proposed framework. In Section 5, we conclude with our conclusions and future research directions.

2. Literature review

The selection of relevant criteria and suitable selection methods are two critical prerequisites for successful sustainable supplier selection. Accordingly, the literature review presented in this study consists of two sections in line with the research questions. Section 2.1 provides a review of the literature on triple bottom line criteria used in supplier selection problems, and Section 2.2 presents a review of the methods used in the sustainable supplier selection literature.

2.1. Supplier selection criteria in sustainable supply chains

One of the major challenges in supplier selection is identifying relevant and suitable criteria for inclusion in the assessment and selection process (Xue et al., 2018). The most commonly used criteria for supplier selection can be categorized into three groups of economic, environmental, and social criteria (Fallahpour et al., 2017). Kannan et al. (2020) proposed a new categorization of economic, social, and circular criteria for supplier evaluation, where the circular production system is a special manifestation of the environmental criteria that pertains to the supplier evaluation in the circular or closed-loop supply chains (Govindan et al., 2020). Cost, quality, flexibility, and service are among the most widely used economic criteria in the literature (Jain and Singh, 2020; Liu et al., 2019; Lo et al., 2018). Dickson (1966), one of the pioneers in supplier selection, has proposed 23 criteria for supplier selection based on the preferences of the purchasing managers. Noci (1997) considered environmental concerns and introduced a rating system to evaluate suppliers. Environmental management systems, green technology, green packaging, and pollution control are some of the widely used environmental criteria in the literature relating to sustainable supplier selection (Haeri and Rezaei, 2019; Mishra et al., 2019; Qazvini et al., 2019). Đalić et al. (2020) used seven environmental criteria: green competencies, recycling, environmental image, environmental management system, environmentally friendly products, resource consumption, and pollution control for supplier evaluation in green supply chains. Mina et al. (2021) developed a hybrid circular supplier selection method to evaluate and rank suppliers in the petrochemical industry using delivery, quality, circular, and capability criteria.

The increasing attention to social issues has led to the emergence of sustainable supply chain management with economic, social, and environmental considerations (Luthra et al., 2017). Khan et al. (2018) embarked on supplier evaluation in the automotive industry by considering economic, social, and environmental factors. They considered social commitment, health and safety, information disclosure, employer rights, and employment practices as social criteria in their study. A new method entitled full consistency method for evaluating sustainable suppliers was proposed by Durmić (2019). The proposed method considered economic, social, and environmental dimensions in the evaluation process. Safety and health at work, employees' rights, disclosing information, and respect for rights and policies were among the criteria used in his study. Kannan et al. (2020) proposed an approach for supplier selection in the wire-and-cable industry using economic, social, and environmental criteria. The social criteria proposed in their research are job creation, health and safety systems, rights of stockholders, rights of employees, and information disclosure. Amiri et al. (2021) embarked on supplier evaluation in the automotive industry and used fuzzy BWM and economic, social, and environmental criteria to consider employee satisfaction, after-sales service, ease of communication, and employee training and development as social sub-criteria.

Conventional or forward supply chains convert raw materials into final products in a linear fashion with no regard to the end-of-life (EOL) products; however, sustainable or reverse supply chains operate in a circular fashion by using EOL products as raw materials. Wang et al. (2019) identified closed-loop, green, and socially responsible supply chains as three main categories of sustainable supply chains. Although these terms have been used interchangeably in the literature, there are important differences among them (González-Sánchez et al., 2020). While green and socially responsible supply chains engage manufacturers and customers to promote cooperation that will result in environmental and social gains, circular or closed-loop supply chains pursue remanufacturing and zero-waste practices. Circular supply chains are self-sustaining production systems designed to reduce production waste and return EOL products to the production cycle (Genovese et al., 2017). In this study, we consider economic, social, and circular environmental factors to concentrate on the remanufacturing and zero-waste benefits of circular supply chains. Table 1 presents the most widely used criteria for sustainable supplier selection.

2.2. Supplier selection methods in sustainable supply chains

One of the most significant advances in sustainable supply chain management has been the development of various green and socially responsible supplier evaluation and selection methods. The MCDM methods are often used for supplier selection in supply chain management (Asadabadi, 2018). With the increasing attention to sustainable supply chain management, MCDM methods have been widely used to solve green and socially responsible supply chain problems with multiple and often conflicting criteria because of their flexibility and simplicity (Memari et al., 2019). The AHP is a popular MCDM method for solving supplier evaluation and selection problems (Qazvini et al., 2019). The conventional AHP requires exact values to express the decision maker's opinions through a series of pairwise comparisons. However, real-world problems often involve ambiguities and uncertainties. The fuzzy AHP, based on Zadeh's fuzzy set theory (1965), is developed to overcome this weakness in sustainable supply chain management (Ecer, 2020; Gold and Awasthi, 2015; Mani et al., 2014). Other MCDM methods, such as analytic network process (ANP) (Giannakis et al., 2020; Tavana et al., 2017) and fuzzy ANP (Bakeshlou et al., 2017; Mina et al., 2014), the decision making trial and evaluation laboratory (DEMATEL) (Gören, 2018), the technique of order preference similarity to the ideal solution (TOPSIS) (Sureeyatanapas et al., 2018) and fuzzy TOPSIS (Rani et al., 2020; Li et al., 2019; Yu et al., 2019), the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), also known as multi-criteria optimization and compromise solution method (Fei et al., 2019), and fuzzy VIKOR (Liu et al., 2019; Awasthi and Govindan., 2016), and the data envelopment analysis (DEA) (Dobos and Vörösmarty, 2019) and fuzzy DEA (Tavassoli et al., 2020) are among the most widely used methods in sustainable supply chain management. The BWM is a new MCDM method proposed by Rezaei (2015). Rezaei et al. (2016) proposed a BWM-based approach for supplier selection in the food industry by considering both traditional and sustainable criteria. Each MCDM method has unique strengths and weaknesses.

Many hybrid MCDM methods have been proposed to capitalize on the strengths and avoid the weaknesses of the single MCDM methods. The following presents some of the studies which have used hybrid MCDM methods for sustainable or green supplier selection. Luthra et al. (2017) used a hybrid MCDM method for sustainable supplier selection. They computed the weights of the criteria and sub-criteria with AHP and ranked the suppliers with the VIKOR method. Azimifard et al. (2018) suggested a hybrid AHP and TOPSIS method for sustainable supplier selection in the steel industry. Banaeian et al. (2018) used a green supplier selection problem in the agri-food industry to compare the results from three methods, i.e., TOPSIS, VIKOR, and grey relational analysis in a fuzzy environment. Kusi-Sarpong et al. (2019) proposed a hybrid approach by integrating the BWM and VIKOR for supplier selection in circular supply chains. The BWM was used to determine the importance weight of the evaluation criteria, and the VIKOR method was used to rank the suppliers. Govindan et al. (2020) proposed an integrated fuzzy ANP and fuzzy DEMATEL for supplier evaluation in the circular supply chains. They calculated the weights of the criteria and then considered the interdependencies among them with the fuzzy DEMATEL method to rank the suppliers in the automotive industry. Kannan et al. (2020) proposed a practical approach for sustainable supplier selection in the circular supply chains using MCDM methods. They used fuzzy BWM to weigh the criteria in the wire-and-cable industry and the interval VIKOR method to rank the suppliers.

In addition to MCDM methods, artificial intelligence methods are also widely used for supplier evaluation and selection problems. Tahriri et al. (2014) developed an integrated fuzzy Delphi and FIS method for supplier evaluation. Amindoust and Saghafinia (2017) introduced a practical framework for supplier evaluation in a sustainable supply chain using FIS. They demonstrated the effectiveness and efficiency of their proposed approach in the textile industry. Similarly, an efficient FIS-based approach was proposed by Ghadimi et al. (2017) for evaluating the suppliers in the automotive industry by considering the economic, social, and environmental sustainability factors. Jain and Singh (2020) developed an approach for supplier selection based on FIS to evaluate suppliers in the large-scale iron and steel industry.

Moreover, the combination of MCDM methods and artificial intelligence has received particular attention in recent years. Amindoust (2018) presented a novel method for evaluating resilient and sustainable suppliers using FIS and DEA. Mina et al. (2021) proposed a hybrid MCDM and FIS approach for circular supplier selection. They first calculated the weights of sub-criteria using fuzzy AHP and a score for each supplier using TOPSIS. Finally, they used FIS to evaluate and select the most suitable suppliers. Table 2 presents some of the most recent and widely used multi-criteria supplier selection methods in sustainable supply chain management.

2.3. Best-worst method

The BWM proposed by Rezaei (2015) operates based on the systematic pairwise comparison of multiple criteria. Initially, the best and the worst criteria are identified by the decision-maker. The decision-maker then compares the best and the worst criteria with the other criteria in two subsequent steps. A scale consisting of points from 1 to 9 is used to determine the pairwise comparisons' strengths. Next, an optimization problem is formulated using the two pairwise comparison sets as inputs. The weights of criteria are identified as the optimum result of this optimization problem. The small number and the strong consistency of pairwise comparisons are the unique features of the BWM. For example, AHP needs $n(n-1)/2$ pairwise comparisons for formulating a pairwise matrix between n, which is indicative of the number of criteria. In contrast, the BWM only requires $2n-3$ pairwise comparisons. Thus, with the increase in "n," a greater efficiency is gained from the BWM compared to competing methods such as AHP (Rezaei, 2015).

3. Problem statement and the proposed approach

Supplier selection is a challenging problem in manufacturing. Most manufacturing companies are more mindful of this challenging problem since suppliers lie at the starting point of the chain.

Table 1
The sustainable criteria for supplier selection.

Criteria	Fallahpour et al. (2017)	Luthra et al. (2017)	Arabsheybani et al. (2018)	Awasthi et al. (2018)	Azimifard et al. (2018)	Gören (2018)	Kannan (2018)	Vahidi et al. (2018)	Abdel-Baset et al. (2019)	Ahmadi and Amin (2019)	Alikhani et al. (2019)	Guarnieri and Trojan (2019)	Li et al. (2019)	Liu et al. (2019)	Memari et al. (2019)	Mohammed et al. (2019)	Pishchulov et al. (2019)	Yu et al. (2019)	Govindan et al. (2020)	Jia et al. (2020)	Kannan et al. (2020)	Stević et al. (2020)
Cost (E1)	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√		√		√	√	√
Quality (E2)	√	√	√	√	√	√	√			√	√	√	√	√		√	√	√	√	√	√	√
On-time delivery (E3)	√	√	√				√			√	√	√	√		√	√	√	√	√	√	√	√
Reputation (E4)					√					√	√				√						√	√
Flexibility (E5)	√	√		√			√			√		√	√					√			√	
Technological capacity (E6)		√			√	√	√	√		√	√	√			√	√	√	√		√	√	
R&D (E7)		√					√					√										√
Responsiveness (E8)						√				√					√		√					
Financial capability (E9)		√					√			√		√		√			√					
Productivity (E10)						√						√										
Service efficiency (E11)		√					√			√		√										
Risk (E12)			√	√							√											
Attention to energy consumption in production and recycling products (C1)		√		√	√	√		√		√	√		√	√			√	√				
Attention to air pollution in production and recycling products (C2)	√	√		√	√		√	√		√		√	√	√	√	√	√	√	√	√	√	√
Producing products using recyclable raw materials (C3)		√		√		√	√			√	√		√		√			√	√		√	√
Utilizing clean and green technology in production and recycling products (C4)	√						√	√			√		√						√		√	

(*continued on next page*)

Table 1 (*continued*)

Criteria	Fallahpour et al. (2017)	Luthra et al. (2017)	Arabsheybani et al. (2018)	Awasthi et al. (2018)	Azimifard et al. (2018)	Gören (2018)	Kannan (2018)	Vahidi et al. (2018)	Abdel-Baset et al. (2019)	Ahmadi and Amin (2019)	Alikhani et al. (2019)	Guarnieri and Trojan (2019)	Li et al. (2019)	Liu et al. (2019)	Memari et al. (2019)	Mohammed et al. (2019)	Pishchulov et al. (2019)	Yu et al. (2019)	Govindan et al. (2020)	Jia et al. (2020)	Kannan et al. (2020)	Stević et al. (2020)
Employing eco-friendly materials for packaging products (C5)	√	√							√			√		√	√			√	√		√	
Respecting environmental regulations and standards (C6)	√						√	√		√	√				√				√		√	√
Waste management (C7)	√	√		√			√	√	√	√		√		√	√	√	√			√		√
Environmental management system (C8)	√	√	√								√	√		√		√	√			√		√
Managing returned products (C9)										√									√			
Reverse logistics (C10)										√		√	√	√				√				√
Human rights (S1)	√	√	√	√	√		√				√	√	√		√			√			√	√
Product responsibility (S2)				√			√															
Occupational health and safety management system (S3)	√	√	√				√	√	√				√		√	√	√	√		√	√	√
Information disclosure (S4)		√							√			√				√		√		√	√	√
Social commitment (S5)				√							√		√	√			√					
Ethical issues (S6)					√		√		√					√								
Employment practices (S7)				√										√								√
Social management (S8)											√						√					
Attention to the child and forced labor problem (S9)					√										√		√					

Table 2
Multi-criteria decision-making methods for sustainable supplier selection.

MCDM Method	Girubha et al. (2016)	Govindan and Sivaku-mar (2016)	Ahmadi et al. (2017)	Falahpour et al. (2017)	Hamdan and Cheaitou (2017)	Gupta and Barua (2017)	Kumar et al. (2017)	Luthra et al. (2017)	Wan et al. (2017)	Awasthi et al. (2018)	Cheraghalipour and Farsad (2018)	Gören (2018)	Lo et al. (2018)	Mohammed et al. (2018)	Abdel-Baset et al. (2019)	Alikhani et al. (2019)	Dobos and Vörös-marty (2019)	Govindan et al. (2019)	Mohammed et al. (2019)	Moheb-Alizadeh and Handfield (2019)	Qazvini et al. (2019)	Rashidi and Cullinane (2019)	Wu et al. (2019)	Chen et al. (2020)	Garg and Sharma (2020)	Govindan et al. (2020)	Kannan et al. (2020)
AHP/fuzzy				√	√			√		√				√					√		√						
AHP																											
ANP/fuzzy	√								√						√											√	
ANP																											
TOPSIS/fuzzy				√	√	√							√	√					√			√		√			
TOPSIS																											
VIKOR								√		√					√	√							√		√		√
BWM/fuzzy			√			√					√		√										√		√		√
BWM																											
DEA																√	√			√		√					
DEMATEL												√												√		√	
ELECTRE	√						√		√									√									

Their poor selection can lead to detrimental consequences, such as increased costs, reduced product quality, and decreased efficiency in the chain at large. The supplier selection problem in a holding company is more complex, costly, and time-consuming because of the large number of subsidiaries in different domains. We propose a dynamic DSS for sustainable supplier selection in the circular supply chains. The proposed DSS is composed of a hybrid MCDM model management component, a database management system powered by machine learning, and a user interface equipped with a visualization dashboard. Some of the unique features of the proposed DSS include:

- There is no need for expert intervention in the collection and processing of user's judgments concerning the criteria weights since the system collects, processes, and interactively determines the consistencies.
- There is no need to score each supplier on each criterion since machine learning is used to maintain and synthesize detailed criteria scores concerning historical supplier selection engagements.
- Despite its complexity, the proposed DSS has a user-friendly interface with a visualization dashboard and facility for criteria selection and comparison using linguistic terms and phrases.

Fig. 1 illustrates the structure of the proposed DSS, which is composed of a database management system, user interface, and model management components. The database component maintains historical data on supplier scores for all criteria and all user engagements. The user interface manages all interactions with the user. The first user interaction step involves industry selection, where the user is required to identify a specific industry from the holding company's portfolio of companies. The user is then asked to choose the relevant criteria for his/her supplier selection problem from a comprehensive set of economic, social, and circular criteria. The user is also required to determine the importance of his/her selected criteria. The model management component is composed of the fuzzy BWM and FIS modules. The fuzzy BWM module determines the importance weights of the criteria, and the FIS ranks the potential suppliers according to the user's preferences and historical data. Fuzzy logic is used to handle the uncertainties and ambiguities inherent in subjective judgments. The user is provided with a visualization dashboard to study the suppliers' performance on each criterion. In addition, the overall supplier scores and rankings are provided through the user interface dashboard. All relevant data and scores on each supplier are stored in the database and retrieved and synthesized using machine learning during each supplier selection engagement.

The proposed framework involves nine steps, as follows:

Pre-engagement step: In this step, the user selects a specific industry within the holding company in search of a sustainable supplier.

Step 1. In this step, the user identifies relevant criteria from a comprehensive list of sustainable supplier selection criteria available in the database management system. If the user feels a criterion is missing, he or she is provided with the opportunity to add the missing criterion and update the system. All criteria in the system are classified into economic, social, and circular groups based on the related literature, expert opinions, and previous user interactions and engagements.

Step 2. In this step, the user is required to determine the importance of his/her selected criteria by using Table 3a and classifying the selected criteria into five groups. For example, moderately important criteria are assigned to Class 3, while very important criteria are assigned to Class 5. All subsequent steps are managed automatically by the model management component of the DSS.

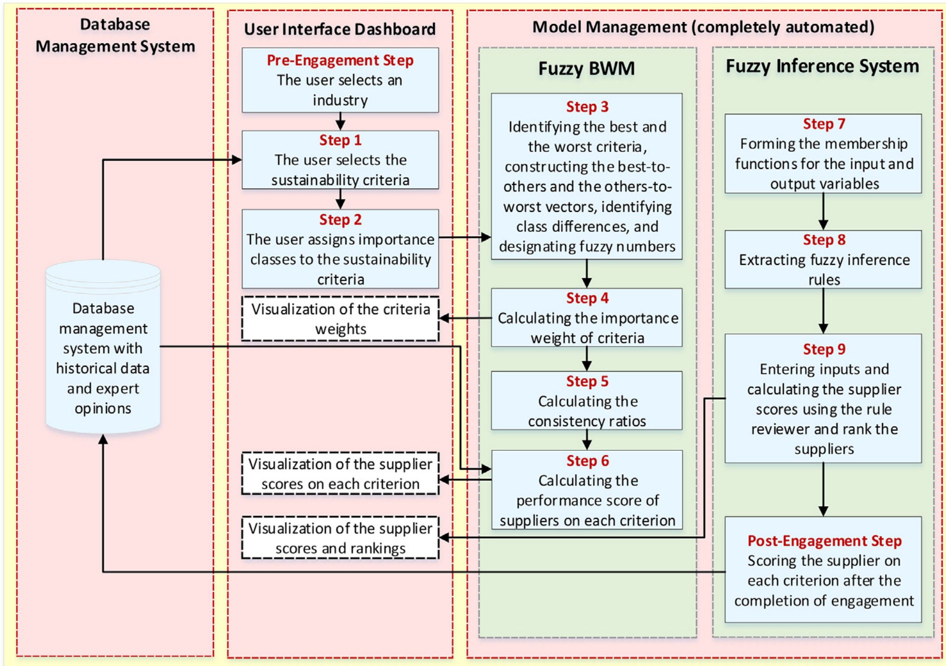


Fig. 1. The proposed decision support system.

Table 3
Importance levels and fuzzy numbers.
3a. Importance levels and their associated classes
3b. Triangular fuzzy numbers and their associated class differences (Tavana et al., 2020).

Class	Importance level	
1	Very low importance	
2	Low importance	
3	Moderate importance	
4	High importance	
5	Very high importance	
Linguistic term	**Triangular fuzzy numbers**	**Class difference**
Equally important	(1,1,1)	0
Slightly important	(2/3,1,3/2)	1
Moderately important	(3/2,2,5/2)	2
Very important	(5/2,3,7/2)	3
Absolutely important	(7/2,4,9/2)	4

Step 3. In this step, the criteria classification data collected from the user in Step 2 is used to identify the best and the worst criteria, construct the best-to-others and the others-to-worst vectors, identify the class differences, and designate the appropriate fuzzy numbers according to Table 3b. The model management system first identifies the best and worst criteria. The best criterion may belong to class n ($\forall n \geq 2$), and the other criterion may belong to class n-1. In that case, the two criteria have one class difference (slightly important), and the triangular fuzzy numbers 2/3, 1, and 3/2 are used by the system for the pairwise comparison score. Similarly, if the two criteria being compared have two class differences (moderately important), the triangular fuzzy numbers 3/2, 2, and 5/2 are used by the system for the pairwise comparison. After completing all pairwise comparisons, the fuzzy best-to-others vector is constructed. Similarly, the fuzzy others-to-worst vector is created through pairwise comparisons between the worst criterion and the other criteria. For example, if the worst criterion belongs to class one and the other criterion belongs to class four, the class difference of the two criteria is three, and, thereby, the triangular fuzzy numbers 5/2, 3, and 7/2 are used by the system for the pairwise comparison.

Step 4. In this step, the fuzzy weights of criteria are calculated using the nonlinear mathematical model proposed by Guo and Zhao (2017). The deterministic form of this model was first presented by Rezaei (2015) as follows:

$$Min\ \gamma^* \tag{1.a}$$

s.t.

$$\left|\frac{w_b}{w_j} - w_{bj}\right| \leq \gamma^* \quad \forall j \tag{1.b}$$

$$\left|\frac{w_j}{w_w} - w_{jw}\right| \leq \gamma^* \quad \forall j \tag{1.c}$$

$$\sum_j w_j = 1 \tag{1.d}$$

$$w_j > 0 \tag{1.e}$$

According to Rezaei (2015), the optimal weights for criteria result when $\frac{w_b}{w_j} = w_{bj}$ and $\frac{w_j}{w_w} = w_{jw}$. In other words, the maximum absolute differences among $|\frac{w_b}{w_j} - w_{bj}|$ and $|\frac{w_j}{w_w} - w_{jw}|$ should be less than the objective function given in constraints (1.b) and (1.c). According to the constraint (1.d), the criteria's total weight should be equal to 1. Finally, constraint (1.e) guarantees that the obtained weights are positive. Guo and Zhao (2017) presented Model (1) in fuzzy form as follows:

$$Min\ \gamma^* \tag{2.a}$$

s.t.

$$\left|\frac{\left(w_b^l, w_b^m, w_b^u\right)}{\left(w_j^l, w_j^m, w_j^u\right)} - \left(w_{bj}^l, w_{bj}^m, w_{bj}^u\right)\right| \leq (\gamma^*, \gamma^*, \gamma^*)\forall j \tag{2.b}$$

$$\left|\frac{\left(w_j^l, w_j^m, w_j^u\right)}{\left(w_w^l, w_w^m, w_w^u\right)} - \left(w_{jw}^l, w_{jw}^m, w_{jw}^u\right)\right| \leq (\gamma^*, \gamma^*, \gamma^*)\ \forall j \tag{2.c}$$

Table 4
Consistency index for fuzzy best-worst method.

Linguistic terms	Equally important	slightly important	moderately important	Very important	Absolutely important
$\tilde{A}_{BW}$	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(5/2,3,7/2)	(7/2,4,9/2)
CI	3	3.8	5.29	6.69	8.04

$$\sum_j \frac{w_j^l + 4 \times w_j^m + w_j^u}{6} = 1 \tag{2.d}$$

$$w_j^l \le w_j^m \le w_j^u \tag{2.e}$$

$$w_j^l \ge 0 \tag{2.f}$$

where (w_j^l, w_j^m, w_j^u) are the triangular fuzzy numbers representing the importance weights of criterion j. In addition, $(w_{bj}^l, w_{bj}^m, w_{bj}^u)$ and $(w_{jw}^l, w_{jw}^m, w_{jw}^u)$ represent the fuzzy best-to-others and the fuzzy others-to-worst vectors, respectively. Furthermore, γ^*, is a variable used to calculate the consistency ratios. The optimal fuzzy weights of criteria are obtained by running Model (2) with GAMS software.

Step 5. In this step, the consistency of the pairwise comparisons is calculated. Since a rational pattern is employed for the pairwise comparisons in Step 3, the consistency of pairwise comparisons is confirmed. However, a consistency ratio is obtained using Eq. (3) and Table 4 to confirm this claim. Consistency ratios close to zero are preferred because they represent higher consistency.

$$CR = \frac{\gamma^*}{CI} \tag{3}$$

where CR and CI are an abbreviation of consistency ratio and consistency index, respectively.

Step 6. In this step, the historical data from previous evaluations are retrieved from the database management system and used to calculate a performance score for each criterion selected by the user in Step 1. A supplier score for each classification (i.e., economic, social, and circular) is obtained as a weighted sum of the criteria weights times the scores retrieved from the database.

Step 7. In this step, the membership functions for the input and output variables are formed to be used in a Mamdani FIS. The economic, social, and circular criteria are considered the input variables, and the suppliers' scores are the output variables in the FIS. Figs. 2a and 2b present the membership functions for the input and output variables, respectively. The number of fuzzy inference rules is a function of the number of input variables and membership functions. An increase in the number of membership functions for the input variables will increase the number of rules exponentially but may not improve accuracy. However, an increase in the number of membership functions for the output variables has no impact on the number of rules, but it does improve accuracy. To this end, we considered five membership functions for the input variables and seven membership functions for the output variables to keep the number of rules manageable and avoid unnecessary complexity and processing time.

Step 8. In this step, the fuzzy inference rules are extracted from expert knowledge. In doing so, experts are asked to connect a link between the input and output variables in the FIS using an "if-then" questionnaire. The relationship between the input and output variables is formed as follows:

If input1 be ... and input2 be ... and input3 be ... then output is ... .

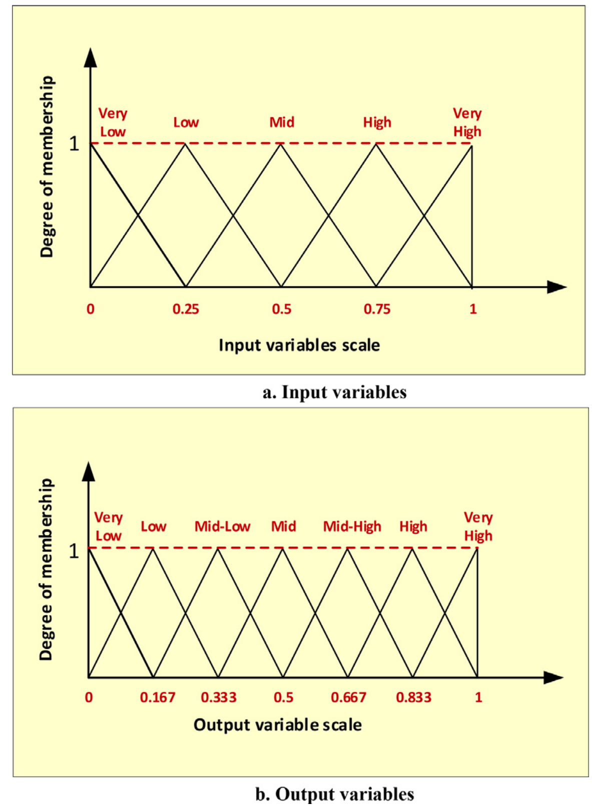


Fig. 2. Membership functions
2a. Input variables
2b. Output variables.

Considering the above relationship, each of the five membership functions is placed in the blank space pertaining to *input1, input2*, and *input3*. Therefore, it is possible to write 5^3 non-iterative rules with three input variables and five membership functions. To construct the FIS, experts are asked to assign a suitable membership function for the output variables in the blank spaces pertaining to the outputs, according to each rule.

Step 9. In this step, an economic, social, and circular score for each potential supplier is obtained from Step 6 and inserted in the rule reviewer as an input in the proposed FIS. Next, a final score is calculated for each supplier, and the suppliers are ranked according to their final scores. The supplier with the highest score is selected as the most preferred supplier.

Post-engagement step: In this step, the user is asked to provide three periodical reviews of the selected supplier in Step 8 on all criteria from Step 1 in one month, three months, and six months after the selection process is completed. This information is maintained in the database and will be used in Step 5 for future users who might be considering this supplier on the same criteria.

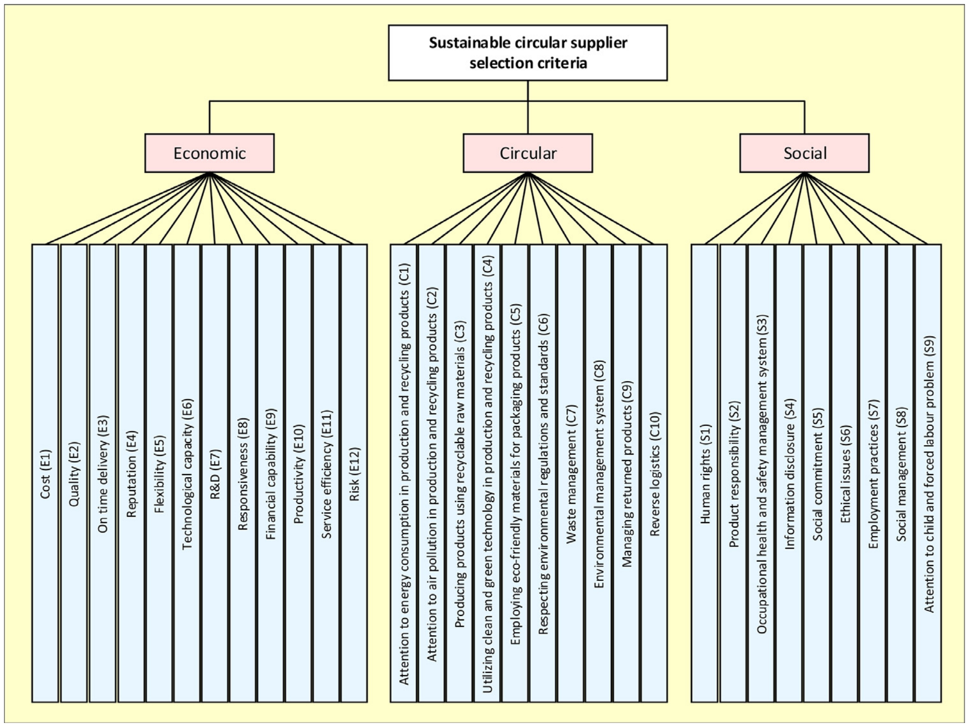


Fig. 3. The proposed economic, social, and circular criteria.

4. Case study

In this section, we present a case study at the Gulf Petrochemical Consortium (GPC)[1], the largest international petrochemical company operating in the Persian Gulf, to demonstrate the applicability of the proposed DSS. GPC is a holding company with a controlling interest in 18 subsidiary companies and more than 45 million tons of output capacity. The company is the first petrochemical consortium in the Middle East and North Africa to commit to sustainability and promotion of a circular economy. The company recently commissioned the first carbon dioxide recovery plant to manage greenhouse gas emissions. Ammonia, methanol, urea, ethylene, sulfur, and their derivatives are among the core products produced and sold by GPC worldwide. The majority of plastics waste worldwide ends up in landfills and incinerators. Plasco[2] is a chemical recycling company owned by GPC to meet the ambitious circular economy targets established by GPC. Plasco uses chemical recycling to process plastics waste into raw materials for the downstream companies and manufacturing plants owned by GPC. In this case study, Plasco is searching for a sustainable supplier for polyethylene glycol.

Pre-engagement step: The user selected Plasco from the list of 18 subsidiary companies owned by GPC.

Step 1. In this step, the user retrieved all available criteria in the system for polyethylene glycol supplier selection. The system listed 31 criteria classified into 12 economic, 10 circular, and 9 social criteria (see Fig. 3). After careful consideration and consultation with the company experts, the user selected 14 criteria composed of five economic (E1, E2, E3, E5, and E6), four circular (C2, C3, C6, and C9), and five social criteria (S1, S3, S4, S5, and S9).

Table 5
Selected and classified criteria by the user.

Aspect	Class				
	1	2	3	4	5
Economic	-	E6	E3, E5	E1	E2
Circular	C9	-	C6	C2	C3
Social	S5	S4	S3	S9	S1

Step 2. In this step, the user identified the importance of the 14 selected criteria by using Table 3a and classifying these criteria into five classes (1 through 5), as shown in Table 5.

Step 3. In this step, the best-to-others and others-to-best vectors were formed using the classifications made in Step 2. The Class 5 criteria (i.e., E2, C3, and S1) are considered the best criteria, and the criteria placed in the lowest class (i.e., E6, C9, and S5) are considered the worst criteria. The best-to-others vectors are presented in Table 6, and the others-to-worst vectors are shown in Table 7 using the pattern presented in Table 3b.

Step 4. In this step, the weights of criteria were calculated using the Guo and Zhao's (2017) model. The fuzzy best-to-others and others-to-worst vectors were run in GAMS software using the PATHNLP solver. For example, for calculating the weights of economics' criteria, the proposed model by Guo and Zhao (2017) was developed using the fuzzy best-to-others and others-to-worst vectors presented in Table 6a and Table 7a, respectively. The model developed for calculating the weights of economic criteria is presented in Appendix.

[1] The name of the company is changed to protect the anonymity of the holding company.
[2] The name of the company is changed to protect the anonymity of this subsidiary company.

Table 6
The best-to-others vectors for the economic, social, and circular criteria
6a. Economic criteria
6b. Circular criteria
6c. Social criteria

Best	Others				
	E1	E2	E3	E5	E6
E2	(2/3,1,3/2)	(1,1,1)	(3/2,2,5/2)	(3/2,2,5/2)	(5/2,3,7/2)
Best	Others				
	C2	C3	C6	C9	
C3	(2/3,1,3/2)	(1,1,1)	(3/2,2,5/2)	(7/2,4,9/2)	
Best	Others				
	S1	S3	S4	S5	S9
S1	(1,1,1)	(3/2,2,5/2)	(5/2,3,7/2)	(7/2,4,9/2)	(2/3,1,3/2)

Table 7
The others-to-worst vector for the economic, social, and circular
7a. Economic criteria
7b. Circular criteria
7c. Social criteria

Others	Best
	E6
E1	(3/2,2,5/2)
E2	(5/2,3,7/2)
E3	(2/3,1,3/2)
E5	(2/3,1,3/2)
E6	(1,1,1)
Others	Best
	C9
C2	(5/2,3,7/2)
C3	(7/2,4,9/2)
C6	(3/2,2,5/2)
C9	(1,1,1)
Others	Best
	S5
S1	(7/2,4,9/2)
S3	(3/2,2,5/2)
S4	(2/3,1,3/2)
S5	(1,1,1)
S9	(5/2,3,7/2)

Table 8
The optimal weights of criteria.

Criteria	Fuzzy weight	Defuzzified weight	γ^*		
	w_j^l	w_j^m	w_j^u	$\frac{w_j^l+4\times w_j^m+w_j^u}{6}$	
E1	0.217	0.273	0.281	0.265	0.289
E2	0.269	0.324	0.324	0.314	
E3	0.116	0.154	0.180	0.152	
E5	0.116	0.154	0.180	0.152	
E6	0.101	0.119	0.121	0.117	
C2	0.257	0.320	0.382	0.320	0.216
C3	0.338	0.389	0.440	0.389	
C6	0.162	0.183	0.235	0.188	
C9	0.103	0.103	0.103	0.103	
S1	0.289	0.331	0.331	0.324	0.299
S3	0.150	0.194	0.220	0.191	
S4	0.087	0.114	0.131	0.113	
S5	0.079	0.088	0.090	0.087	
S9	0.252	0.291	0.299	0.286	

Table 8 presents the optimal weights of criteria and the optimal value of γ^* calculated by implementing the proposed model in GAMS software and PATHNLP solver.

Step 5. In this step, Eq. (3) and Table 4 were used to calculate the consistency ratio ($CR = \frac{\gamma^*}{CI}$) of the pairwise comparisons as 0.043, 0.027, and 0.037 for the economic, circular, and social criteria, respectively. These near-zero ratios confirm the consistency of the pairwise comparisons.

Step 6. In this step, the historical polyethylene glycol supplier evaluation data for 159 sustainable suppliers on 14 evaluation criteria were retrieved. Table 9 presents the data for ten suppliers on 14 criteria for the sake of brevity.

Next, the system calculated the weighted sum of the criteria weights multiplied by the supplier scores to determine the suppliers' economic, circular, and social scores. The supplier sores presented in Table 10 were used as the FIS input variables.

Step 7. In this step, the membership functions for the input and output variables were formed in the MATLAB R2020a software using fuzzy inference system Editor GUI toolbox. The economic, social, and circular criteria were considered the input variables, and the suppliers' scores were considered the output variables. Fig. 4 presents the overall structure of the FIS for the supplier selection case study at Plasco, and Figs. 5a and 5b present the membership functions for the input and output variables.

Step 8. The fuzzy inference rules, determined by the experts, were used to link the input and output variables. The supplier selection FIS in this case study consisted of three input variables formed from five membership functions. This required obtaining 125 rules from expert knowledge in the FIS. Fig. 6 presents an overview of the rules defined in the MATLAB R2020a software using fuzzy inference system Editor GUI toolbox. Fig. 7 presents the rules resulting from the relationship between input and output variables depicted in three dimensions. Fig. 7a presents the fuzzy inference rules for the output variable and the economic and circular input variables. Fig. 7b presents the fuzzy inference rules for the output variable and the economic and social input variables. Finally, Fig. 7c presents the fuzzy inference rules for the output variable and the circular and social input variables.

Step 9. In this step, the input values obtained in Step 6 for each supplier were inserted in the rule reviewer box in the FIS to calculate, and the final score of the suppliers is calculated as the output. These operations for Supplier 1 are shown in Fig. 8. Similar operations are performed for the remaining nine suppliers. Table 11 presents the final score of the suppliers and their ranks.

Post-engagement step: As shown here, Supplier 5 was selected as the most suitable supplier of polyethylene glycol for Plasco. After working with Supplier 5, the user is expected to return to the system and evaluate the selected supplier according to 14 selection criteria in Step 2 in one month, three months, and six months. These supplier review data are stored in the system for future selection engagements.

Next, we constructed four sensitivity analysis scenarios to demonstrate the proposed method's applicability and robustness. Each scenario considers changing the class corresponding to the best criterion with the other criteria. As shown in Table 12, these changes are enforced in the economic, circular, and social dimensions simultaneously.

Using steps 3 to 6, suppliers' economic, circular, and social scores are calculated in each scenario and presented in Table 13.

Finally, the suppliers' final scores are calculated for each scenario using the proposed FIS (Steps 7 and 8). The supplier rankings are presented in Table 14.

Table 14 shows the revised supplier scores and rankings in response to the changes in the criteria weights. These changes indicate a reasonable level of sensitivity to the criteria weights as expected in any robust MCDM model.

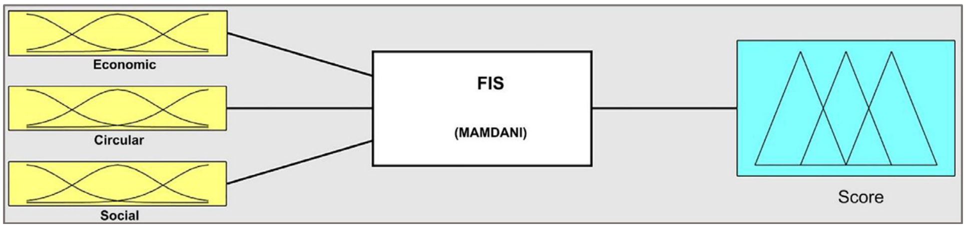
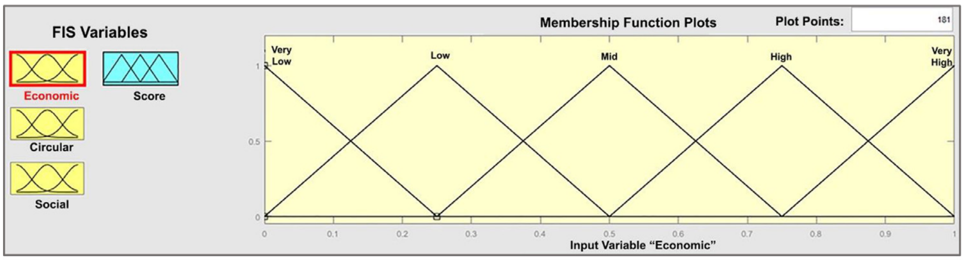
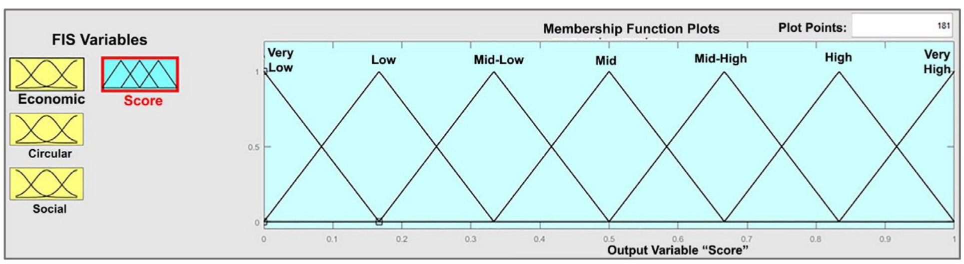


Fig. 4. The proposed fuzzy inference system.



a. Membership functions for the input variables



b. Membership functions for the output variables

Fig. 5. Fuzzy inference system Membership functions
5a. Membership functions for the input variables
5b. Membership functions for the output variables.

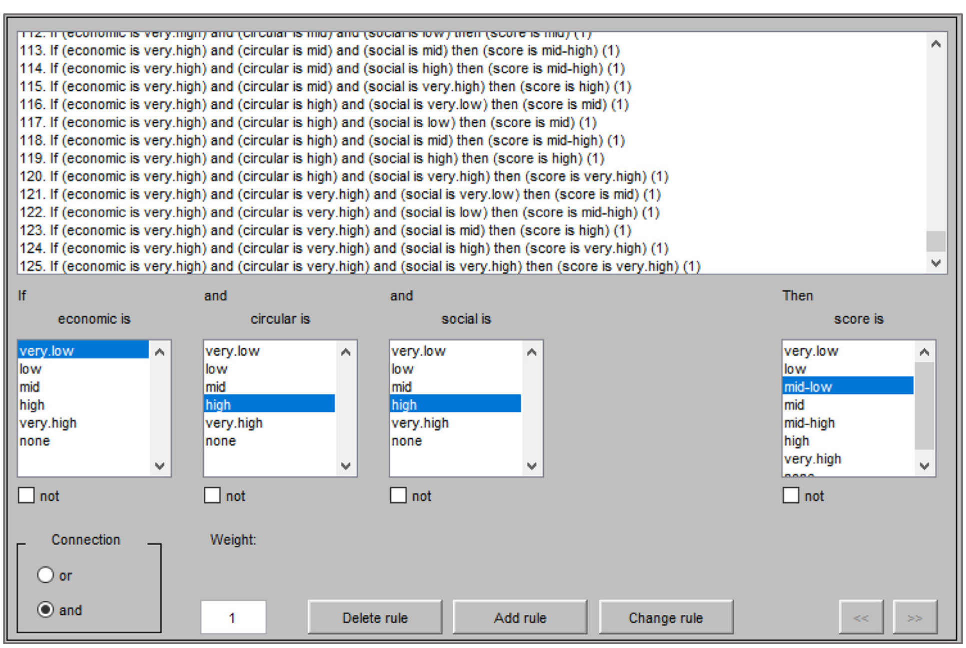
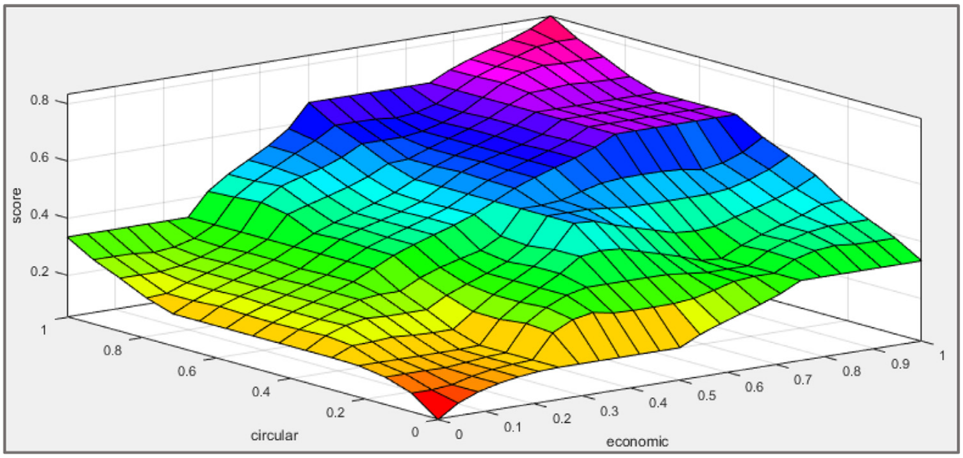
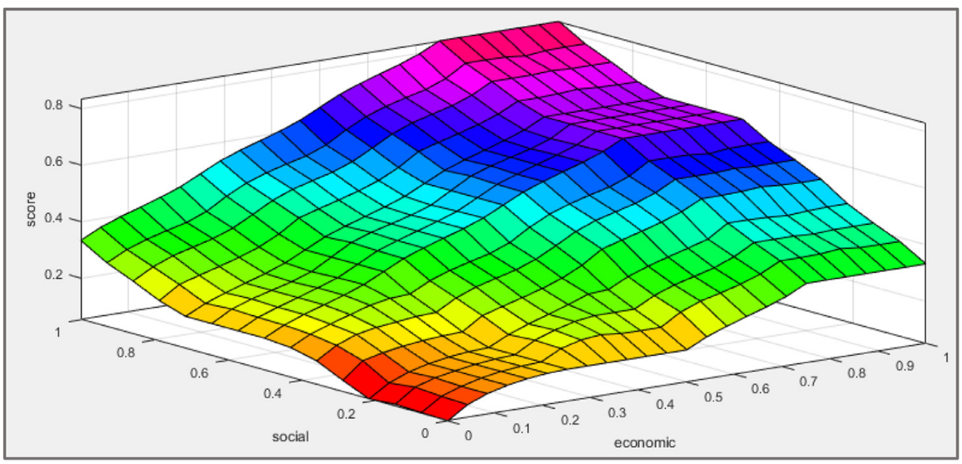


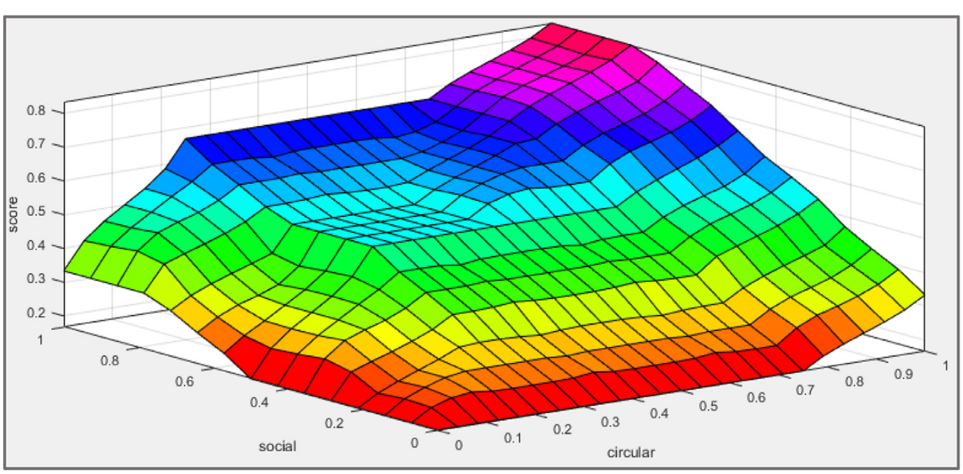
Fig. 6. Fuzzy inference system rules.



a. Relationship between the economic, circular, and final score of supplier



b. Relationship between the economic, social, and final score of supplier



c. Relationship between the circular, social, and final score of supplier

Fig. 7. Fuzzy inference rules. 7a. Relationship between the economic, circular, and final score of supplier 7b. Relationship between the economic, social, and final score of supplier. 7c. Relationship between the circular, social, and final score of supplier.

Table 9
Suppliers data extracted from the database.

Criteria	Supplier									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
E1	0.67	0.83	0.68	0.78	0.75	0.79	0.77	0.71	0.91	0.80
E2	0.95	0.71	0.89	0.79	0.91	0.84	0.75	0.93	0.68	0.72
E3	0.77	0.75	0.73	0.75	0.88	0.71	0.69	0.83	0.74	0.65
E5	0.73	0.68	0.79	0.71	0.78	0.75	0.64	0.80	0.72	0.78
E6	0.68	0.65	0.82	0.80	0.93	0.58	0.68	0.88	0.65	0.78
C2	0.54	0.61	0.48	0.56	0.67	0.62	0.48	0.75	0.55	0.55
C3	0.58	0.58	0.55	0.69	0.73	0.64	0.62	0.78	0.59	0.64
C6	0.65	0.72	0.68	0.72	0.84	0.74	0.75	0.82	0.48	0.60
C9	0.72	0.81	0.75	0.66	0.95	0.74	0.64	0.72	0.67	0.73
S1	0.83	0.72	0.64	0.73	0.81	0.66	0.71	0.84	0.53	0.77
S3	0.85	0.75	0.70	0.75	0.78	0.75	0.69	0.80	0.64	0.65
S4	0.62	0.72	0.62	0.65	0.69	0.63	0.73	0.77	0.68	0.74
S5	0.73	0.65	0.57	0.68	0.79	0.75	0.65	0.83	0.52	0.68
S9	0.78	0.60	0.72	0.46	0.97	0.52	0.72	0.92	0.55	0.70

Table 10
The suppliers' performance on each criterion.

Suppliers	Economic	Circular	Social
1	0.78341	0.59478	0.78792
2	0.7363	0.63961	0.68604
3	0.78664	0.57264	0.66663
4	0.77028	0.65095	0.64394
5	0.84562	0.75414	0.83554
6	0.76289	0.6627	0.64225
7	0.72127	0.6017	0.70679
8	0.83089	0.77174	0.8473
9	0.75264	0.56476	0.57334
10	0.7467	0.61295	0.71661

Table 11
Supplier scores.

Suppliers	Final score	Rank
1	0.736	7
2	0.744	5
3	0.722	8
4	0.760	3
5	0.845	1
6	0.759	4
7	0.711	10
8	0.844	2
9	0.717	9
10	0.740	6

Table 12
Scenarios for the sensitivity analysis process.

Scenario 1	Aspect	Class				
		1	2	3	4	5
	Economic	-	E2	E3, E5	E1	E6
	Circular	C3	-	C6	C2	C9
	Social	S1	S4	S3	S9	S5
Scenario 2	Economic	-	E6	E2, E5	E1	E3
	Circular	C9	-	C3	C2	C6
	Social	S5	S1	S3	S9	S4
Scenario 3	Economic	-	E6	E3, E2	E1	E5
	Circular	C9	-	C3	C2	C6
	Social	S5	S4	S1	S9	S3
Scenario 4	Economic	-	E6	E3, E5	E2	E1
	Circular	C9	-	C6	C3	C2
	Social	S5	S4	S3	S1	S9

5. Discussion

In this study, a practical and flexible DSS is developed for sustainable supplier evaluation in circular supply chains under uncertainty. The proposed approach is composed of MCDM, artificial intelligence, and machine learning. A case study in a large petrochemical company is presented to demonstrate the applicability and efficacy of the proposed approach. The synergy between the methods proposed in this integrated framework produces a robust and effective DSS applicable to a wide range of problems in the public and private sectors. Unlike the competing methods in the literature, users can customize their evaluation criteria and suggest their importance weights. An important and unique feature of the proposed DSS is that an intelligent model is used for conducting the necessary pairwise comparisons. Other unique features of this DSS are efficiency and user-friendliness. Machine learning is incorporated into the proposed DSS to allow for automated data update after the completion of the collaboration process with the suppliers. Another unique feature of the proposed DSS is its flexi-

Table 13
Suppliers' economic, circular, and social score in each scenario.

Scenario 1	Aspect	Supplier 1	2	3	4	5	6	7	8	9	10
	Economic	0.7302	0.7245	0.7729	0.7723	0.8496	0.7117	0.7075	0.8210	0.7467	0.7585
	Circular	0.6348	0.7054	0.6298	0.6424	0.8171	0.6913	0.6074	0.7546	0.5876	0.6387
	Social	0.7642	0.6695	0.6500	0.6321	0.8308	0.6636	0.6926	0.8449	0.5710	0.6953
Scenario 2	Economic	0.7543	0.7428	0.7607	0.7638	0.8408	0.7418	0.7116	0.8147	0.7624	0.7354
	Circular	0.6089	0.6678	0.5988	0.6570	0.7763	0.6828	0.6278	0.7798	0.5427	0.6049
	Social	0.7436	0.6860	0.6624	0.6271	0.8102	0.6359	0.7110	0.8325	0.6050	0.7103
Scenario 3	Economic	0.7478	0.7314	0.7704	0.7573	0.8246	0.7483	0.7035	0.8098	0.7591	0.7564
	Circular	0.6089	0.6678	0.5988	0.6570	0.7763	0.6828	0.6278	0.7798	0.5427	0.6049
	Social	0.7906	0.6900	0.6746	0.6466	0.8316	0.6542	0.7041	0.8420	0.5880	0.7007
Scenario 4	Economic	0.7697	0.7422	0.7764	0.7698	0.8378	0.7604	0.7223	0.8201	0.7639	0.7506
	Circular	0.5920	0.6417	0.5678	0.6420	0.7500	0.6613	0.5920	0.7697	0.5620	0.6067
	Social	0.7860	0.6815	0.6697	0.6337	0.8416	0.6369	0.7072	0.8503	0.5741	0.7140

Table 14
Suppliers' final scores and rankings in each scenario.

		Supplier 1	2	3	4	5	6	7	8	9	10
Main problem	Final score	0.736	0.744	0.722	0.76	0.845	0.759	0.711	0.844	0.717	0.74
	Rank	7	5	8	3	1	4	10	2	9	6
Scenario 1	Final score	0.735	0.746	0.753	0.754	0.844	0.733	0.703	0.842	0.719	0.757
	Rank	7	6	5	4	1	8	10	2	9	3
Scenario 2	Final score	0.741	0.765	0.736	0.751	0.84	0.747	0.716	0.84	0.707	0.725
	Rank	5	2	6	3	1	4	8	1	9	7
Scenario 3	Final score	0.739	0.753	0.736	0.762	0.842	0.763	0.71	0.84	0.705	0.739
	Rank	6	5	7	4	1	3	8	2	9	6
Scenario 4	Final score	0.733	0.751	0.72	0.755	0.845	0.756	0.707	0.842	0.716	0.74
	Rank	7	5	8	4	1	3	10	2	9	6

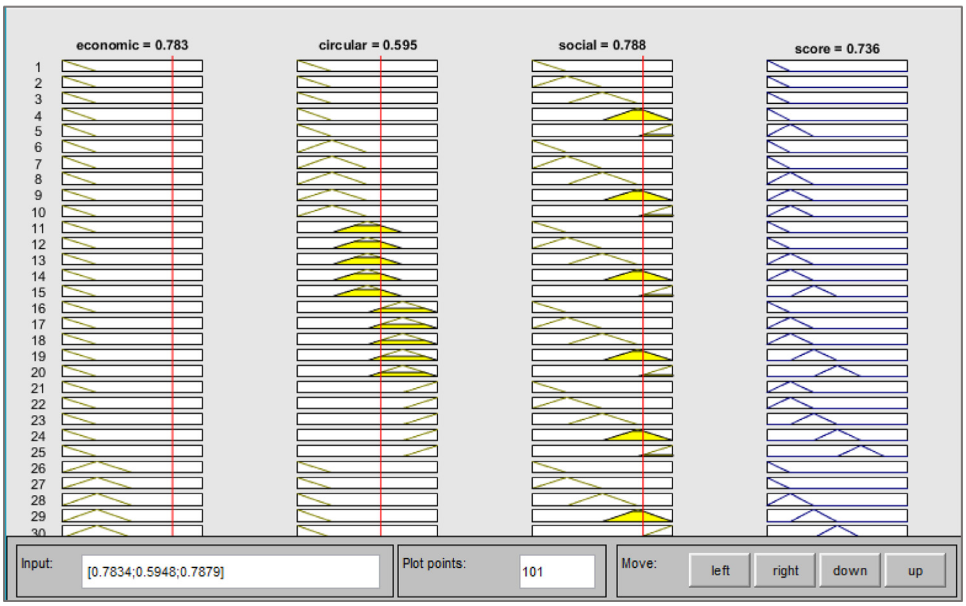


Fig. 8. Fuzzy inference system rule-viewer box.

bility. The proposed DSS can be used in various fields such as risk assessment, healthcare, and manufacturing systems, among others. The fuzzy rules are used in this DSS to manage uncertainties inherent in MCDM problems. The results of the DSS can help managers and decision-makers make informed decisions efficiently and effectively.

6. Conclusion

Suppliers have a significant impact on supply chain productivity and profitability. Sustainable and circular supply chains have been building up steam as customers have become more and more socially and environmentally conscious. Selecting the right supplier is a critical decision for sustainable supply chains. A large number of sustainable supplier selection criteria and methods have been proposed in the literature. This paper was an attempt to develop a novel DSS for a holding company by integrating the fuzzy BWM, FIS, and machine learning concepts into a comprehensive and structured framework for sustainable supplier evaluation and selection. The fuzzy BWM and FIS are used to weigh the criteria and calculate the final score of suppliers. The contributions of this study are fourfold. We (i) developed a practical and user-friendly DSS with customization capabilities for sustainable supplier selection in circular supply chains; (ii) used fuzzy BWM and FIS in a dynamic DSS to enhance efficiency and effectiveness in organizational decision-making; (iii) employed machine learning to maintain supplier information and synthesize historical data for scoring criteria; and (iv) presented a real-world case study to demonstrate the applicability of the proposed system at the largest petrochemical company operating in the Persian Gulf.

In this research, we assumed no interdependencies among the selection criteria. Further research could enhance the DSS proposed in this study by considering the causal relationships or dependencies among the selection criteria within an integrated framework with methods such as the weighted influence nonlinear gauge system (WINGS) or DEMATEL. A first step was made in this study to build a comprehensive and integrated DSS, aiding practicing managers in selecting the most suitable suppliers in circular supply chains. We consider sustainability as an integrated concept with economic, social, and circularity aspects. Further research is needed to explore whether sustainable supplier selection should consider circular (environmental) issues separately or integrated with the economic and social aspects.

Declaration of Competing Interest

None.

Acknowledgements

Dr. Madjid Tavana is grateful for the partial financial support he received from the Czech Science Foundation (GAČR 19-13946S).

Appendix

$$\begin{array}{ll}
Min\,\gamma^* & \text{(a)} \\
\text{s.t.} & \\
w^l_{E2} - \frac{2}{3} \times w^u_{E1} \leq \gamma^* \times w^u_{E1}; \quad w^l_{E2} - \frac{2}{3} \times w^u_{E1} \geq -\gamma^* \times w^u_{E1} & \text{(b)} \\
w^m_{E2} - w^m_{E1} \leq \gamma^* \times w^m_{E1}; \quad w^m_{E2} - w^m_{E1} \geq -\gamma^* \times w^m_{E1} & \text{(c)} \\
w^u_{E2} - \frac{3}{2} \times w^l_{E1} \leq \gamma^* \times w^l_{E1}; \quad w^u_{E2} - \frac{3}{2} \times w^l_{E1} \geq -\gamma^* \times w^l_{E1} & \text{(d)} \\
w^l_{E2} - \frac{3}{2} \times w^u_{E3} \leq \gamma^* \times w^u_{E3}; \quad w^l_{E2} - \frac{3}{2} \times w^u_{E3} \geq -\gamma^* \times w^u_{E3} & \text{(e)} \\
w^m_{E2} - 2 \times w^m_{E3} \leq \gamma^* \times w^m_{E3}; \quad w^m_{E2} - 2 \times w^m_{E3} \geq -\gamma^* \times w^m_{E3} & \text{(f)} \\
w^u_{E2} - \frac{5}{2} \times w^l_{E3} \leq \gamma^* \times w^l_{E3}; \quad w^u_{E2} - \frac{5}{2} \times w^l_{E3} \geq -\gamma^* \times w^l_{E3} & \text{(g)} \\
w^l_{E2} - \frac{3}{2} \times w^u_{E5} \leq \gamma^* \times w^u_{E5}; \quad w^l_{E2} - \frac{3}{2} \times w^u_{E5} \geq -\gamma^* \times w^u_{E5} & \text{(h)} \\
w^m_{E2} - 2 \times w^m_{E5} \leq \gamma^* \times w^m_{E5}; \quad w^m_{E2} - 2 \times w^m_{E5} \geq -\gamma^* \times w^m_{E5} & \text{(i)} \\
w^u_{E2} - \frac{5}{2} \times w^l_{E5} \leq \gamma^* \times w^l_{E5}; \quad w^u_{E2} - \frac{5}{2} \times w^l_{E5} \geq -\gamma^* \times w^l_{E5} & \text{(j)} \\
w^l_{E2} - \frac{5}{2} \times w^u_{E6} \leq \gamma^* \times w^u_{E6}; \quad w^l_{E2} - \frac{5}{2} \times w^u_{E6} \geq -\gamma^* \times w^u_{E6} & \text{(k)} \\
w^m_{E2} - 3 \times w^m_{E6} \leq \gamma^* \times w^m_{E6}; \quad w^m_{E2} - 3 \times w^m_{E6} \geq -\gamma^* \times w^m_{E6} & \text{(l)} \\
w^u_{E2} - \frac{7}{2} \times w^l_{E6} \leq \gamma^* \times w^l_{E6}; \quad w^u_{E2} - \frac{7}{2} \times w^l_{E6} \geq -\gamma^* \times w^l_{E6} & \text{(m)} \\
w^l_{E1} - \frac{3}{2} \times w^u_{E6} \leq \gamma^* \times w^u_{E6}; \quad w^l_{E1} - \frac{3}{2} \times w^u_{E6} \geq -\gamma^* \times w^u_{E6} & \text{(n)} \\
w^m_{E1} - 2 \times w^m_{E6} \leq \gamma^* \times w^m_{E6}; \quad w^m_{E1} - 2 \times w^m_{E6} \geq -\gamma^* \times w^m_{E6} & \text{(o)} \\
w^u_{E1} - \frac{5}{2} \times w^l_{E6} \leq \gamma^* \times w^l_{E6}; \quad w^u_{E1} - \frac{5}{2} \times w^l_{E6} \geq -\gamma^* \times w^l_{E6} & \text{(p)} \\
w^l_{E3} - \frac{2}{3} \times w^u_{E6} \leq \gamma^* \times w^u_{E6}; \quad w^l_{E3} - \frac{2}{3} \times w^u_{E6} \geq -\gamma^* \times w^u_{E6} & \text{(q)} \\
w^m_{E3} - w^m_{E6} \leq \gamma^* \times w^m_{E6}; \quad w^m_{E3} - w^m_{E6} \geq -\gamma^* \times w^m_{E6} & \text{(r)} \\
w^u_{E3} - \frac{3}{2} \times w^l_{E6} \leq \gamma^* \times w^l_{E6}; \quad w^u_{E3} - \frac{3}{2} \times w^l_{E6} \geq -\gamma^* \times w^l_{E6} & \text{(s)} \\
w^l_{E5} - \frac{2}{3} \times w^u_{E6} \leq \gamma^* \times w^u_{E6}; \quad w^l_{E5} - \frac{2}{3} \times w^u_{E6} \geq -\gamma^* \times w^u_{E6} & \text{(t)} \\
w^m_{E5} - w^m_{E6} \leq \gamma^* \times w^m_{E6}; \quad w^m_{E5} - w^m_{E6} \geq -\gamma^* \times w^m_{E6} & \text{(u)} \\
w^u_{E5} - \frac{3}{2} \times w^l_{E6} \leq \gamma^* \times w^l_{E6}; \quad w^u_{E5} - \frac{3}{2} \times w^l_{E6} \geq -\gamma^* \times w^l_{E6} & \text{(v)} \\
\left(\frac{w^l_{E1}+4\times w^m_{E1}+w^u_{E1}}{6}\right) + \left(\frac{w^l_{E2}+4\times w^m_{E2}+w^u_{E2}}{6}\right) + \left(\frac{w^l_{E3}+4\times w^m_{E3}+w^u_{E3}}{6}\right) + & \\
\left(\frac{w^l_{E5}+4\times w^m_{E5}+w^u_{E5}}{6}\right) + \left(\frac{w^l_{E6}+4\times w^m_{E6}+w^u_{E6}}{6}\right) = 1 & \text{(w)} \\
w^l_{E1} \leq w^m_{E1} \leq w^u_{E1}; \quad w^l_{E2} \leq w^m_{E2} \leq w^u_{E2}; \quad w^l_{E3} \leq w^m_{E3} \leq w^u_{E3} & \\
w^l_{E5} \leq w^m_{E5} \leq w^u_{E5}; \quad w^l_{E6} \leq w^m_{E6} \leq w^u_{E6} & \text{(x)} \\
w^l_{E1}, w^l_{E2}, w^l_{E3}, w^l_{E5}, w^l_{E6} > 0 & \text{(y)} \\
\gamma^* > 0 & \text{(z)}
\end{array}$$

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