Cleaner Logistics and Supply Chain 2 (2021) 100009

Contents lists available at ScienceDirect

Cleaner Logistics and Supply Chain

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

An integrated group fuzzy best-worst method and combined compromise solution with Bonferroni functions for supplier selection in reverse supply chains

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ARTICLE INFO

Keywords:
Supplier selection
Group best-worst method
Combined compromise solution
Bonferroni functions
Fuzzy sets
LARG strategy

ABSTRACT

Choosing the right supplier has a significant impact on the efficiency and productivity of a supply chain (SC). Different supplier selection models and approaches have been developed for reverse SCs. The lean, agile, resilient, and green (LARG) strategy is an innovative paradigm for supply chain competitiveness and sustainability. This study proposes a fuzzy-based methodology that integrates the fuzzy group best-worst method (FG-BWM) and the fuzzy combined compromise solution (FCoCoSo) method for supplier selection in reverse SCs within a LARG strategic paradigm. The FG-BWM is used to measure the importance weights of the supplier selection criteria. Subsequently, FCoCoSo is coupled with the normalized weighted geometric Bonferroni mean functions to select the most suitable supplier. The BWM is used for its simplicity and efficacy. The CoCoSo model is used for its unique ability to produce a compromise solution. The Bonferroni functions are used to capture the interrelationships among the decision attributes and eliminate the influence of extreme data. The main proposed framework aims at providing an easy-to-implement but reliable method to help manufacturers active in recycling and concerned with sustainability issues to rank and select suppliers. We present a real-world case study whose results demonstrate the applicability of the proposed integrated framework to supplier selection in reverse SCs, focusing in particular on the wood and paper industry.

1. Introduction

A comprehensive and practical evaluation and selection of suitable suppliers is essential to building a successful supply chain (SC) due to the increasing reliance on outsourcing multifaceted services and products (Lee et al., 2015). Outsourcing allows companies to cut down costs and improve their competitive edge by focusing on core competencies (Torabi et al., 2015). Suitable suppliers can provide quality raw materials consistently with little or no interruption (Alimardani et al., 2014). Suppliers have an essential role in increasing the chain's performance in many directions by eliminating waste, improving quality, and reducing lead time (Alimardani et al., 2013b). The relationship between the companies and their suppliers is the key to SC efficiency and effectiveness (Azadeh & Alem, 2010; Mina et al., 2021). The SC success depends heavily on selecting the most suitable suppliers (Matawale et al., 2016; Yücenur et al., 2011). While global sourcing has shown promising benefits to SC planning, it may also introduce unpredictable risks that may impact its effectiveness (Zimmer et al., 2017). Therefore, the supplier selection process can substantially impact outsourcing (Mohammady & Amid, 2011).

Supplier selection has become crucial in today's highly competitive and global environment, where it is becoming challenging to produce quality products successfully without suitable suppliers (Hasan et al., 2008). This study introduces a new and comprehensive lean, agile, resilient, and green (LARG) SC strategy for competitiveness and sustainability. The LARG method is considered (1) lean for developing a value stream that eliminates all wastes, including time wastes (Abdollahi et al., 2015), and leads to a reliable schedule for the consistent and speedy delivery of the products (Ogunbiyi & Goulding, 2013); (2) agile for thriving to succeed in a competitive and dynamic environ-

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https://doi.org/10.1016/j.clscn.2021.100009
Received 26 May 2021; Revised 25 July 2021; Accepted 23 September 2021

ment (Kahraman & Kaya, 2010), and respond quickly to changes in demand volume and variety (Cabral et al., 2012); (3) resilient for focusing on the SC ability to recover to the desired state after a disruption; and (4) green for reducing the environmental risks and negative impacts (Carvalho et al., 2014).

The main purpose and motivation of this research are to provide a novel and robust approach to evaluate and select the suppliers in reverse supply chains within a LARG strategic paradigm. The proposed framework aims in particular at helping manufacturers active in recycling and concerned with sustainability issues to rank and select the most suitable suppliers. We use a fuzzy group best-worst method (FG-BWM) to estimate the weights of the evaluation criteria and sub-criteria. Subsequently, the performance of the suppliers is evaluated based on a new approach that couples a fuzzy combined compromise solution (CoCoSo) method with the normalized weighted geometric Bonferroni mean functions. This new approach is denoted by FCoCoSo-B.

Overall, the main contributions of this research can be summarized as follows:

- It proposes LARG criteria for supplier selection in reverse SCs.
- It uses the FG-BWM to calculate the weights of criteria and sub-criteria.
- It couples FCoCoSo with the normalized weighted geometric Bonferroni mean functions to exploit both the ability of FCoCoSo to produce a compromise solution and the capacity of the Bonferroni functions to reflect the interrelationships between the decision attributes, removing the influence of extreme data.
- It combines FG-BWM and FCoCoSo-B, defining a reliable evaluation method for evaluating suppliers within a fuzzy environment.
- It includes a real-world case study whose results show the applicability of the integrated fuzzy-based methodology to supplier selection in reverse SCs, with a particular focus on the wood and paper industry.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature on supplier selection according to the LARG concept. We synthesize this literature and propose a novel and comprehensive supplier selection model in Section 3. Section 4 presents an application of the proposed model to the wood and paper industry. In this section, a comparison among the ranking results obtained by the proposed model and those provided by other MCDM methods is also discussed. The conclusions are presented in Section 5.

2. Literature review

This section presents a review of the related literature on reverse SC and supplier selection modeling within a LARG framework.

2.1. Reverse supply chains

Reverse SCs involve moving products from customers back to sellers or manufacturers (Kahhat & Navia, 2013) and disassembling them in an ecological way (Yılmaz et al., 2021). The reverse SC idea fully reflects the vision of environmental protection and the efficient use and reuse of resources (Domgala & Wolniak, 2013; Li et al., 2017; Özceylan & Paksoy, 2013). The advantage of reverse SCs is that by reusing, remanufacturing, and recycling used products and components, it is possible to reduce landfill waste drastically (Mahajan & Vakharia, 2016).

In particular, paper is a lush and natural forest product whose consumption is associated with a large share of waste from office centers, schools, and household activities. As a consequence, paper recycling processes, as well as all outsourcing activities related to them, are of key importance. With the growth of the population and the increase in the consumption of paper products, not recycling wasted paper can have destructive effects on the environment. Paper recycling can substantially reduce the environmental cost of converting plant fibers to paper products and reduce energy and water cost-effectively. This is the main reason why the real-life case study presented in this paper was conducted at a large wood and paper manufacturing company.

More in general, the results of the case study show that the proposed methodology can be implemented to support manufacturers active in the field of recycling to meet their supply needs. Given the increasing attention paid by consumers and governmental policies to the eco-friendly behavior of industries and companies, these results can also be considered as an important contribution of the paper.

2.2. Supplier selection

Suppliers are essential and vital components in SCs, delivering all the requirements for producing finished goods (Moslem Alimohammadlou & Bonyani, 2018; Hashemi et al., 2015; Tang & Yang, 2021; Tavana et al., 2021a; Yazdani et al., 2017). The selection of suitable suppliers plays an essential role in reducing production and material costs and sustainability in SC management (Mishra et al., 2013). Supplier selection has been recognized as a critical decision for organizations aiming to maintain a competitive position due to its direct impact on profitability (Banaeian et al., 2018; Songhori et al., 2011). For example, a proper combination of suppliers in a SC can significantly impact the SC productivity and sustainability. In that case, it has a significant impact on the quantity, price, quality, and timeliness of purchased goods and services (Wu & Barnes, 2009).

2.2.1. Lean supplier

The term lean is defined as a long-term growth philosophy for the customer, society, and economy (Lukic, 2012). Lean manufacturing leads to a value stream by eliminating waste (Cabral et al., 2011; Cabral et al., 2012), ensures a level schedule (Mason-Jones et al., 2000) by shortening the cycle times, and eliminates losses through quality enhancement and cost reduction (Vorkapić et al., 2017), and leads to continuous quality improvement (Ogunbiyi & Goulding, 2013). In addition, The concept of lean requires the successful integration of several philosophies into the business processes (Black, 2000). Many companies use lean principles to increase the efficiency of their SCs (Rezaei et al., 2020). Lean manufacturing can significantly improve the operational efficiency of companies by focusing on costs, quality, and delivery (Ulewicz & Kucęba, 2016). The successful implementation of the lean management philosophy depends heavily on the quality of the suppliers (Tsai, 2009; Guo and Xu, 2008). The key outcome of the lean SC strategy is low cost and high-quality products (Carvalho et al., 2011). Hence, the choice of indicators for lean suppliers is often focused on quality, cost, cycle time, and delivery (Guo and Xu, 2008). Some of the delivery criteria include the delivery date, delay, efficiency, and lead time and condition, among others (Hashemi et al., 2015). In the case study, we consider two criteria as suggested by Abdollahi et al. (2015), that is, lead time and safety and security. Quality is also a critical concern for most enterprises. The need for high-quality suppliers has always been an important concern. The factors to assess quality include quality systems, process quality, total quality management, and rate of certified product (Yang & Wu, 2007). In the case study, we consider two criteria: product durability and product performance (Abdollahi et al., 2015). Furthermore, we consider two widely-used criteria to improve the bottom-line and profitability in reverse SCs (Abdollahi et al., 2015; Hashemi et al., 2015), namely, product prices and logistics costs.

2.2.2. Agile supplier

The term agile manufacturing emphasizes the ability of manufacturing operations to respond effectively to unpredictable customer needs (El Mokadem, 2017). Agility can be defined as the ability to

respond to unexpected changes quickly and effectively (Dursun et al., 2016; Kahraman & Kaya, 2010) and implement the necessary arrangements to successfully modify the design, manufacture, marketing, and organization of the company (Dursun & Ogunclu, 2021; Li et al., 2020). Agility also means being able to react promptly to sudden and unforeseen changes in demand (Cabral et al., 2012; Tahriri & Taha, 2010). Agility in SC is defined as a swift and effective response to market and customer demand changes (Dotoli et al., 2015). In today's competitive business environment, to stabilize and improve their standing in the marketplace, organizations should be more agile and sensitive to changes in demand (Abdollahi et al., 2015). The agility strategy aims at creating the ability to respond quickly and effectively to unexpected market and environmental changes (Cabral et al., 2011). Suppliers play a crucial role in achieving agility in manufacturing. Hence, selecting the most suitable and agile suppliers is a vital component of efficient and productive manufacturing (Ghahremanloo & Tarokh, 2011). Generally, the key attributes of agile suppliers include speed, flexibility, and quality (Carvalho et al., 2011). One of the most critical dimensions of agility is time. In our case study, as suggested by Alimardani et al. (2013a,b), we consider two criteria, that is, delivery time and on-time response to customer requests. The ability to provide quality products and services according to customers' needs and demands plays a vital role in the agility and speed of growth and development. Regarding this aspect, we consider three criteria: consistent conformance to specifications, quality stability, and capabilities to provide quality product/service (Mishra et al., 2013).

2.2.3. Resilient supplier

Resiliency is a multidisciplinary concept and an exciting subject of scientific research in different disciplines such as psychology, ecology, economy, emergency management, sustainable development, and SC risk management (Torabi et al., 2015). Resiliency is the ability to bounce back from disruptive events or hardship (Sutcliffe & Vogus, 2003; Wildavsky, 1988) and return to the original situation after experiencing an anomaly or failure in the manufacturing system (Haldar et al., 2012). Referred to SCs, resiliency also indicates the capability of SCs to cope with uncertainty while maintaining operational continuity (Haldar et al., 2014). Evaluating and selecting suitable suppliers is the key to quality products and reasonable prices (Sen et al., 2016). Some resilient supplier attributes are flexibility in sourcing (Carvalho et al., 2011) and effective and efficient inventory management for the on-time product delivery (Sen et al., 2016). Companies using adaptive capability can effectively utilize knowledge to deliver products faster and cheaper than their competition (Pramanik et al., 2017). In addition, maintaining a surplus of raw material can avoid disaster during an SC disruption. While maintaining safety stock and additional inventory is expensive, it helps return operations to their normal state during a disaster (Hosseini and Khaled, 2019). Büyüközkan (2012) and Sahu et al. (2016) suggest that responsiveness and the ability to respond to customer demand effectively and efficiently must be considered in agile and resilient manufacturing strategies.

2.2.4. Green supplier

Green supplier evaluation and selection have become a widespread phenomenon in SC management (Büyüközkan & Ifi, 2012; Kannan et al., 2015; Banaeian et al., 2018) and has gained considerable interest with the recent increase of environmental awareness (Mabrouk, 2021). With the development of local regulations and policies designed to reduce pollution and improve environmental sustainability, green supplier management has become a critical factor in today's competitive marketplace (Lee et al., 2015; Lo et al., 2018). Traditionally, supplier selection and order allocation problems focus mainly on product cost, delivery time, and quality without considering environmental effects and issues (Hamdan & Cheaitou, 2015). Green suppliers reduce pollution and aim to minimize waste and ecological destruction (Handfield et al., 2002; Humphreys et al., 2006; Humphreys et al., 2003; Kannan et al., 2015), adding several new dimensions to supplier selection problems.

2.3. Applications of fuzzy sets to multi-criteria decision making

In general, supplier selection can be regarded as a multi-criteria decision-making (MCDM) process, which is a systematic methodology helping DMs to both weight multiple and often conflicting criteria and rank alternatives (Silva & Figueiredo, 2018; Mardani et al., 2017).

Numerous MCDM techniques have been used for supplier selection over the last two decades. A large part of these techniques was developed within a fuzzy setting.

For example, Verma et al. (2018) developed the partitioned Bonferroni mean under fuzzy assumptions defining a triangular fuzzy partitioned Bonferroni mean (TFPBM) for aggregating triangular fuzzy numbers (TFNs) and then the triangular fuzzy weighted partitioned Bonferroni mean (TFWPBM) to deal with multiple attribute decision-making problems within a TFN environment. Khalili Nasr et al. (2021) used the fuzzy BWM (FBWM) to select suppliers and a multi-objective mixed-integer linear programming model to design a multi-product, multi-period, CLSC network and provide inventory-location-routing, vehicle scheduling, and quantity discounts considerations. Verma & Sharma (2014) proposed a fuzzy generalized prioritized weighted average (FGPWA) framework to aggregate TFNs to deal with multiple attribute group decision-making problems. Hendiani et al. (2020) proposed an extension of BWM to trapezoidal fuzzy membership functions to select the most sustainable supplier. Rajkumar Verma (2011) defined a way of measuring the inaccuracy between two fuzzy sets. Tavana et al. (2020) proposed a new hierarchical fuzzy BWM and integrated it with fuzzy Complex Proportional ASsessment (FCOPRAS), fuzzy Multi-Objective Optimization on the basis of Ratio Analysis plus full multiplicative form (FMULTIMOORA) and fuzzy Technique for Order Preference by Similarity of an Ideal Solution (FTOPSIS) for performing sustainable supplier evaluation and selection. Hasheminezhad et al. (2021) integrated the FCOPRAS and fuzzy DEcision-MAking Trial and Evaluation Laboratory ((FDEMATEL) to evaluate risk factors in the collision of two passenger trains. Tavana et al. (2021a) used fuzzy AHP and FMULTIMOORA to evaluate the risk of supplier selection in the supply chain. Alimohammadlou and Khoshsepehr (2021) investigated the organization's sustainable development with interval-valued intuitionistic fuzzy AHP and Weighted Aggregated Sum Product Assessment (WASPAS). Tavana et al. (2021b) integrated Failure Modes and Effects Anal-

Table 1
Linguistic variables for criteria weights.

(a)

Linguistic variables	Triangular fuzzy number for FG-BWM
Equally Important (EI)	(1, 1, 1)
Weakly Important (WI)	(1, 2, 3)
Moderately Important (MI)	(2, 3, 4)
Moderately to Strongly Important (MP)	(3, 4, 5)
Strongly Important (SI)	(4, 5, 6)
Strongly to Very Strongly Important (SP)	(5, 6, 7)
Very Strongly Important (VS)	(6, 7, 8)
Extremely Important (EX)	(7, 8, 9)

(b)

Linguistic variables	Triangular fuzzy number for Fuzzy CoCoSo Bonferroni
Very low (VL)	(0.0, 0.1, 0.3)
Very Low to Moderate (L)	(0.1, 0.3, 0.5)
Moderate (M)	(0.3, 0.5 ,0.7)
Moderate to Very High (H)	(0.5, 0.7, 0.9)
Very High (VH)	(0.7, 0.9, 1.0)

ysis (FMEA) with fuzzy Shannon's entropy, FTOPSIS, FMOORA, and fuzzy Simple Additive Weighting (FSAW) for investigating the barriers to the implementation of continuous improvement in manufacturing.

3. The proposed LARG supplier selection approach

MCDM models are effective tools for selecting green and sustainable suppliers in SC management (Yazdani et al., 2016; Tsai, 2009). Decisions related to supplier selection are often influenced by economic globalization, economic and political uncertainty, and environmental performance. Deciding the most suitable suppliers is not always precise due to the uncertainty and vagueness of the information. Fuzzy set (FS) theory has been successfully used to address this problem (Boosothonsatit et al., 2012; Kumar et al., 2013; Zadeh, 1975; Zadeh, 1965). Tables 1(a) and (b) present the set of linguistic variables that we assume DMs and group supervisors to use for their evaluations, as well as their corresponding FS representation (Amiri, 2010; Amiri et al., 2020).

We propose an integrated fuzzy group BWM (FG-BWM) and fuzzy CoCoSo Bonferroni (FCoCoSo-B) approaches for supplier selection in reverse SCs. Amiri et al. (2020) developed an extension of fuzzy BWM to fuzzy group BWM for investigating the weights of criteria. Building on this extension, we develop an FG-BWM for exploring the weights of LARG criteria and sub-criteria. Passing to the supplier selection phase, the LARG sub-criteria become the evaluation criteria, and their weights are used in the proposed FCoCoSo-B model (see Fig. 1).

3.1. Supplier assessment with LARG

Step 1: Define the LARG paradigm and parameters.

Step 2: Assemble an expert team and interview them for the LARG paradigm and suppliers.

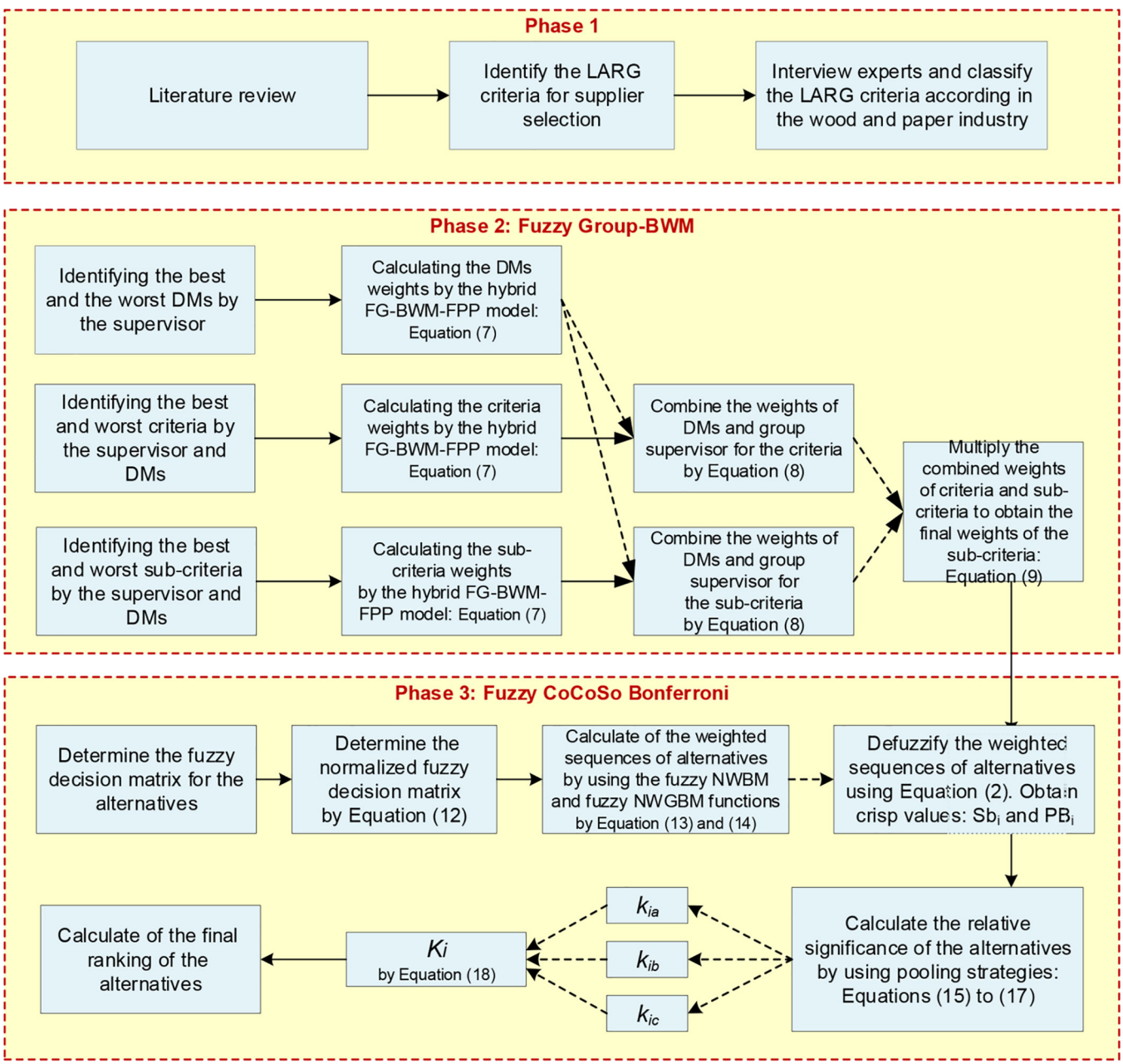

Fig. 1. The phases of the proposed integrated fuzzy approach.

Step 3: Obtain linguistic assessments for the LARG paradigm and suppliers.

The linguistic assessments are performed based on the linguist variables included in Tables 1(a) and (b). The linguistic variables are then translated into a numerical scale consisting of TFNs.

Definition 1. A fuzzy set (FS), A, in a universe X , is a set characterized by a membership function $\mu_A : X \to [0,1]$, that is, $\tilde{A} = \left\{ \left(x, \mu_{\tilde{A}}(x) \right) \mid x \in X \right\}$. For every $x \in X$, $0 \leqslant \mu_{\tilde{A}}(x) \leqslant 1$ represents the degree of membership of x to the set A.

Definition 2. A triangular fuzzy number (TFN), usually denoted by $\tilde{a} = (l, m, u)$, where $l, m, u \in$ R and $l \leqslant m \leqslant u$, is a FS in the set of real numbers R whose membership function is defined as follows:

$$\mu_{\tilde{a}}(x) = \begin{cases} 0, & \text{if } x < l \\ (x-l)/(m-l), & \text{if } l \leqslant x \leqslant m \\ (u-x)/(x-m), & \text{if } m \leqslant x \leqslant u \\ 0, & \text{if } x > u \end{cases} \tag{1}$$

Definition 3. Let $\tilde{a} = (l, m, u)$ be a TFN. The defuzzification rule that will be used to determine the crisp value associated with $\tilde{a}$ is as follows:

$$D_{\tilde{a}} = \frac{l + 4m + u}{6} \tag{2}$$

3.2. Fuzzy group best-worst method

The BWM is a robust and new approach introduced by Rezaei (2015) to diminish the incoherencies intrinsic to the extraction of criteria weights by lowering the number of pairwise comparisons usually necessary in AHP and ANP approaches. BWM includes solving a linear model to estimate the weights from the comparisons (Hashemkhani Zolfani et al., 2019).

The BWM is used in many studies, including sustainable supplier selection (Amiri et al., 2020), supplier selection in closed-loop SCs (Khalili Nasr et al., 2021), evaluation of wind plants (Ecer, 2021), sustainable-resilient supplier selection (Fallahpour et al., 2021), airline service quality (Gupta, 2018), supplier development (Aboutorab et al., 2018), R&D performance management (Salimi & Rezaei, 2018), green supplier selection (Tian et al., 2018), and medical tourism strategy assessment (Abouhashem Abadi et al., 2018).

The fuzzy BWM method was proposed by Guo and Zhao (2017) to account for the ambiguity and uncertainty intrinsic to human judgments. Indeed, fuzzy BWM enables DMs to incorporate linguistic judgments into decision-making (Hafezalkotob & Hafezalkotob, 2017).

Amiri et al. (2020) proposed a fuzzy group BWM (FG-BWM) method. They combined FG-BWM with fuzzy preference programming (FG-BWM-FPP) for group decision-making (Amiri et al., 2020):

Step 1: Determining the decision criteria as $\{C_1, C_2, \ldots, C_n\}$.

Step 2: Determining the best and the worst DMs by the supervisor using fuzzy numbers scale presented in Table 1(a). Assuming that there are d DMs, $\{DM_1, DM_2, \ldots, DM_d\}$, the supervisor obtains the Best-to-Others and Others-to-Worst vectors for the DMs in terms of TFNs as follows:

$$\begin{aligned} &\left(\tilde{a}^g_{B1} = (l^g_{B1}, m^g_{B1}, u^g_{B1}),\ \ldots,\ \tilde{a}^g_{Bi} = (l^g_{Bi}, m^g_{Bi}, u^g_{Bi}), \ldots,\ \tilde{a}^g_{Bd} = (l^g_{Bd}, m^g_{Bd}, u^g_{Bd}) \right) \\ &\left(\tilde{a}^g_{1W} = (l^g_{1W}, m^g_{1W}, u^g_{1W}),\ \ldots,\ \tilde{a}^g_{iW} = (l^g_{iW}, m^g_{iW}, u^g_{iW}), \ldots,\ \tilde{a}^g_{dW} = (l^g_{dW}, m^g_{dW}, u^g_{dW}) \right) \end{aligned} \tag{3}$$

where $\tilde{a}^g_{BB} = 1$ and $\tilde{a}^g_{WW} = 1$.

Step 3: Determining the best and worst criteria and determining the priorities of the best and worst criteria by the supervisor using fuzzy numbers scale presented in Table 1(a). The supervisor obtains the Best-to-Others and Others-to-Worst vectors for the criteria in terms of TFNs as follows:

$$\begin{aligned} &\left(\tilde{a}_{B1} = (l_{B1}, m_{B1}, u_{B1}),\ \ldots,\ \tilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj}), \ldots,\ \tilde{a}_{Bn} = (l_{Bn}, m_{Bn}, u_{Bn}) \right) \\ &\left(\tilde{a}_{1W} = (l_{1W}, m_{1W}, u_{1W}),\ \ldots,\ \tilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW}), \ldots,\ \tilde{a}_{nW} = (l_{nW}, m_{nW}, u_{nW}) \right) \end{aligned} \tag{4}$$

where $\tilde{a}_{BB} = 1$and $\tilde{a}_{WW} = 1$.

Step 4: Determining the best and worst criteria and their priorities by each DM using fuzzy numbers scale presented in Table 1(a). For every $i = 1, \ldots, d$,DM_i obtains the Best-to-Others and Others-to-Worst vectors for the criteria in terms of TFNs as follows:

$$\begin{aligned} &\left(\tilde{a}^i_{B1} = (l^i_{B1}, m^i_{B1}, u^i_{B1}),\ \ldots,\ \tilde{a}^i_{Bj} = \left(l^i_{Bj}, m^i_{Bj}, u^i_{Bj}\right), \ldots,\ \tilde{a}^i_{Bn} = (l^i_{Bn}, m^i_{Bn}, u^i_{Bn}) \right) \\ &\left(\tilde{a}^i_{1W} = (l^i_{1W}, m^i_{1W}, u^i_{1W}),\ \ldots,\ \tilde{a}^i_{iW} = \left(l^i_{jW}, m^i_{jW}, u^i_{jW}\right), \ldots,\ \tilde{a}^i_{nW} = (l^i_{nW}, m^i_{nW}, u^i_{nW}) \right) \end{aligned} \tag{5}$$

where $\tilde{a}^i_{BB} = 1$and $\tilde{a}^i_{WW} = 1$.

Step 5: The DMs' weights $\left(\lambda^*_1, \lambda^*_2, \ldots, \lambda^*_d\right)$ and the criteria weights obtained by the managers $\left(w^*_1, w^*_2, \ldots, w^*_n\right)$, along with the criteria weights obtained by the DMs, $\left(w^{i*}_1, w^{i*}_2, \ldots, w^{i*}_n\right)$, where $i = 1, \ldots, d$, are evaluated with the FG-BWM-FPP procedure shown in Model (6) below.

The consistency conditions relative to the solutions to Model (6) are listed below:

1. $\xi \geqslant 0$, the managers' comparisons are consistent; $\xi = 1$, if the managers' comparisons are completely consistent; otherwise, there are inconsistencies in the judgments.
2. $\xi_i \geqslant 0$, the ith DM' comparisons are consistent; $\xi_i = 1$, if the ith DM' comparisons are completely consistent; otherwise, there are inconsistencies in the judgments.

$$\max \xi + \xi' + \sum_i \xi_i$$

$$s.t. \begin{cases} \frac{(\lambda_B/\lambda_i) - l_{Bi}}{m_{Bi} - l_{Bi}} \geqslant \xi; \quad \frac{u_{Bi}(\lambda_B/\lambda_i)}{u_{Bi} - m_{Bi}} \geqslant \xi; \quad \forall i = 1, \ldots, d \\ \frac{(\lambda_i/\lambda_W) - l_{iW}}{m_{iW} - l_{iW}} \geqslant \xi; \quad \frac{u_{iW}(\lambda_i/\lambda_W)}{u_{iW} - m_{iW}} \geqslant \xi; \quad \forall i = 1, \ldots, d \\ \frac{(w_B/w_j) - l_{Bi}}{m_{Bi} - l_{Bj}} \geqslant \xi'; \quad \frac{u_{Bj}(w_B/w_j)}{u_{Bj} - m_{Bj}} \geqslant \xi'; \quad \forall j = 1, \ldots, n \\ \frac{(w_j/w_W) - l_{jW}}{m_{jW} - l_{jW}} \geqslant \xi'; \quad \frac{u_{jW}(w_j/w_W)}{u_{jW} - m_{jW}} \geqslant \xi'; \quad \forall j = 1, \ldots, n \\ \frac{\left(w^i_B/w^i_j\right) - l^i_{Bj}}{m^i_{Bj} - l^i_{Bj}} \geqslant \xi'; \quad \frac{u^i_{Bj}\left(w^i_B/w^i_j\right)}{u^i_{Bj} - m^i_{Bj}} \geqslant \xi_i; \quad \forall i = 1, \ldots, d, \forall j = 1, \ldots, n \\ \frac{\left(w^i_j/w^i_W\right) - l^i_{jW}}{m^i_{jW} - l^i_{jW}} \geqslant \xi'; \quad \frac{u^i_{jW}\left(w^i_j/w^i_W\right)}{u^i_{jW} - m^i_{jW}} \geqslant \xi_i; \quad \forall i = 1, \ldots, d, \forall j = 1, \ldots, n \\ \sum_i \lambda_i = 1 \\ \sum_j w_j = 1 \\ \sum_j w^i_j = 1 \\ \lambda_i \geqslant 0,\ w_j \geqslant 0,\ w^i_j \geqslant 0 \\ \xi, \xi', \xi_i \text{ free variables} \end{cases} \tag{6}$$

To accommodate group decision problems, Model (6) is transformed in the following nonlinear model, Model (7). The optimal weights to assign to the LARG criteria and sub-criteria are obtained by solving Model (7).

$$\max \xi + \xi' + \sum_i \xi_i$$

$$s.t. \begin{cases} -\lambda_B + l_{Bi}\lambda_i + \xi(m_{Bi} - l_{Bi})\lambda_i \leqslant 0, \forall i = 1, ..., d \\ \lambda_B - u_{Bi}\lambda_i + \xi(u_{Bi} - m_{Bi})\lambda_i \leqslant 0, \forall i = 1, ..., d \\ -\lambda_i + l_{iW}\lambda_W + \xi(m_{iW} - l_{iW})\lambda_W \leqslant 0, \forall i = 1, ..., d \\ \lambda_i - u_{iw}\lambda_W + \xi(u_{iW} - m_{iW})\lambda_W \leqslant 0, \forall i = 1, ..., d \\ -w_B + l_{Bj}w_j + \xi'(m_{Bj} - l_{Bi})w_j \leqslant 0, \forall j = 1, ..., n \\ w_B - l_{Bj}w_j + \xi'(u_{Bj} - m_{Bj})w_j \leqslant 0, \forall j = 1, ..., n \\ -w_j + l_{jW}w_W + \xi'(m_{jW} - l_{jW})w_W \leqslant 0, \forall j = 1, ..., n \\ w_j - u_{jW}w_W + \xi'(u_{jW} - m_{jW})w_W \leqslant 0, \forall j = 1, ..., n \\ -w_B^i + l_{Bj}^i w_j^i + \xi_i\left(w_{Bj}^i - l_{Bj}^i\right)w_j^i \leqslant 0, \forall i = 1, ..., d, \forall j = 1, ..., n \\ w_B^i - u_{Bj}^i w_j^i + \xi_i\left(u_{Bj}^i - m_{Bj}^i\right)w_j^i \leqslant 0, \forall i = 1, ..., d, \forall j = 1, ..., n \\ -w_j^i + l_{jW}^i w_W^i + \xi_i\left(m_{jW}^i - l_{jW}^i\right)w_W^i \leqslant 0, \forall i = 1, ..., d, \forall j = 1, ..., n \\ -w_j^i + u_{jW}^i w_W^i + \xi_i\left(u_{jW}^i - m_{jW}^i\right)w_W^i \leqslant 0, \forall i = 1, ..., d, \forall j = 1, ..., n \\ \sum_i \lambda_i = 1 \\ \sum_j w_j = 1 \\ \sum_j w_j^i = 1 \\ \lambda_i \geqslant 0,\ w_j \geqslant 0,\ w_j^i \geqslant 0 \\ \xi, \xi', \xi_i \text{ free variables} \end{cases} \tag{7}$$

Note that, unlike what happens in BWM, where the consistency rate value is required to assess the consistency of the comparisons performed by the single experts, in the proposed model, there is no need to compute a final consistency rate. The values ξ, ξ', ξ_i that are obtained as part of the solution to Model (7) can be interpreted as consistency rate components. To guarantee the consistency of the comparisons, it suffices to show that $\xi, \xi', \xi_i \geqslant 0$.

Step 6: Determining the value α ranging from 0 to 1 for the combined weights of the criteria. The value α represents the importance of the DMs' judgments. The combined weight of criterion C_j based on those assigned by both the group supervisor and DMs is determined by Eq. (8) below:

$$\mu_{C_j} = \alpha w_j + (1 - \alpha) \sum_i w_j^i \lambda_i \tag{8}$$

Step 7: If there are criteria and sub-criteria, we need to compute the final weights of the sub-criteria. The sub-criteria are the criteria used in the supplier selection phase. The final weights are obtained as follows:

$$W_{SC} = \mu_C \times \mu_{SC} \tag{9}$$

where SC and C stand for a sub-criterion and the corresponding main criterion, respectively.

3.3. Fuzzy combined compromise solution

The CoCoSo method is a new MCDM method introduced by Yazdani et al. (2019). The CoCoSo method integrates two MCDM methods, the exponentially weighted product and simple additive weighting (Hashemkhani Zolfani et al., 2019; Peng & Huang, 2020; Ulutaş et al., 2020), combining them with the construction of a comparability sequence (Karaşan & Bolturk, 2019). The first method operates by the usual multiplication rule. The second method is based on the weighted power of the distances from the comparability sequence. Finally, three aggregation strategies are used to determine the ranking index of the alternatives (Karaşan & Bolturk, 2019).

Ecer & Pamucar (2020) propose the following steps to solve the fuzzy CoCoSo Bonferroni model:

Step 1: Determine the decision matrix (X). In this step, m alternatives, $S = \{S_1, S_2, \ldots, S_m\}$, are assessed with respect to n criteria,$C = \{C_1, C_2, \ldots, C_n\}$ $\frac{n!}{r!(n-r)!}$, creating the matrix X.

$$X = \left[\tilde{\kappa}_{ij}\right] \tag{10}$$

$$\tilde{\kappa}_{ij} = \left(\kappa_{ij}^{(l)}, \kappa_{ij}^{(m)}, \kappa_{ij}^{(u)}\right)$$

Step 2: Create the normalized decision matrix in Eq. (11).

$$N = \left[\tilde{Y}_{ij}\right] \tag{11}$$

The elements $\tilde{Y}_{ij} = (Y_{ij}^{(l)}, Y_{ij}^{(m)}, Y_{ij}^{(u)})$ of the normalized matrix (N) are calculated as follows:

$$\tilde{Y}_{ij} = (Y_{ij}^{(l)}, Y_{ij}^{(m)}, Y_{ij}^{(u)}) = \begin{cases} \gamma\gamma_{ij}^{(l)} = \frac{\kappa_{ij}^{(l)}}{\gamma\gamma_j^+};\ \gamma\gamma_{ij}^{(m)} = \frac{\kappa_{ij}^{(m)}}{\gamma\gamma_j^+};\ \gamma\gamma_{ij}^{(u)} = \frac{\kappa_{ij}^{(u)}}{\gamma\gamma_j^+} & \text{if } j \text{ stands for a beneficial criterion} \\ \gamma\gamma_{ij}^{(l)} = \frac{\gamma\gamma_j^-}{\kappa_{ij}^{(u)}};\ \gamma\gamma_{ij}^{(m)} = \frac{\gamma\gamma_j^-}{\kappa_{ij}^{(m)}};\ \gamma\gamma_{ij}^{(u)} = \frac{\gamma\gamma_j^-}{\kappa_{ij}^{(l)}} & \text{if } j \text{ stands for a non - beneficial criterion} \end{cases} \tag{12}$$

where $\gamma\gamma_j^+ = \max_i \left(\kappa_{ij}^{(u)}\right)$ and $\gamma\gamma_j^- = \min_i \left(\kappa_{ij}^{(l)}\right)$ are used to compute the normalized components of the decision matrix.

Step 3: Determine the weighted sequences of alternatives. These weights are determined using the fuzzy normalized weighted Bonferroni mean (NWBM) function and the fuzzy normalized weighted geometric Bonferroni mean (NWGBM) function. They are denoted by SB_i and $PB_i (i = 1, ..., m)$, respectively:

$$SB_i^{p,q} = \left(\sum_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} \gamma\gamma_{ij_1}^{p} \gamma\gamma_{ij_2}^{q}\right)^{\frac{1}{p+q}} = \begin{pmatrix} \left(\sum_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} \gamma\gamma_{ij_1}^{(l)p} \gamma\gamma_{ij_2}^{(l)q}\right)^{\frac{1}{p+q}}, \\ \left(\sum_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} \gamma\gamma_{ij_1}^{(m)p} \gamma\gamma_{ij_2}^{(m)q}\right)^{\frac{1}{p+q}}, \\ \left(\sum_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} \gamma\gamma_{ij_1}^{(u)p} \gamma\gamma_{ij_2}^{(u)q}\right)^{\frac{1}{p+q}} \end{pmatrix} \tag{13}$$

and

$$PB_i = \frac{1}{p+q} \prod_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \left(p\gamma\gamma_{ij_1} + q\gamma\gamma_{ij_2}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}} = \begin{pmatrix} \frac{1}{p+q} \prod_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \left(p\gamma\gamma_{ij_1}^{(l)} + q\gamma\gamma_{ij_2}^{(l)}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}}, \\ \frac{1}{p+q} \prod_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \left(p\gamma\gamma_{ij_1}^{(m)} + q\gamma\gamma_{ij_2}^{(m)}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}}, \\ \frac{1}{p+q} \prod_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{n} \left(p\gamma\gamma_{ij_1}^{(u)} + q\gamma\gamma_{ij_2}^{(u)}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}} \end{pmatrix} \tag{14}$$

where $p, q \geqslant 0$, w_j $(j = 1, 2, ..., n)$shows the criteria weights, $w_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$. p and q are the stabilization parameters. Changes in the stabilization parameters may affect the final results. Ecer & Pamucar (2020) suggest using $p = q = 1$.

Step 4: Defuzzify the weighted sequences of alternatives. Using Eq. (2), SB_i and $PB_i (i = 1, ..., m)$ are transformed into crisp values. In the following equations, these crisp values are still denoted by SB_i and PB_i.

Step 5: Determine the relative importance of the alternatives using three pooling strategies defined as follows.

$$k_{ia} = \frac{PB_i + SB_i}{\sum_{i=1}^{m} (PB_i + SB_i)} \tag{15}$$

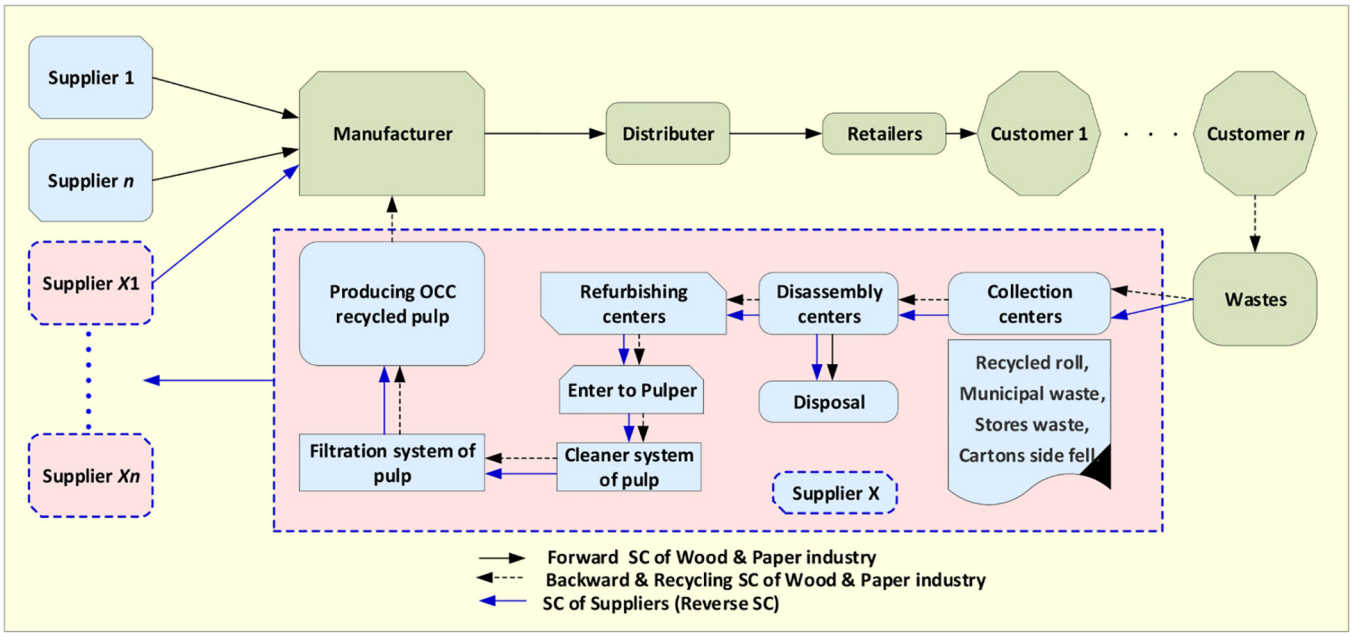

Fig. 2. Reverse supply chain management at Peyman wood and paper company.

$$k_{ib} = \frac{SB_i}{\min\limits_i(SB_i)} + \frac{PB_i}{\min\limits_i(PB_i)} \tag{16}$$

$$k_{ic} = \frac{\lambda SB_i + (1-\lambda)PB_i}{\lambda \max\limits_i(SB_i) + (1-\lambda)\max\limits_i(PB_i)}; \quad 0 \leqslant \lambda \leqslant 1 \tag{17}$$

Eq. (15) calculates the additive normalized importance and Eq. (16) calculates the relative importance of the fuzzy NWBM and fuzzy NWGBM functions. The trade-off importance of the alternatives is calculated by Eq. (17). The coefficient λ in Eq. (17) indicates the flexibility and stability of the FCoCoSo-B model and is chosen by the DMs.

Step 6: Determine the final ranking for the alternatives according to the k_i values. The best alternative is the one associated with the highest k_i value.

$$k_i = (k_{ia} \times k_{ib} \times k_{ic})^{1/3} + (k_{ia} + k_{ib} + k_{ic})/3 \tag{18}$$

4. Case study

The proposed LARG supplier selection model has been implemented at Peyman Group[1], a wood and paper manufacturing company in Iran. Peyman is one of the largest manufacturers of paper in Iran. Due to the increasing decline of forest resources in Iran, wasted paper recycling has been considered a viable and necessary option for supplying cellulosic materials for the paper industry. Developing countries are now required to implement sustainable strategies for various reasons, including cellulosic cellular restrictions, increasing consumption of paper products, environmental problems caused by harvesting forests, and the high cost of paper and paperboard production from cellulosic raw material. Peyman uses recycled paper collected from suppliers to produce old corrugated container (OCC) pulp. The OCC pulp re-enters the production cycle as raw material and builds cardboard, cardboard for packaging, and other used items. With consumers becoming increasingly eco-conscious, Peyman is going to great lengths to select environmentally friendly suppliers, as depicted in Fig. 2.

Note that in the following, the notations used for criteria, DMs and suppliers have been slightly simplified to make the text and the tables reporting the results of the case study easier to follow.

[1] The name of the company is changed to protect its anonymity.

4.1. Proposed model

The criteria used in the case study are the 20 criteria identified through the literature review and described in Table 2. These criteria, C1, C2, C3, …, C20, are grouped according to the four main criteria of the LARG strategy, that is, lean, agile, resilient, and green. The suppliers to evaluate were 12, denoted as S1, S2, S3, …, and S12. Finally, a

Table 2
The criteria of LARG supplier selection.

Criteria	Sub-criteria	Sub-criteria	References
Lean	C1	Lead Time	(Abdollahi et al., 2015)
	C2	Safety & Security	
	C3	Product Durability	
	C4	Product Performance	
	C5	Products Prices	
	C6	Logistics Cost	
Agile	C7	Delivery time	(Alimardani et al., 2013a; Mishra et al., 2013)
	C8	On-time response to a request	
	C9	Consistent conformance to specifications	
	C10	Quality stability	
	C11	Capabilities to provide quality product/service	
Resilient	C12	Safety stock capacity	(Sahu et al., 2016; Sen et al., 2016; Pramanik et al., 2017; Hosseini and Khaled, 2019; Sen et al., 2016; Büyüközkan, 2012)
	C13	Adaptive capability	
	C14	Buffer capacity	
	C15	Surplus inventory	
	C16	Responsiveness	
Green	C17	Pollution control Initiatives	(Kannan et al., 2015; Humphreys et al., 2006; Humphreys et al., 2003)
	C18	Pollution reduction capability	
	C19	Pollution prevention capability	
	C20	Environmental protection plans	

team of DMs including a group supervisor and three experts, DM1, DM2, and DM3, was chosen.

4.2. Criteria and sub-criteria weights

In this phase, we followed the steps of the proposed extension of FG-BWM (Amiri et al., 2020) to and obtained the weights of criteria and sub-criteria using the linguistic variables presented in Table 1 (a). Table 3 shows the best, worst, and fuzzy pairwise comparison matrices of the criteria and sub-criteria for the supervisor and the DMs. Table 4 shows the fuzzy preferences of the supervisor for the DMs.

Model (7) was solved to obtain the weights of criteria and sub-criteria. We used LINGO 17.0 software to run Model (7). Table 5 presents all the optimal weights determined for criteria and sub-criteria based on the fuzzy preferences of Tables 3. Table 6 shows the optimal weights assigned to the DMs by the supervisor according to the evaluations of Table 4.

By solving Model (7), we also obtained the following values for the consistency rate components of the model, that is: $\xi = 0.645$, $\xi' = 0$, $\xi_1 = 0.5311$, $\xi_2 = 0.7286$, and $\xi_3 = 0.4201$. It follows that the comparisons used within Model (7) and the solution to it were consistent.

Next, we used Eq. (8) and the results from Tables 5 and 6 to determine the combined weights of the LARG main criteria considering the opinions of the group supervisor and DMs. As required by Step 6 in

Table 3
The best and worst criteria and fuzzy pairwise comparisons.

	Decision-makers	Best criterion	Worst criterion	Criteria and Sub-criteria					
				L	A	R	G		
LARG	Group Supervisor	A	–	(1,2,3)	(1,1,1)	(2,3,4)	(4,5,6)		
		–	G	(3,4,5)	(4,5,6)	(2,3,4)	(1,1,1)		
	DM1	L	–	(1,1,1)	(1,2,3)	(2,3,4)	(4,5,6)		
		–	G	(4,5,6)	(2,3,4)	(1,2,3)	(1,1,1)		
	DM2	A	–	(2,3,4)	(1,1,1)	(3,4,5)	(5,6,7)		
		–	G	(4,5,6)	(5,6,7)	(3,4,5)	(1,1,1)		
	DM3	R	–	(2,3,4)	(1,2,3)	(1,1,1)	(3,4,5)		
		–	G	(1,2,3)	(2,3,4)	(3,4,5)	(1,1,1)		
Lean				**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
	Group supervisor	C4	–	(2,3,4)	(7,8,9)	(1,2,3)	(1,1,1)	(3,4,5)	(4,5,6)
		–	C2	(4,5,6)	(1,1,1)	(5,6,7)	(7,8,9)	(3,4,5)	(2,3,4)
	DM1	C3	–	(1,2,3)	(7,8,9)	(1,1,1)	(1,2,3)	(2,3,4)	(3,4,5)
		–	C2	(5,6,7)	(1,1,1)	(7,8,9)	(5,6,7)	(4,5,6)	(3,4,5)
	DM2	C4	–	(2,3,4)	(4,5,6)	(1,2,3)	(1,1,1)	(3,4,5)	(7,8,9)
		–	C6	(4,5,6)	(2,3,4)	(5,6,7)	(7,8,9)	(3,4,5)	(1,1,1)
	DM3	C1	–	(1,1,1)	(2,3,4)	(1,2,3)	(1,2,3)	(7,8,9)	(1,2,3)
		–	C5	(7,8,9)	(4,5,6)	(5,6,7)	(5,6,7)	(1,1,1)	(5,6,7)
Agile				**C7**	**C8**	**C9**	**C10**	**C11**	
	Group Supervisor	C10	–	(7,8,9)	(1,2,3)	(2,3,4)	(1,1,1)	(1,2,3)	
		–	C7	(1,1,1)	(5,6,7)	(4,5,6)	(7,8,9)	(5,6,7)	
	DM1	C8	–	(7,8,9)	(1,1,1)	(1,2,3)	(1,2,3)	(1,2,3)	
		–	C7	(1,1,1)	(7,8,9)	(5,6,7)	(5,6,7)	(5,6,7)	
	DM2	C10	–	(3,4,5)	(1,2,3)	(7,8,9)	(1,1,1)	(1,2,3)	
		–	C9	(3,4,5)	(5,6,7)	(1,1,1)	(7,8,9)	(5,6,7)	
	DM3	C11	–	(2,3,4)	(1,2,3)	(7,8,9)	(1,2,3)	(1,1,1)	
		–	C9	(4,5,6)	(5,6,7)	(1,1,1)	(5,6,7)	(7,8,9)	
Resilient				**C12**	**C13**	**C14**	**C15**	**C16**	
	Group Supervisor	C13	–	(1,2,3)	(1,1,1)	(2,3,4)	(7,8,9)	(1,2,3)	
		–	C15	(5,6,7)	(7,8,9)	(4,5,6)	(1,1,1)	(5,6,7)	
	DM1	C16	–	(1,2,3)	(1,2,3)	(7,8,9)	(3,4,5)	(1,1,1)	
		–	C14	(5,6,7)	(5,6,7)	(1,1,1)	(3,4,5)	(7,8,9)	
	DM2	C13	–	(1,2,3)	(1,1,1)	(7,8,9)	(3,4,5)	(1,2,3)	
		–	C14	(5,6,7)	(7,8,9)	(1,1,1)	(3,4,5)	(5,6,7)	
	DM3	C16	–	(1,2,3)	(1,2,3)	(2,3,4)	(7,8,9)	(1,1,1)	
		–	C15	(5,6,7)	(5,6,7)	(4,5,6)	(1,1,1)	(7,8,9)	
Green				**C17**	**C18**	**C19**	**C20**		
	Group Supervisor	C17	–	(1,1,1)	(3,4,5)	(4,5,6)	(6,7,8)		
		–	C20	(6,7,8)	(3,4,5)	(2,3,4)	(1,1,1)		
	DM1	C17	–	(1,1,1)	(1,2,3)	(5,6,7)	(3,4,5)		
		–	C19	(5,6,7)	(4,5,6)	(1,1,1)	(2,3,4)		
	DM2	C18	–	(1,2,3)	(1,1,1)	(1,2,3)	(4,5,6)		
		–	C20	(2,3,4)	(4,5,6)	(2,3,4)	(1,1,1)		
	DM3	C17	–	(1,1,1)	(1,2,3)	(2,3,4)	(4,5,6)		
		–	C20	(4,5,6)	(3,4,5)	(2,3,4)	(1,1,1)		

Table 4
The fuzzy preferences of the supervisor for the DMs.

Decision-makers	Best criterion	Worst criterion	DM1	DM2	DM3
Group Supervisor	DM2	–	(2,3,4)	(1,1,1)	(3,4,5)
	–	DM3	(1,2,3)	(3,4,5)	(1,1,1)

Table 5
Optimal weights of the criteria.

	Decision-makers	Optimal criteria weights					
		W_L	W_A	W_R	W_G		
LARG	Group Supervisor	0.3419	0.376	0.188	0.094		
	DM1	0.464	0.2672	0.1705	0.0984		
	DM2	0.253	0.506	0.1687	0.0723		
	DM3	0.1733	0.2912	0.4133	0.1221		
Lean		$\mathbf{W_{C1}}$	$\mathbf{W_{C2}}$	$\mathbf{W_{C3}}$	$\mathbf{W_{C4}}$	$\mathbf{W_{C5}}$	$\mathbf{W_{C6}}$
	Group Supervisor	0.1602	0.0377	0.2642	0.3397	0.1132	0.0848
	DM1	0.2222	0.0317	0.2857	0.2222	0.1429	0.0952
	DM2	0.1642	0.0843	0.263	0.3382	0.1127	0.0376
	DM3	0.3012	0.1407	0.1747	0.1747	0.034	0.1747
Agile		$\mathbf{W_{C7}}$	$\mathbf{W_{C8}}$	$\mathbf{W_{C9}}$	$\mathbf{W_{C10}}$	$\mathbf{W_{C11}}$	
	Group Supervisor	0.0412	0.2117	0.1705	0.3649	0.2117	
	DM1	0.0384	0.3249	0.2122	0.2122	0.2122	
	DM2	0.1111	0.2593	0.037	0.3333	0.2593	
	DM3	0.1705	0.2117	0.0412	0.2117	0.3649	
Resilient		$\mathbf{W_{C12}}$	$\mathbf{W_{C13}}$	$\mathbf{W_{C14}}$	$\mathbf{W_{C15}}$	$\mathbf{W_{C16}}$	
	Group Supervisor	0.2117	0.3649	0.1705	0.0412	0.2117	
	DM1	0.2593	0.2593	0.037	0.1111	0.3333	
	DM2	0.2593	0.3333	0.037	0.1111	0.2593	
	DM3	0.2117	0.2117	0.1705	0.0412	0.3649	
Green		$\mathbf{W_{C17}}$	$\mathbf{W_{C18}}$	$\mathbf{W_{C19}}$	$\mathbf{W_{C20}}$		
	Group Supervisor	0.5854	0.1951	0.1463	0.0732		
	DM1	0.4163	0.3756	0.0694	0.1387		
	DM2	0.2439	0.4227	0.2439	0.0894		
	DM3	0.3754	0.3431	0.1877	0.0938		

Table 6
Optimal DMs' weights.

Decision-makers	Optimal weights of criteria		
	DM1	DM2	DM3
Group Supervisor	0.2351	0.622	0.1429

Table 7
Combined weights of DMs and group supervisor for LARG criteria.

Criteria	Combined weights	a = 0.5
LARG	μ_L	0.3166
	μ_A	0.3976
	μ_R	0.196
	μ_G	0.0898
Lean	μ_{C1}	0.1788
	μ_{C2}	0.0589
	μ_{C3}	0.26
	μ_{C4}	0.3136
	μ_{C5}	0.1109
	μ_{C6}	0.0778
Agile	μ_{C7}	0.0718
	μ_{C8}	0.2398
	μ_{C9}	0.1247
	μ_{C10}	0.3262
	μ_{C11}	0.2375
Resilient	μ_{C12}	0.2321
	μ_{C13}	0.3317
	μ_{C14}	0.1133
	μ_{C15}	0.0712
	μ_{C16}	0.2517
Green	μ_{C17}	0.4443
	μ_{C18}	0.2977
	μ_{C19}	0.1706
	μ_{C20}	0.0874

Section 3.2, we assigned a value to α. We set $\alpha = 0.5$ so giving the same importance to the opinions of the group supervisor and the DMs.

Table 8
Final weights of LARG criteria.

LARG Criteria	Final weight	
Lean	W_{C1}	0.0566
	W_{C2}	0.0186
	W_{C3}	0.0823
	W_{C4}	0.0993
	W_{C5}	0.0351
	W_{C6}	0.0246
Agile	W_{C7}	0.0286
	W_{C8}	0.0953
	W_{C9}	0.0496
	W_{C10}	0.1297
	W_{C11}	0.0944
Resilient	W_{C12}	0.0455
	W_{C13}	0.065
	..	0.0222
	W_{C15}	0.0139
	W_{C16}	0.0493
Green	W_{C17}	0.0399
	W_{C18}	0.0267
	W_{C19}	0.0153
	W_{C20}	0.0078

$$\mu_C = \alpha w_j + (1-\alpha)\sum_i w_j^i \lambda_i \Rightarrow$$
$$\mu_L = 0.5(0.3419) + 0.5((0.463 \times 0.235) + (0.253 \times 0.622) + (0.173 \times 0.142)) = 0.3165$$
$$\mu_A = 0.5(0.376) + 0.5((0.267 \times 0.235) + (0.506 \times 0.622) + (0.291 \times 0.142)) = 0.3976$$
$$\mu_R = 0.5(0.188) + 0.5((0.17 \times 0.235) + (0.168 \times 0.622) + (0.413 \times 0.142)) = 0.196$$
$$\mu_G = 0.5(0.094) + 0.5((0.098 \times 0.235) + (0.072 \times 0.622) + (0.122 \times 0.142)) = 0.0897$$

The combined weights of the sub-criteria were also determined by Eq. (8).

$$\mu_{SC} = \alpha w_j + (1-\alpha)\sum_i w_j^i \lambda_i \Rightarrow$$
$$\mu_{C1} = 0.5(0.1602) + 0.5((0.222 \times 0.235) + (0.164 \times 0.622) + (0.301 \times 0.142)) = 0.1788$$
$$\mu_{C2} = 0.5(0.0377) + 0.5((0.0317 \times 0.235) + (0.084 \times 0.622) + (0.1402 \times 0.142)) = 0.0588$$
$$\vdots$$
$$\mu_{C19} = 0.5(0.146) + 0.5((0.0693 \times 0.235) + (0.243 \times 0.622) + (0.187 \times 0.142)) = 0.1706$$
$$\mu_{C20} = 0.5(0.0731) + 0.5((0.138 \times 0.235) + (0.00893 \times 0.622) + (0.0938 \times 0.142)) = 0.0874$$

All the combined weights are presented in Table 7.

Finally, using Eq. (9), we calculated the final weights of the sub-criteria. These final weights are presented in Table 8 and are the ones to use in the supplier selection phase when applying the proposed FCoCoSo-B method.

$$W_C = \mu_C \times \mu_{SC}$$

$$W_{C1} = \mu_L \times \mu_{C1} = 0.3165 \times 0.1788 = 0.0566$$
$$W_{C2} = \mu_L \times \mu_{C2} = 0.3165 \times 0.0588 = 0.0186$$
$$\vdots$$
$$W_{C7} = \mu_A \times \mu_{C7} = 0.3976 \times 0.0718 = 0.0285$$
$$\vdots$$
$$W_{C12} = \mu_R \times \mu_{C12} = 0.196 \times 0.232 = 0.0455$$
$$\vdots$$
$$W_{C19} = \mu_G \times \mu_{C19} = 0.0897 \times 0.1706 = 0.0153$$
$$W_{C20} = \mu_G \times \mu_{C20} = 0.0897 \times 0.0874 = 0.0078$$

4.3. LARG supplier selection using fuzzy CoCoSo Bonferroni

In this phase, the weights obtained by FG-BWM were used to evaluate and select the most suitable LARG suppliers. The fuzzy numbers presented in Table 1(b) were used to evaluate the suppliers. Table 9 presents the experts' judgments relative to the 20 criteria and 12 suppliers, and Table 10 shows the aggregated decision matrix.

Next, Eq. (12) was used to obtain the normalized decision matrix shown in Table 11.

We then used Eqs. (13) and (14) and the weights obtained in Table 8 to calculate the weighted fuzzy FCoCoSo-B sequences of alternatives, that is, SB_i and $PB_i (i = 1, ..., 12)$, respectively. Table 12 presents the resulting sequences. For the sake of completeness, we show below the calculations of the sequences relative to supplier S1, that is:

$$PB_{S1}^{B-q-1} = \begin{pmatrix} PB_{S1}^{B-q-1(l)} = \frac{1}{2}\begin{pmatrix} (0.50\times 0.5)^{\left(\frac{0.0566-0.0186}{1-0.0566}\right)} \times (0.5\times 0.25)^{\left(\frac{0.0566-0.0823}{1-0.0566}\right)} \times \cdots \times \\ (0.241\times 0.3)^{\left(\frac{0.0267-0.0078}{1-0.0267}\right)} \times (0.103\times 0.3)^{\left(\frac{0.0153-0.0078}{1-0.0153}\right)} \end{pmatrix} = 0.13 \\ PB_{S1}^{B-q-1(m)} = \frac{1}{2}\begin{pmatrix} (0.7\times 0.7)^{\left(\frac{0.0566-0.0186}{1-0.0566}\right)} \times (0.7\times 0.464)^{\left(\frac{0.0566-0.0823}{1-0.0566}\right)} \times \cdots \times \\ (0.448\times 0.5)^{\left(\frac{0.0267-0.0078}{1-0.0267}\right)} \times (0.31\times 0.5)^{\left(\frac{0.0153-0.0078}{1-0.0153}\right)} \end{pmatrix} = 0.53 \\ PB_{S1}^{B-q-1(u)} = \frac{1}{2}\begin{pmatrix} (0.9\times 0.9)^{\left(\frac{0.0566-0.0186}{1-0.0566}\right)} \times (0.9\times 0.678)^{\left(\frac{0.0566-0.0823}{1-0.0566}\right)} \times \cdots \times \\ (0.655\times 0.7)^{\left(\frac{0.0267-0.0078}{1-0.0267}\right)} \times (0.517\times 0.7)^{\left(\frac{0.0153-0.0078}{1-0.0153}\right)} \end{pmatrix} = 0.72 \end{pmatrix} = (0.13, 0.53, 0.72)$$

$$SB_{S1}^{B-q-1} = \begin{pmatrix} SB_{S1}^{B-q-1^{(l)}} = \left(\frac{0.0566\times 0.0186}{1-0.0566}\times 0.50\times 0.5 + \frac{0.0566\times 0.0823}{1-0.0566}0.5\times 0.25 + \cdots + \frac{0.0267\times 0.0078}{1-0.0267}0.241\times 0.3 + \frac{0.0153\times 0.0078}{1-0.0153}0.103\times 0.3\right)^{1/2} = 0.34 \\ SB_{S1}^{B-q-1^{(m)}} = \left(\frac{0.0566\times 0.0186}{1-0.0566}0.7\times 0.7 + \frac{0.0566\times 0.0823}{1-0.0566}0.7\times 0.464 + \cdots + \frac{0.0267\times 0.0078}{1-0.0267}0.448\times 0.5 + \frac{0.0153\times 0.0078}{1-0.0153}0.31\times 0.5\right)^{1/2} = 0.53 \\ SB_{S1}^{B-q-1^{(u)}} = \left(\frac{0.0566\times 0.0186}{1-0.0566}0.9\times 0.9 + \frac{0.0566\times 0.0823}{1-0.0566}0.9\times 0.678 + \cdots + \frac{0.0267\times 0.0078}{1-0.0267}0.655\times 0.7 + \frac{0.0153\times 0.0078}{1-0.0153}0.517\times 0.7\right)^{1/2} = 0.71 \end{pmatrix} = (0.34, 0.53, 0.71)$$

Eq. (2) was used to defuzzify the sequences of alternatives. Eqs. (15)–(17) and the results from Table 12 were used next to obtain the relative significance of the suppliers within the pooling strategies. In particular, we considered $\lambda = 0.5$ for calculating k_{ic} in Eq. (17).

Finally, Eq. (18) was used to obtain the final ranking of the suppliers based on the decreasing values of k_i. The final ranking of the suppliers obtained from the proposed integration of FG-BWM and FCoCoSo-B approaches is shown in Table 13:

$$S_8 > S_2 > S_{10} > S_9 > S_{12} > S_4 > S_5 > S_1 > S_3 > S_6 > S_{11} > S_7.$$

4.4. Comparing the proposed fuzzy CoCoSo Bonferroni with other fuzzy MCDM models

To complete our analysis, we have compared the ranking results obtained by implementing the proposed FCoCoSo-B method with those produced by other three well-known methods, namely, FCOPRAS, FMOORA, and FWASPAS.

Fig. 3 and Table 14 summarize the ranking results obtained by using the different methods, providing a visual comparison of them. FCOPRAS and FMOORA produce exactly the same ranking for the sup-

Table 9
Experts' judgments on the 20 criteria and 12 suppliers.

Criteria	Optimization	Suppliers											
		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
C1	MAX	H, H, H	H, H, H	M, M, M	H, H, H	H, M, H	H, H, H	L, L, M	H, H, H	M, M, M	VH, VH, VH	M, M, M	H, H, VH
C2	MAX	H, H, H	VH, VH, H	H, H, M	H, H, M	H, H, VH	H, H, H	M, L, VL	H, H, VH	H, H, H	VH, VH, H	M, L, L	VH, VH, VH
C3	MAX	M, L, M	H, H, H	H, M, H	, H, M	H, H, H	H, H, H	M, L, VL	VH, H, H	H, H, H	H, H, H	M, M, M	H, H, H
C4	MAX	H, H, M	VH, H, VH	M, M, M	H, H, M	M, H, H	VH, H, H	VL, L, VL	H, H, H	H, H, H	H, H, H	M, M, M	VH, VH, VH
C5	MIN	M, M, M	H, H, H	M, H, M	M, M, M	H, H, H	H, H, H	M, M, M	M, M, M	L, M, M	L, L, L	H, H, H	L, L, L
C6	MIN	H, M, M	H, H, H	M, M, M	H, H, M	VH, H, H	M, M, M	H, H, H	M, M, M	L, L, L	L, L, L	H, H, H	L, L, L
C7	MAX	M, M, M	H, H, H	L, M, M	H, H, H	M, H, H	M, L, M	L, L, M	H, VH, H	H, H, H	VH, VH, VH	M, M, M	H, H, H
C8	MAX	M, M, M	H, H, H	L, M, M	H, H, H	M, M, M	L, M, M	L, L, L	H, H, H	H, H, H	VH, VH, H	M, L, L	H, H, H
C9	MAX	M, M, L	H, H, H	H, H, M	M, M, M	M, M, H	M, L, M	L, L, L	H, H, H	H, H, H	H, H, H	M, L, L	M, M, M
C10	MAX	H, H, M	H, VH, H	H, M, H	H, H, H	M, M, M	M, M, M	L, L, L	H, VH, VH	H, H, H	H, H, H	M, L, L	M, H, H
C11	MAX	H, H, H	H, H, H	H, M, H	H, H, H	M, M, M	M, M, M	L, L, L	VH, VH, VH	H, H, H	H, H, H	M, L, L	M, H, M
C12	MAX	M, L, M	H, H, H	M, M, M	M, M, M	VH, VH, H	M, M, M	M, L, L	H, H, H	M, M, M	M, M, M	H, H, H	M, M, M
C13	MAX	H, H, M	H, H, H	M, M, H	M, M, M	H, VH, H	M, M, M	L, L, L	H, VH, VH	M, L, L	M, M, M	H, H, H	M, M, M
C14	MAX	H, H, M	H, H, H	M, M, H	M, M, M	H, H, VH	M, L, M	M, L, M	VH, H, H	L, L, M	M, M, M	H, H, H	M, M, M
C15	MAX	H, H, H	H, H, H	M, M, H	M, M, M	H, H, H	M, L, M	L, M, M	H, H, H	L, L, M	M, M, M	H, H, H	M, M, M
C16	MAX	H, H, H	VH, VH, VH	H, H, H	H, VH, H	H, H, H	M, L, M	L, L, VL	H, H, VH	M, L, L	H, H, H	H, H, H	M, M, M
C17	MAX	M, M, M	H, H, H	VL, L, VL	L, M, L	M, M, M	M, M, L	VL, L, VL	VH, VH, VH	H, H, VH	L, L, L	VH, H, H	L, VL, VL
C18	MAX	M, M, L	H, H, VH	L, L, M	L, M, L	M, M, M	L, L, L	L, VL, VL	VH, H, H	M, M, M	L, L, L	H, VH, VH	L, L, L
C19	MAX	L, L, L	H, VH, H	L, L, L	L, L, M	M, M, M	L, M, L	VL, L, L	H, VH, VH	M, M, M	L, L, VL	H, VH, VH	L, VL, L
C20	MAX	M, M, M	H, H, VH	L, VL, VL	L, L, VL	M, M, M	M, M, M	L, L, L	VH, VH, VH	H, H, H	L, VL, VL	VH, H, H	L, L, VL

pliers, while the results of FWASPAS and FCoCoSo-B are very similar. However, the results of FCOPRAS and FMOORA are significantly different from those provided by FWASPAS and FCoCoSo-B.

The coincidence of the results of FCOPRAS and FMOORA does not surprise much since these two methods consist of two similar sequences of logical steps (see, for example, Tavana et al. (2021)). On the other hand, the similarity between the rankings of FCoCoSo and FWASPAS reflects the intended design of the original CoCoSo algorithm (Yazdani et al., 2019). Indeed, the technique introduced by Yazdani et al. (2019) is similar to WASPAS and VIKOR and, it makes sense that this similarity is preserved when considering their applications to fuzzy settings.

The marked difference between the two sets of rankings, those returned by FCOPRAS and FMOORA on a side and those produced by FWASPAS and FCoCoSo-B on the other, are intuitively due to the fuzzy sequences that are created by both WASPAS and CoCoSo when interpreting experts' comparisons as fuzzy numbers.

As already pointed out above, Bonferroni functions have the capacity to account for the interrelationships among decision attributes while eliminating the influence of extreme data. Thus, Bonferroni functions add consistency to the proposed fuzzy extension of the CoCoSo algorithm and a certain level of flexibility. The differences with the ranking results of FCOPRAS and FMOORA can be interpreted as a reflection of this flexibility feature.

5. Conclusion and future research directions

This study proposes a MCDM approach for supplier selection in reverse supply chains within a lean, agile, resilient, and green (LARG) strategic paradigm. The proposed methodology integrates two innovative pairwise comparison-based methods within a fuzzy environment. The first method is a fuzzy group BWM (FG-BWM), which builds on the fuzzy preference programming (FPP) variant proposed by Amiri et al. (2020). FG-BWM is used to extract crip values for the optimal

Table 10
The aggregated decision matrix

Criteria	Suppliers															
	S1			S2			S3			…	S11			S12		
C1	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	…	0.3	0.5	0.7	0.567	0.767	0.933
C2	0.5	0.7	0.9	0.633	0.833	0.967	0.433	0.633	0.833	…	0.167	0.367	0.567	0.7	0.9	1
C3	0.233	0.433	0.633	0.5	0.7	0.9	0.433	0.633	0.833	…	0.3	0.5	0.7	0.5	0.7	0.9
C4	0.433	0.633	0.833	0.633	0.833	0.967	0.3	0.5	0.7	…	0.3	0.5	0.7	0.7	0.9	1
C5	0.3	0.5	0.7	0.5	0.7	0.9	0.367	0.567	0.767	…	0.5	0.7	0.9	0.1	0.3	0.5
C6	0.367	0.567	0.767	0.5	0.7	0.9	0.3	0.5	0.7	…	0.5	0.7	0.9	0.1	0.3	0.5
C7	0.3	0.5	0.7	0.5	0.7	0.9	0.233	0.433	0.633	…	0.3	0.5	0.7	0.5	0.7	0.9
C8	0.3	0.5	0.7	0.5	0.7	0.9	0.233	0.433	0.633	…	0.233	0.433	0.633	0.5	0.7	0.9
C9	0.233	0.433	0.633	0.5	0.7	0.9	0.433	0.633	0.833	…	0.233	0.433	0.633	0.3	0.5	0.7
C10	0.433	0.633	0.833	0.567	0.767	0.933	0.433	0.633	0.833	…	0.233	0.433	0.633	0.433	0.633	0.833
C11	0.5	0.7	0.9	0.5	0.7	0.9	0.433	0.633	0.833	…	0.233	0.433	0.633	0.367	0.567	0.767
C12	0.233	0.433	0.633	0.5	0.7	0.9	0.3	0.5	0.7	…	0.5	0.7	0.9	0.3	0.5	0.7
C13	0.433	0.633	0.833	0.5	0.7	0.9	0.367	0.567	0.767	…	0.5	0.7	0.9	0.3	0.5	0.7
C14	0.433	0.633	0.833	0.5	0.7	0.9	0.367	0.567	0.767	…	0.5	0.7	0.9	0.3	0.5	0.7
C15	0.5	0.7	0.9	0.5	0.7	0.9	0.367	0.567	0.767	…	0.5	0.7	0.9	0.3	0.5	0.7
C16	0.5	0.7	0.9	0.7	0.9	1	0.433	0.633	0.833	…	0.5	0.7	0.9	0.3	0.5	0.7
C17	0.3	0.5	0.7	0.5	0.7	0.9	0.033	0.167	0.367	…	0.567	0.767	0.933	0.033	0.167	0.367
C18	0.233	0.433	0.633	0.567	0.767	0.933	0.167	0.367	0.567	…	0.633	0.833	0.967	0.1	0.3	0.5
C19	0.1	0.3	0.5	0.567	0.767	0.933	0.1	0.3	0.5	…	0.633	0.833	0.967	0.067	0.233	0.433
C20	0.3	0.5	0.7	0.567	0.767	0.933	0.033	0.167	0.367	…	0.567	0.767	0.933	0.067	0.233	0.433

Table 11
The normalized decision matrix.

Criteria	Suppliers															
	S1			S2			S3			…	S11			S12		
C1	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	…	0.3	0.5	0.7	0.567	0.767	0.933
C2	0.5	0.7	0.9	0.633	0.833	0.967	0.433	0.633	0.833	…	0.167	0.367	0.567	0.7	0.9	1
C3	0.25	0.464	0.679	0.536	0.75	0.964	0.464	0.679	0.893	…	0.321	0.536	0.75	0.536	0.75	0.964
C4	0.433	0.633	0.833	0.633	0.833	0.967	0.3	0.5	0.7	…	0.3	0.5	0.7	0.7	0.9	1
C5	0.143	0.2	0.333	0.111	0.143	0.2	0.13	0.176	0.273	…	0.111	0.143	0.2	0.2	0.333	1
C6	0.13	0.176	0.273	0.111	0.143	0.2	0.143	0.2	0.333	…	0.111	0.143	0.2	0.2	0.333	1
C7	0.3	0.5	0.7	0.5	0.7	0.9	0.233	0.433	0.633	…	0.3	0.5	0.7	0.5	0.7	0.9
C8	0.31	0.517	0.724	0.517	0.724	0.931	0.241	0.448	0.655	…	0.241	0.448	0.655	0.517	0.724	0.931
C9	0.259	0.481	0.704	0.556	0.778	1	0.481	0.704	0.926	…	0.259	0.481	0.704	0.333	0.556	0.778
C10	0.448	0.655	0.862	0.586	0.793	0.966	0.448	0.655	0.862	…	0.241	0.448	0.655	0.448	0.655	0.862
C11	0.5	0.7	0.9	0.5	0.7	0.9	0.433	0.633	0.833	…	0.233	0.433	0.633	0.367	0.567	0.767
C12	0.241	0.448	0.655	0.517	0.724	0.931	0.31	0.517	0.724	…	0.517	0.724	0.931	0.31	0.517	0.724
C13	0.448	0.655	0.862	0.517	0.724	0.931	0.379	0.586	0.793	…	0.517	0.724	0.931	0.31	0.517	0.724
C14	0.464	0.679	0.893	0.536	0.75	0.964	0.393	0.607	0.821	…	0.536	0.75	0.964	0.321	0.536	0.75
C15	0.556	0.778	1	0.556	0.778	1	0.407	0.63	0.852	…	0.556	0.778	1	0.333	0.556	0.778
C16	0.5	0.7	0.9	0.7	0.9	1	0.433	0.633	0.833	…	0.5	0.7	0.9	0.3	0.5	0.7
C17	0.3	0.5	0.7	0.5	0.7	0.9	0.033	0.167	0.367	…	0.567	0.767	0.933	0.033	0.167	0.367
C18	0.241	0.448	0.655	0.586	0.793	0.966	0.172	0.379	0.586	…	0.655	0.862	1	0.103	0.31	0.517
C19	0.103	0.31	0.517	0.586	0.793	0.966	0.103	0.31	0.517	…	0.655	0.862	1	0.069	0.241	0.448
C20	0.3	0.5	0.7	0.567	0.767	0.933	0.033	0.167	0.367	…	0.567	0.767	0.933	0.067	0.233	0.433

Table 12
The weighted FCoCoSo-B sequences.

Supplier	Fuzzy SBi			Fuzzy PBi			Crisp SBi	Crisp PBi
S1	0.34	0.53	0.71	0.13	0.53	0.72	0.5257	0.4968
S2	0.48	0.66	0.83	0.38	0.65	0.81	0.6594	0.6337
S3	0.32	0.50	0.68	0.09	0.51	0.69	0.4986	0.4713
S4	0.38	0.56	0.74	0.12	0.56	0.74	0.5584	0.5184
S5	0.37	0.55	0.73	0.20	0.56	0.73	0.5511	0.5245
S6	0.31	0.49	0.67	0.10	0.50	0.68	0.491	0.4645
S7	0.10	0.27	0.46	0.02	0.31	0.49	0.275	0.289
S8	0.52	0.70	0.85	0.42	0.68	0.84	0.6936	0.6651
S9	0.39	0.57	0.77	0.21	0.58	0.77	0.5735	0.5481
S10	0.44	0.63	0.83	0.09	0.62	0.82	0.6284	0.5661
S11	0.29	0.47	0.65	0.26	0.49	0.66	0.4741	0.4789
S12	0.39	0.58	0.79	0.09	0.58	0.78	0.5835	0.5311

Table 13
Final supplier ranking

Supplier	*kia*	*kib*	*kic*	*ki*	Rank
S1	0.0805	3.6307	0.7526	2.0917	8
S2	0.1018	4.59	0.9517	2.6445	2
S3	0.0764	3.4438	0.7139	1.984	9
S4	0.0848	3.8241	0.7925	2.2029	6
S5	0.0847	3.8186	0.7916	2.2	7
S6	0.0752	3.3927	0.7033	1.9546	10
S7	0.0444	2	0.4151	1.1527	12
S8	0.107	4.8231	1	2.7788	1
S9	0.0883	3.9815	0.8255	2.2939	4
S10	0.0941	4.2437	0.8792	2.4443	3
S11	0.075	3.3807	0.7014	1.9482	11
S12	0.0878	3.9593	0.8204	2.2806	5

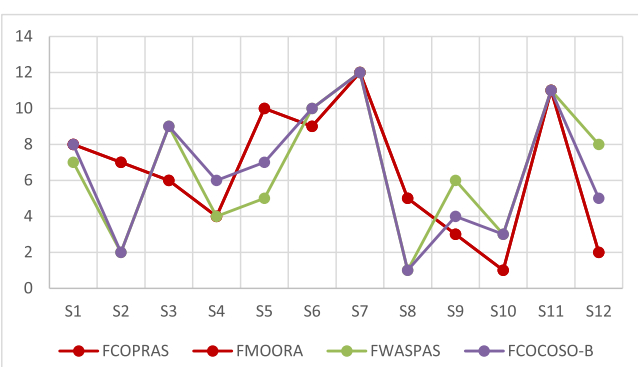

Fig. 3. Comparing the proposed FCoCoSo-B method to other MCDM methods.

Table 14
Ranking results of the proposed FCoCoSo-B and other MCDM methods

Supplier	FCOPRAS	FMOORA	FWASPAS	FCOCOSO-B
S1	8	8	7	8
S2	7	7	2	2
S3	6	6	9	9
S4	4	4	4	6
S5	10	10	5	7
S6	9	9	10	10
S7	12	12	12	12
S8	5	5	1	1
S9	3	3	6	4
S10	1	1	3	3
S11	11	11	11	11
S12	2	2	8	5

weights of criteria and subcriteria defined according to the LARG strategy. The second method is a fuzzy CoCoSo (F-CoCoSo) where fuzzy normalized weighted and fuzzy normalized weighted geometric Bonferroni mean functions are employed to determine the weighted sequences of alternatives. Three pooling strategies are defined using the weighted sequences of alternatives, and a final index is synthesized to select the most suitable supplier.

The BWM is used for its simplicity and efficacy. The CoCoSo model is used for its unique ability to produce a compromise solution. The Bonferroni functions are used to capture the interrelationship between decision attributes and eliminate the influence of extreme data. All evaluations performed by the manager (or supervisor) and the selected group of experts (or decision-makers) when implementing both GF-BWM and F-CoCoSo-Bonferroni are formalized in terms of triangular fuzzy numbers (TFNs). The use of fuzzy numbers allows the manager to account for the ambiguity and uncertainty inherent to the evaluations of the experts and make more accurate and objective assessments.

The integration of TFNs within a LARG paradigm makes the proposed approach flexible enough for managers to make an informed decision regarding the supplier selection in reverse supply chains, without the necessity of using more complex tools of fuzzy theory such as type-2 fuzzy sets, intuitionistic fuzzy sets, or neutrosophic sets. Indeed, the implementation of a LARG strategy allows for both the main criteria to be defined in line with several major features of green supplier selection and the specific sub-criteria to account for the distinctive characteristics of the company. These sub-criteria can be specifically tailored considering the environmental, engineering, and managerial factors influencing the manager's choices within the company context. Given the high level of specificity that can be applied to the LARG sub-criteria, the fuzzy environment does not need to be complicated in order to capture potential imprecisions and doubts in experts' judgments.

We have presented the results obtained by implementing the proposed methodology in a real case study conducted at a large wood and paper manufacturing company. The main reason behind the choice of this company was its commitment to sustainable production and pro-environmental policies. Indeed, this study aims at providing a methodology that not only can support manufacturers active in the field of recycling to meet their supply needs but also allows for applications to other selection problems within the realm of sustainable production and consumption.

The managerial implications of a methodology like the one herein introduced can be easily derived. The increasing attention paid by consumers and governmental policies to the eco-friendly behavior of industries and companies is affecting managers' choices about production and selling strategies. In this sense, the development of reverse supply chains is a key element, and being able to correctly select adequate suppliers delivering raw materials is essential.

LARG criteria allow for a complete analysis of suppliers' activities from all possible viewpoints. Thus, once very detailed and exhaustive

sub-criteria have been defined within a LARG strategy, the effectiveness of TFNs in compensating for the presence of uncertain and/or vague evaluations depends on the knowledge and confidence of the experts. A limitation in this sense is the capacity of managers to correctly select the experts who will be performing the pairwise comparisons. This drawback can be reduced by adjusting the level of fuzziness according to the level of imprecision assumed by the manager.

In conclusion, this paper contributes to the increasing literature concerned with the development of technically sound assessment tools able to deal with sustainable production and environmental issues. The proposed methodology enhances the idea of combining BWM and the CoCoSo method for further applications to real-life problems. The proposed framework was used to analyze a case study of a large wood and paper manufacturer, but it can be plainly modified to be applied by other companies with similar features to approach eco-friendly-oriented selection problems. Besides, future research could concentrate on studying the applicability of the proposed integrated fuzzy-based framework to other kinds of selection problems involving sustainability-related issues such as partner selection, waste disposal location selection, energy plant location selection, and sustainable location selection for e-waste collection.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Dr. Madjid Tavana is grateful for the partial support he received from the Czech Science Foundation (GAˇCR19-13946S) for this research.

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