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Solving supplier selection problem in a textile industry using an integrated grey-MABAC method

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Abstract: Like other industries, selection of suppliers in a textile mill also plays a decisive role by providing right quality of raw materials/components/dyes and chemicals in right quantities at right time and affordable cost, thereby establishing an effective supply chain. Acknowledging supplier selection/evaluation as a multi-criteria decision-making (MCDM) problem, various mathematical tools have been proposed to resolve the issue. In this paper, a grey-based MCDM approach, i.e. grey-multi-attributive border approximation area comparison (G-MABAC) method is proposed for solving a textile supplier selection problem, expressing relative importance of the decision makers, criteria and alternatives using grey numbers. Based on the performance scores, G-MABAC partitions six alternative suppliers into upper approximation (reliable) and lower approximation (unreliable) areas, identifying the relative strengths and weaknesses of each of them. It would act as an intelligent decision support framework in effectively adopting multi-sourcing strategy for enhanced resilience with minimum disruption in the textile supply chain.

Keywords: supplier selection; textile industry; grey number; MABAC; multi-attributive border approximation area comparison; ranking.

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1 Introduction

With accelerated globalised competition, and growth of information and communication technology, along with diversified customers' requirements and changing market environment, supplier selection has become one of the critical components of supply chain management (Taherdoost and Brand, 2019; Naqvi and Amin, 2021). For having an efficient supply chain, it is ardently required that all the raw/semi-finished materials/components should have adequate quality, bought from appropriate sources, at suitable time and location, with suitable prices and service responsiveness (Vacar, 2019; Ljiljana and Svetlana, 2020). A correct supplier selection decision would help an organisation in reducing cost with improved quality, on-time delivery of the end products, optimal inventory level, increased customer satisfaction, operational effectiveness and competitive advantage. On the other hand, a wrongly chosen supplier may adversely affect goodwill of the organisation with over-stocking or under-stocking of inventory items and lead to disruptive supply chain. Thus, the supplier selection process should be focused on reducing purchasing risks, maximising overall value for the customers, and developing long-term relationships between the suppliers and customers.

Like all other manufacturing organisations, supplier selection is also an important decision for a textile industry because of its significant contribution to the national economy and employment opportunity. In a typical cotton mill, cotton fibres are treated as the raw material, catering 60–70% of the total cost of the end product. Good quality cotton fibre results in streamlined operation of the subsequent processes, like carding, roving, spinning, dyeing and wet processing. It would also help in reducing yarn breakage, nep formation and dyeing defects, while helping in waste reduction leading to sustainable green processing environment. Therefore, procurement of cotton fibres from a selected set of suppliers with adequate performance levels would significantly influence the competitiveness of any textile industry (Guarnieri and Trojan, 2019).

However, supplier selection involving several quantitative and qualitative evaluation criteria is a complex task requiring participation of multiple decision makers with varying interest and requirements. It can be treated as a typical multi-criteria decision making (MCDM) problem characterised by the presence of numerous competing suppliers and set of conflicting criteria (Jing, 2018). Acknowledging the complexity of supplier selection process, nowadays, it not only relies on cost criterion, but also depends on a broader range of criteria, like quality, delivery, capability, technical support, reputation, responsiveness etc. (Nong and Ho, 2019). It can be noted that some of those evaluation criteria are qualitative in nature, making it difficult for the decision makers to express their evaluations in exact numeric values (Özfiat et al., 2014). They would feel more relaxed in assessing the relative significance of those criteria using linguistic variables, like ‘very important’, ‘moderately important’, ‘unimportant’, and so on. On the other hand, it would also be easy for them to appraise performance of the alternative suppliers against each of the criteria as ‘very good’, ‘fair’, ‘very poor’, and so on.

There are several models available to take into account uncertainty and vagueness in the decision making process, like fuzzy set theory (Zadeh, 1965) and its various extensions, interval numbers (Moore, 1979), grey system theory (Deng, 1982) etc. Grey system theory can efficiently deal with uncertain and vague information in many of the real-time decision making scenarios, without the requirement of large sample data or any underlying distribution. In grey system theory, a white system has all of its information known, while a black system has all the information unknown. A grey system is the one which has only partially known information. A grey number is a real number that can be described as the basic element of the grey system. Thus, grey number represents information whose exact value is unknown, but the range within it lies is known with absolute certainty (Li and Lin, 2014). Although there are several variants of grey numbers, interval grey numbers have become quite popular due to their ability to represent a set of potential values as a single continuous interval.

As the conventional MCDM methods cannot effectively deal with complex and unstructured nature of the present-day supplier selection decisions having qualitative evaluation criteria, they have been occasionally integrated with various uncertainty models to resolve the issues. In this paper, a newly developed MCDM technique, in the form of multi-attributive border approximation area comparison (MABAC) (Pamučar and Ćirovic, 2015), is applied along with interval grey numbers to solve a textile supplier selection problem in the human-centric decision making environment. In MABAC method, based on the computed performance scores, all the alternative suppliers can be partitioned into upper and lower approximation areas, helping in their subsequent

clustering as efficient and inefficient ones. It can also identify the potential strengths and weaknesses of each of the suppliers using the corresponding criterion function values. It would thus assist the textile mill to effectively adopt multi-sourcing strategy for enhanced resilience while minimising the chances of sudden disruption in the supply chain. Integration of interval grey numbers with MABAC would thereby eliminate inherent insufficiencies of the individual techniques and possible biases in interpretation of the results, providing multiple perspectives with greater insights (Torkayeshi et al., 2023).

In the Indian economy, textile industry plays a crucial role both in terms of revenue generation and employability. The Indian textile industry is characterised by the use of capital-intensive technology for mass production of textile products, involving spinning, weaving, wet processing and apparel manufacturing. According to a recent report, the Indian domestic textile and apparel industry contributes approximately 2.3% to its Gross Domestic Product (GDP), 13% to industrial production and 12% to exports. It has a 4% share of the global trade in textiles and apparel. The size of the Indian textile market has been estimated around 165 billion USD in 2022, and would reach 350 billion USD by 2030 with a compound annual growth rate of approximately 10%. The Indian textile and apparel industry is the second largest employer providing direct employment to 45 million people and 100 million people in other related industries. It is the largest producer of cotton (23%) in the globe and has also the highest area under cotton cultivation (39% of the world area). Cotton plays an important role in sustaining the livelihood of more than 6.5 million farmers.

In a typical cotton mill, cotton fibres are treated as the main raw material, which are characterised with respect to several quality features, like fibre length, tenacity, elongation, maturity, colour, fineness etc. (Mitra and Majumdar, 2023). They pass through a series of production processes, like blowroom (for removal of dirt and dust particles), carding (for their parallel alignment), combing (for removal of short fibres and uniform distribution of the fibres), roving (for straightening of the fibres), spinning (for imparting strength and twist suitable for withstanding the weaving forces) and winding (for collection of the final yarn onto bobbins). The final yarn should possess some unique quality characteristics, such as appropriate tensile strength and elongation, uniform thickness with minimum thick and thin places, minimum hairiness, absence of foreign materials, minimum count variation, minimum neps etc. Thus, it can be propounded that quality of the final yarn is highly dependent of the input cotton fibre quality. As the cotton fibres are processed through a series of operations, any inferior quality would be compounded resulting in the worst yarn. It is quite obvious that good quality cotton yarn can only be achieved if the raw fibres are delivered by a set of equally competent suppliers strongly maintaining the quality standards. Therefore, keeping in mind the immense importance of suppliers in the supply chain, especially in the textile industry, this paper employs an integrated MCDM approach for supplier selection, where six alternatives are ranked using MABAC method, expressing importance of the decision makers/experts, evaluation criteria and performance of the suppliers against those criteria using grey numbers.

This paper is organised as follows: Section 2 provides a concise literature review of different MCDM methods employed for solving supplier selection problems in textile industries. The mathematical details of grey numbers and grey-multi-attributive border approximation area comparison (G-MABAC) are presented in Section 3.

A demonstrative supplier selection problem is solved in Section 4 using G-MABAC and Section 5 concludes the paper along with future research directions.

2 Literature review

Acknowledging the immense potentiality of various MCDM methods in dealing with complex decision making problems consisting of a set of competing alternatives and conflicting criteria, the past researchers have explored their applicability in solving supplier selection problems in textile industries. It can be unveiled from Table 1 that analytic hierarchy process (AHP) (Ulutas, 2019; Bakhat and Rajaa, 2019; Burney and Ali, 2019; Yang and Wang, 2020; Utama et al., 2021; Kao et al., 2022; Lahdhiri et al., 2022; Wang et al., 2022a, 2022b), analytic network process (ANP) (Wang et al., 2022a), weighted sum model (WSM) (Lahdhiri et al., 2022), weighted product model (WPM) (Lahdhiri et al., 2022), weighted aggregated sum product assessment (WASPAS) (Bakhat and Rajaa, 2019; Rahman et al., 2022; Kao et al., 2022), multi-objective optimisation on the basis of ratio analysis (MOORA) (Utama et al., 2021), technique for order preference by similarity to ideal solution (TOPSIS) (Yang and Wang, 2020; Nakiboglu and Bulgurcu, 2021; Lahdhiri et al., 2022; Kao, 2022; Caristi et al., 2022; Wang et al., 2022b), Vlekkriterijumsko KOMPromisno Rangiranje in Serbian (VIKOR) (Karami et al., 2021), evaluation based on distance from average solution (EDAS) (Paul et al., 2022), preference ranking organisation method for enrichment evaluation (PROMETHEE) (Wang et al., 2022a), operational competitiveness rating analysis (OCRA) (Ulutas, 2019), TOMada de Decisao Interativa Multicriterio (TODIM), an acronym in Portuguese meaning iterative MCDM) (Celik et al., 2020), mixed aggregation by comprehensive normalisation technique (MACONT) (Ecer and Torkayesh, 2024) etc. have found their applications for ranking of the textile suppliers.

Table 1 MCDM-based selection of suppliers in textile industries

<i>Author(s)</i>	<i>No. of suppliers</i>	<i>Criteria</i>	<i>MCDM tool(s)</i>
Ulutas (2019)	5	Quality, delivery, capability, reputation, flexibility, cost, communication issues, technical assistances	AHP, OCRA, FST
Bakhat and Rajaa (2019)	7	Quality, cost, capability, technical support, delivery, flexibility, reputation, discount opportunities	AHP, WASPAS, grey numbers
Burney and Ali (2019)	3	Cost, quality, service, delivery, payment terms	AHP, FST
Yang and Wang (2020)	8	Economic, social, environmental	AHP, TOPSIS, FST
Celik et al. (2020)	3	Environmental, social, quality, risk, cost, capability, business structure	Interval type-2 fuzzy numbers, BWM, TODIM

Table 1 MCDM-based selection of suppliers in textile industries (continued)

<i>Author(s)</i>	<i>No. of suppliers</i>	<i>Criteria</i>	<i>MCDM tool(s)</i>
Nakiboglu and Bulgurcu (2021)	5	Defect rate, conformance to specification, quality consistency, offering competitive prices, payment terms, on-time delivery, damage-free order, lead time, capacity, environmental certifications	TOPSIS, intuitionistic fuzzy numbers
Karami et al. (2021)	12	Quality, cost, location, lead-time, monetary position, financial position, on-time delivery, ability to product change, support and service, technical capacity	PCA, VIKOR
Utama et al. (2021)	8	Profile, quality, cost, delivery, service, environment	AHP, MOORA
Rahman et al. (2022)	5	Economic, social, environmental	SWARA, WASPAS
Lahdhiri et al. (2022)	3	Cost, quality, compliance to quantity, compliance to deadlines	AHP, TOPSIS, WSM, WPM
Kao et al. (2022)	10	Cost, quality, service, environmental, location, logistics, reputation, performance history, political stability, capability, trade certified	AHP, WASPAS, FST
Kao (2022)	4	Financial stability, quality, reputation, pandemic containment capability, personal protective equipment	TOPSIS, FST
Paul et al. (2022)	4	Cost, quality, delivery, technical support, flexibility, payment terms	IRN, BWM, EDAS
Caristi et al. (2022)	3	Reliability, responsiveness, flexibility, cost, assets	TOPSIS, FST
Wang et al. (2022a)	10	Reliability, responsiveness, flexibility, cost, assets	AHP, ANP, FST, PROMETHEE
Wang et al. (2022b)	3	Quality, technical capability, pollution control, green product, environment management, green competencies	AHP, TOPSIS, FST
Ecer and Torkayesh (2024)	6	Economic, social, environmental	FST, MACONT
This paper	6	Cost, quality, delivery, flexibility, capability, payment terms	Interval grey numbers, MABAC

To deal with the qualitative textile supplier selection criteria, some of the past researchers have also attempted to integrate those MCDM techniques with different uncertainty models, like fuzzy set theory (FST) (Ulutas, 2019; Burney and Ali, 2019; Yang and Wang, 2020; Kao et al., 2022; Kao, 2022; Caristi et al., 2022; Wang et al., 2022a; 2022b; Ecer and Torkayesh, 2024), grey numbers (Bakhat and Rajaa, 2019), interval type-2

fuzzy numbers (Celik et al., 2020), intuitionistic fuzzy numbers (Nakiboglu and Bulgurcu, 2021), interval rough number (IRN) (Paul et al., 2022) etc. For any of the MCDM methods, relative importance (weight) assigned to the criteria plays an important role in deriving the final ranking of the alternatives. Although AHP has appeared as a potent subjective criteria weighting technique, other methods, like best worst method (BWM) (Celik et al., 2020; Paul et al., 2022), principal component analysis (PCA) (Karami et al., 2021) and step-wise weight assessment ratio analysis (SWARA) (Rahman et al., 2022) have also found their applications in the literature for the said purpose.

Bakhat and Rajaa (2019) shortlisted nine criteria after reviewing the past research works and solved a supplier selection problem for a Turkish textile company. Grey numbers were first hybridised with AHP for criteria weighting, and the considered suppliers were subsequently ranked from the best to the worst employing G-WASPAS approach. It was concluded that the proposed grey-based approach had been more efficient and precise than the existing standalone MCDM methods for streamlining the textile supply chain. Considering six criteria, like cost, quality, delivery, technical support, flexibility and payment terms, Paul et al. (2022) identified the most competent supplier for a textile mill using an integrated MCDM approach. The subjective evaluations of the criteria and performance of the alternative suppliers against those criteria were expressed in terms of IRNs, while BWM was adopted for criteria weight measurement. Finally, the considered suppliers were ranked applying IRN-EDAS method. A garment and textile supplier selection problem was solved by Wang et al. (2022a) while combining AHP, ANP and PROMETHEE with FST. Weights of various qualitative criteria were estimated using fuzzy-AHP, their interrelationships were explored applying fuzzy-ANP and PROMETHEE was finally adopted to rank 10 alternative suppliers.

It can be noticed from the literature that keeping in mind the strength of MABAC method, it has been integrated with neutrosophic fuzzy sets (Pamucar et al., 2020), uncertain probabilistic linguistic sets (Guiwu et al., 2020), decision making trial and evaluation laboratory (DEMATEL)-based ANP (DANP) (Ghadikolaei et al., 2022), rough numbers (Chakraborty et al., 2020; Chattopadhyay et al., 2022), interval rough numbers (Pamučar et al., 2018; Shahedi et al., 2023), different fuzzy environments (Gupta et al., 2019; Zhiwei et al., 2022; Chakraborty et al., 2023; Komatina et al., 2023), Z numbers (Bo et al., 2023), D-numbers (Pamučar et al., 2021a) etc. for solving varying decision making problems. Although grey numbers have been coupled with MABAC method across diverse domains, like risk assessment of a wind turbine (Bakhat and Rajaa, 2020), demands-matching for reverse logistics (Wang et al., 2019), project portfolio selection (Debnath et al., 2017) etc., least attempt has been put forward till date to explore the applicability of MABAC in solving supplier selection problems (especially in textile industries) in grey environment. Bakhat and Rajaa (2019) only solved a textile supplier selection problem hybridising grey numbers with WASPAS. MABAC has several advantages over WASPAS (developed combining WSM and WPM methods), like ability to provide consistent solutions against changes in the measurement units of the criteria, insensitive against changes in criterion type (when a beneficial criterion is converted into cost criterion or vice versa) and simplicity in calculation (insensitive to the number of criteria and alternatives) (Torkayeshi et al., 2023).

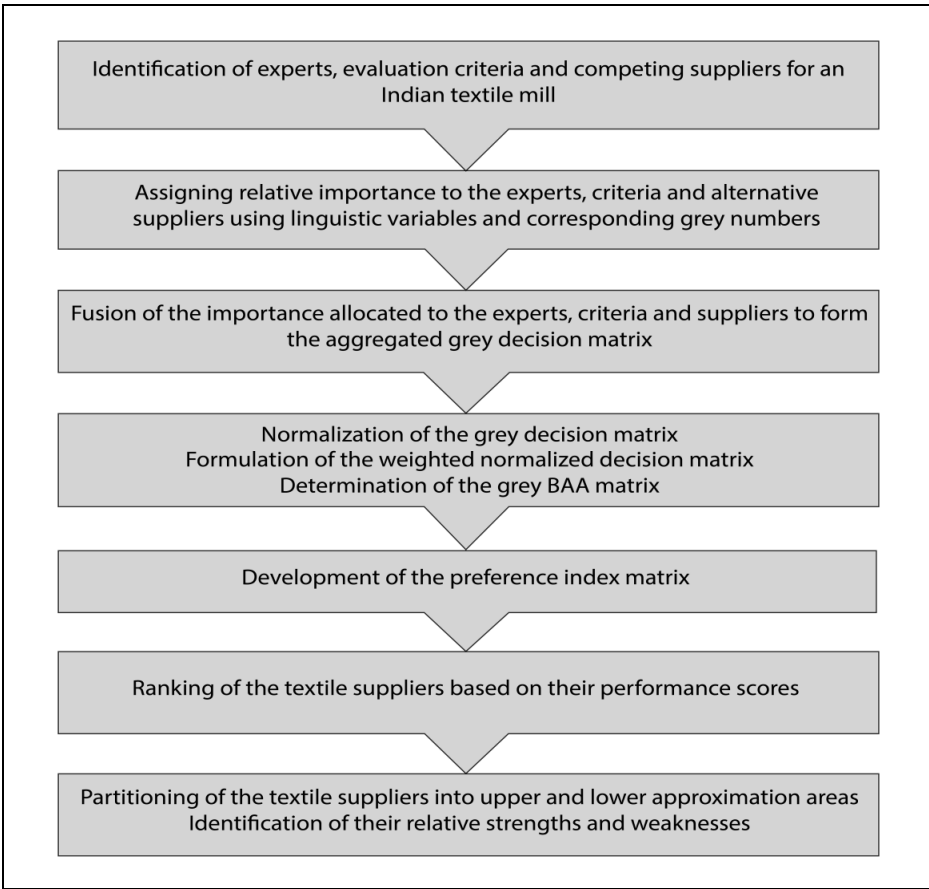
Keeping in mind the identified research gap, this paper proposes integration of grey numbers with MABAC for solving a supplier selection problem for cotton fibres in an Indian textile mill, considering six generic criteria, i.e., cost, quality, delivery, flexibility,

capability and payment terms. Briefly, this paper contributes the followings to the extant domain knowledge:

- a Formulation of a textile supplier selection problem for an Indian textile mill considering three decision makers, six generic criteria and six competing suppliers, while expressing importance of the decision makers, criteria and alternatives in interval grey numbers.
- b Solution of the developed problem using grey-integrated MABAC approach.
- c Shortlisting of the considered textile suppliers, and their subsequent clustering into efficient (best performing) and inefficient (worst performing) groups based on their performance scores, while identifying their relative strengths and weaknesses. It would thus help the textile mill to deploy a resilient multi-sourcing strategy, avoiding the adverse consequences of disruptive supply chain.

The procedural steps of the adopted methodology are shown in Figure 1 in the form of a flowchart.

Figure 1 Flowchart of the adopted methodology



3 Methods

3.1 Grey numbers

The concept of grey system theory and grey decision making systems was first introduced by Deng in the 1980s (Deng, 1982). As stated earlier, a grey number $\otimes G$ refers to as an interval with defined upper and lower limits, and undefined distribution information for G . Mathematically, it can be defined as follows:

$$\otimes G = [\underline{G}, \overline{G}] \quad (1)$$

where $\otimes G$ is an interval grey number having a lower limit $\underline{G}$ and upper limit $\overline{G}$ (here, $\underline{G} < \overline{G}$). The basic arithmetic operations on two grey numbers $\otimes G_1$ and $\otimes G_2$ are provided as below:

$$\otimes G_1 + \otimes G_2 = [\underline{G}_1 + \underline{G}_2, \overline{G}_1 + \overline{G}_2] \quad (2)$$

$$\otimes G_1 - \otimes G_2 = [\underline{G}_1 - \overline{G}_2, \overline{G}_1 - \underline{G}_2] \quad (3)$$

$$\otimes G_1 \times \otimes G_2 = [\min(\underline{G}_1 \underline{G}_2, \underline{G}_1 \overline{G}_2, \overline{G}_1 \underline{G}_2, \overline{G}_1 \overline{G}_2), \max(\underline{G}_1 \underline{G}_2, \underline{G}_1 \overline{G}_2, \overline{G}_1 \underline{G}_2, \overline{G}_1 \overline{G}_2)] \quad (4)$$

$$\otimes G_1 \div \otimes G_2 = [\underline{G}_1, \overline{G}_1] \times [\frac{1}{\overline{G}_2}, \frac{1}{\underline{G}_2}] \quad (5)$$

$$\text{Length of a grey number: } L(\otimes G_1) = \overline{G}_1 - \underline{G}_1 \quad (6)$$

For application in MCDM problems, it is often necessary to compare two grey numbers to determine the superiority of one over the other. To address this issue, the possibility degree of comparison is computed for two grey numbers as defined below:

$$P\{\otimes G_1 \leq \otimes G_2\} = \frac{\max(0, L^* - \max(0, \overline{G}_1 - \underline{G}_2))}{L^*} \quad (7)$$

Here, $L^* = L(\otimes G_1) + L(\otimes G_2)$. The term $P\{\otimes G_1 \leq \otimes G_2\}$ denotes the probability that $\otimes G_1 \leq \otimes G_2$. Therefore, the following conditions hold true:

a If $P\{\otimes G_1 \leq \otimes G_2\} < 0.5$, $\otimes G_1 > \otimes G_2$.

b If $P\{\otimes G_1 \leq \otimes G_2\} > 0.5$, $\otimes G_1 < \otimes G_2$.

The Euclidean distance between two grey numbers is estimated as shown below:

$$d(\otimes G_1, \otimes G_2) = \sqrt{(\underline{G}_1 - \underline{G}_2)^2 + (\overline{G}_1 - \overline{G}_2)^2} \quad (8)$$

In most of the practical problems, due to complexity of the decision making environment, presence of qualitative criteria and multiple experts, it is often difficult to provide the exact value of a criterion, but only the range of its value. The experts also feel

comfortable in expressing their judgements using linguistic variables, instead of crisp values as the information content in real-time database is usually incomplete and vague. To resolve the issue, non-deterministic information systems have been proposed to describe incomplete information, while fuzzy sets have been suitable to represent vague information (Yang and John, 2012). Grey systems have been developed to characterise both incompleteness and vagueness (fuzziness) in information, and have been evolved out as an effective tool to solve problems having partial information. They help in better representing uncertainty in a decision making process as compared to other uncertainty models, like fuzzy sets and rough sets. In grey theory, the exact value of a criterion is not known, but the value range within which it lies is known. The grey number is completely different from interval number (Li and Li, 2024). If a grey number is considered as an interval number, much information would be lost and the results may be inconsistent (Darvishi et al., 2019). Grey numbers have several advantages, like ability to deal with vague, imprecise, poor and noisy information, no need of any membership function, superior performance against fuzzy sets, ability to solve problems with minimum information etc. (Bakhat and Rajaa, 019). In the literature, many of MCDM tools have been fused with grey numbers to provide more pragmatic solutions. In this paper, it is combined with MABAC method to solve a textile supplier selection problem.

3.2 Grey-MABAC

The MABAC method, developed by Pamučar and Čirovic (2015), has already proved itself as an efficient tool in solving complex MCDM problems due to its simple computational steps and inbuilt robustness. In this method, using the computed performance scores, all the alternatives can be partitioned into two clusters, i.e., upper approximation area containing ideal (best performing) alternatives and lower approximation area consisting of anti-ideal (worst performing) alternatives. It has also the capability of evaluating performance of each of the alternatives along with its relative strengths and weaknesses over its competitors with reference to each criterion under consideration. When integrated with grey numbers, MABAC method can efficaciously solve MCDM problems considering qualitative evaluative criteria and linguistic perception of the decision makers. The procedural steps of G-MABAC method are delineated as shown below:

Let us consider an MCDM problem having a set of alternatives $A = [A_1, A_2, \dots, A_m]$ and a set of evaluation criteria $C = [C_1, C_2, \dots, C_n]$. Each alternative is evaluated against each criterion by a set of decision makers/experts $E = [E_1, E_2, \dots, E_K]$.

Step 1: Assign a level of relative importance to each expert based on his/her educational profile, experience and other factors in linguistic terms.

Step 2: Convert the linguistic importance of the experts into their corresponding grey numbers ($\otimes \lambda_k$) using an appropriate scale of conversion.

$$\lambda = [\otimes \lambda_1, \otimes \lambda_2, \dots, \otimes \lambda_K] \quad (9)$$

Step 3: Obtain the relative importance of each criterion from each expert in linguistic terms.

Step 4: Transform the linguistic terms into their corresponding grey numbers to form k weight vectors as follows:

$$W_k = [\otimes w_1, \otimes w_2, \dots, \otimes w_n], \forall k \in 1, 2, \dots, K \quad (10)$$

Step 5: Aggregate the relative weights assigned to each criterion by different experts to derive a single grey weight for each criterion as:

$$\omega = [\otimes \omega_1, \otimes \omega_2, \dots, \otimes \omega_n] \quad (11)$$

$$\otimes \omega_j = \frac{\sum_{k=1}^K \otimes \lambda_k \times \otimes w_j}{K} \quad (12)$$

where ω represents the vector of the aggregated grey criteria weights and each element ($\otimes \omega_j$) in ω denotes the aggregated grey weight for j th criterion.

Step 6: Obtain the linguistic evaluation of the performance of the alternatives against the criteria from the experts.

Step 7: Convert the linguistic ratings into their related grey numbers to form k initial decision matrixes (X_k).

$$X_k = [\otimes x_{ij}^k]_{m \times n}; \otimes x_{ij} = [\underline{x}_{ij}^k, \bar{x}_{ij}^k] \quad (13)$$

Step 8: Combine the initial decision matrices utilising the relative importance of the experts to form the aggregated decision matrix (X^a).

$$X^a = [\otimes x_{ij}]_{m \times n}; \otimes x_{ij} = \frac{\sum_{k=1}^K \otimes \lambda_k \times \otimes x_{ij}^k}{K} \quad (14)$$

Step 9: Normalise the aggregated grey performance ratings to form the normalised decision matrix (N).

$$N = [\otimes n_{ij}]_{m \times n}; \otimes n_{ij} = [\underline{n}_{ij}, \bar{n}_{ij}] \quad (15)$$

$$[\underline{n}_{ij}, \bar{n}_{ij}] = \left[\frac{\underline{x}_{ij}}{x_j^{\max}}, \frac{\bar{x}_{ij}}{x_j^{\max}} \right]; \forall j \in \text{Beneficial criteria} \quad (16)$$

$$[\underline{n}_{ij}, \bar{n}_{ij}] = \left[\frac{x_j^{\min}}{\bar{x}_{ij}}, \frac{x_j^{\min}}{\underline{x}_{ij}} \right]; \forall j \in \text{Cost criteria} \quad (17)$$

where $x_j^{\max} = \max \bar{x}_{ij}$ and $x_j^{\min} = \min \underline{x}_{ij}$.

Step 10: Multiply the aggregated grey criteria weights from Step (5) with the normalised ratings to form the weighted normalised decision matrix (V).

$$V = [\otimes v_{ij}]_{m \times n}; \otimes v_{ij} = \otimes \omega_j \times \otimes n_{ij} \quad (18)$$

Step 11: Compute the grey border approximate area (BAA) for each criterion.

$$\otimes u_j = \left[\underline{u}_j, \bar{u}_j \right] = \left[\left(\prod_{i=1}^m v_{ij} \right)^{1/m}, \left(\prod_{i=1}^m \bar{v}_{ij} \right)^{1/m} \right] \quad (19)$$

Step 12: Formulate the preference index matrix (Q) by measuring the Euclidean distance of the elements of V from the grey BAA of the corresponding criterion.

$$Q = [q_{ij}]_{m \times n} \quad (20)$$

$$q_{ij} = \begin{cases} d(\otimes v_{ij}, \otimes u_j), & \text{if } \otimes v_{ij} > \otimes u_j \\ -d(\otimes v_{ij}, \otimes u_j), & \text{if } \otimes v_{ij} < \otimes u_j \end{cases} \quad \text{for Beneficial criteria} \quad (21)$$

$$q_{ij} = \begin{cases} -d(\otimes v_{ij}, \otimes u_j), & \text{if } \otimes v_{ij} > \otimes u_j \\ d(\otimes v_{ij}, \otimes u_j), & \text{if } \otimes v_{ij} < \otimes u_j \end{cases} \quad \text{for Cost criteria} \quad (22)$$

Step 13: Compute the final score (S_i) for each alternative by taking the row-wise sum of the preference index matrix (Q).

$$S_i = \sum_{j=1}^n q_{ij} \quad (23)$$

The alternatives are ranked in descending order of S_i . In other words, the alternative having the farthest positive distance from the corresponding BAA value is considered to be the optimal choice. Thus, the BAA provides a benchmark to gauge the relative performance of the alternatives.

4 Grey-MABAC-based textile supplier selection

To illustrate application of G-MABAC method in solving a supplier selection problem for an Indian textile mill, six potential suppliers providing cotton fibres (in the form of bales), $S = \{S_1, S_2, S_3, S_4, S_5, S_6\}$ are first shortlisted and assessed based on six generic criteria. These criteria are cost (C_1) (Ulutas, 2019; Burney and Ali, 2019; Bakhat and Rajaa, 2019; Celik et al., 2020; Karami et al., 2021; Utama et al., 2021; Lahdhiri et al., 2022; Kao et al., 2022; Paul et al., 2022; Caristi et al., 2022; Wang et al., 2022a), quality (C_2) (Ulutas, 2019; Burney and Ali, 2019; Bakhat and Rajaa, 2019; Celik et al., 2020; Nakiboglu and Bulgurcu, 2021; Karami et al., 2021; Utama et al., 2021; Lahdhiri et al., 2022; Kao et al., 2022; Kao, 2022; Paul et al., 2022; Wang et al., 2022b), delivery (C_3) (Ulutas, 2019; Burney and Ali, 2019; Bakhat and Rajaa, 2019; Nakiboglu and Bulgurcu, 2021; Karami et al., 2021; Utama et al., 2021; Paul et al., 2022), flexibility (C_4) (Ulutas, 2019; Bakhat and Rajaa, 2019; Paul et al., 2022; Caristi et al., 2022; Wang et al., 2022a), capability (C_5) (Ulutas, 2019; Bakhat and Rajaa, 2019; Celik et al., 2020; Nakiboglu and Bulgurcu, 2021; Kao et al., 2022; Paul et al., 2022) and payment terms (C_6) (Nakiboglu and Bulgurcu, 2021; Paul et al., 2022).

It has already been mentioned that in this paper, based on the works of the past researchers, a textile supplier selection problem is solved considering three experts, six suppliers and six criteria, while making the computational steps simple without losing much information. It can be noticed from Table 1 that the average number of textile suppliers considered by the past researchers is 5.8. Thus, in this paper, six textile suppliers are considered to make the computation simple, without loss of much information. Similarly, almost all the researchers dealing with supplier selection problems have unanimously considered opinions of three decision makers/experts in the group decision making environment. In a typical textile mill, the raw material (mainly in the form of cotton fibres) contributes approximately 60–70% of the total end product cost. Thus, if the cotton fibres can be procured at low cost satisfying the quality requirements, the final yarn cost would also be low capturing a large volume of customers. Quality of the fibres with respect to length, tenacity, elongation, maturity, fineness, colour, short fibre content etc. is also a major determinant in assessing the supplier's performance. Delivery criterion considers reliable, consistent and timely supply of cotton fibres without sacrificing cost and quality. A faulty or late delivery may have adverse effects of the entire supply chain, with loss of customers. On the other hand, a set of flexible suppliers can help a textile mill to respond quickly to the changing customer requirements and sudden emergencies, while avoiding disruption in the supply chain. If the mill shortens the lead time to reach the customers, a supplier proffering fast delivery would be rated more. Capability of a supplier includes several factors, like ability to meet current and future requirements, financial stability, logistics, integration of the IoT etc. Finally, payment terms are the conditions and parameters that a supplier sets for a customer regarding payment for a product/service. These include such considerations as whether the payment can be made in instalments, through credit or cash, whether interest would be charged, when payment should be finalised etc.

For solving the said textile supplier selection problem employing G-MABAC method, the opinions of three experts are first sought in regard of the relative importance allocated to the evaluation criteria and performance of the candidate suppliers against each criterion. The profile of each of the experts is exhibited in Table 2. It can be noticed from Table 2 that depending on their academic qualification, experience and technical knowledge, the opinions of the spinning department in-charge and quality control in-charge are treated as 'very important' and 'important', respectively. The opinion of the procurement department in-charge is considered as 'moderately important'. It is observed that while assigning relative importance to the qualitative criteria and performance of the alternative suppliers with respect to those criteria, the experts have preferred to adopt linguistic variables, instead of discrete crisp numbers. The linguistic variables and the corresponding grey numbers (Nyaoga et al., 2016) considered here for evaluation of criteria significance and expert importance are provided in Table 3. Similarly, for appraising performance of the textile suppliers with respect to each of the criteria, the corresponding linguistic variables and grey numbers, as shown in Table 4, are considered (Pamucar et al., 2021b).

Table 2 Profile of the experts

<i>Expert</i>	<i>E₁</i>	<i>E₂</i>	<i>E₃</i>
Experience	10 years	12 years	8 years
Occupation	In-charge of quality control department	In-charge of the spinning department	In-charge of the procurement department
Qualification	Bachelor's in Textile Technology	Master's in fibre Technology	Master's in Business Administration
Importance	I	VI	MI

Table 3 Grey numbers for linguistic evaluations of criteria and experts

<i>Linguistic variable</i>	<i>Grey number</i>	
Very important (VI)	0.80	1.00
Important (I)	0.60	0.80
Moderately important (MI)	0.40	0.60
Unimportant (UI)	0.20	0.40
Very unimportant (VUI)	0.00	0.20

Table 4 Grey numbers for linguistic evaluation of the suppliers

<i>Linguistic variable</i>	<i>Grey number</i>	
Very poor (VP)	1	10
Poor (P)	11	20
Medium poor (MP)	21	30
Fair (F)	31	40
Medium good (MG)	41	50
Good (G)	51	60
Very good (VG)	61	70

Following the procedural steps of G-MABAC method, each of the experts has been asked to evaluate the criteria importance as well as performance of the textile suppliers with respect to each criterion in terms of linguistic variables (provided in Tables 3 and 4, respectively), as exhibited in Table 5. It can be observed that expert E_1 assesses the importance of the six criteria (C_1 , C_2 , C_3 , C_4 , C_5 and C_6) as VI, I, I, MI, MI and UI, respectively. On the other hand, expert E_1 appraises performance of all the six suppliers against criterion C_1 as VG, G, MG, F, VG and MG, respectively. Thus, according to expert E_1 , supplier S_1 provides cotton fibres at least cost, having good quality, moderately good capability and payment terms, and moderately poor delivery performance and flexibility. In Table 4, higher ratings of the corresponding linguistic variables symbolise superior performance of the suppliers with respect to lower cost, and better quality, delivery, flexibility, capability and payment terms. Now, using the ratings, provided in Table 4, these linguistic evaluations of the suppliers by the experts are transformed into

their corresponding grey numbers, as shown in Table 6. Table 7 depicts the relative significance assigned to each of the experts, which are subsequently converted into their related grey numbers, based on the information provided in Table 3. Now, employing equation (12), weights allocated to each criterion by the individual experts are fused together to calculate the grey aggregated criteria weights, contemplating the relative importance assigned to each expert. These grey aggregated criteria weights are provided in Table 8 and also portrayed in Figure 2. It is revealed that cost (C_1) is the most important criterion (length of the grey numbers/degree of greyness = 0.320), followed by quality (C_2) (0.267). On the other hand, delivery (C_3), flexibility (C_4) and capability (C_5) have similar importance (0.253), while payment terms (C_6) is the least important criterion (0.227).

Table 5 Linguistic evaluations of the criteria and alternatives by the experts

E_1	Criteria weight	VI	I	I	MI	MI	UI
	Supplier/Criteria	C_1	C_2	C_3	C_4	C_5	C_6
	S_1	VG	G	MP	MP	MG	MG
	S_2	G	MG	G	MP	G	P
	S_3	MG	G	G	F	F	P
	S_4	F	VG	G	MP	VP	VP
	S_5	VG	P	G	MG	P	F
	S_6	MG	G	P	F	MG	G
E_2	Criteria weight	VI	MI	MI	MI	I	I
	Supplier/Criteria	C_1	C_2	C_3	C_4	C_5	C_6
	S_1	MG	G	F	P	G	F
	S_2	F	P	MG	F	F	VP
	S_3	VG	G	F	MG	VG	F
	S_4	G	MG	VG	P	MP	MG
	S_5	P	G	MG	VG	F	G
	S_6	MG	P	G	VG	F	P
E_3	Criteria weight	VI	I	MI	I	MI	UI
	Supplier/Criteria	C_1	C_2	C_3	C_4	C_5	C_6
	S_1	G	MG	G	F	MP	VG
	S_2	VG	F	G	P	MG	G
	S_3	MG	MG	F	F	G	VG
	S_4	VG	VG	P	MP	VP	G
	S_5	F	G	MG	VG	G	F
	S_6	MG	G	VG	F	VG	P

Table 6 Performance evaluation of the alternatives by the experts using grey numbers

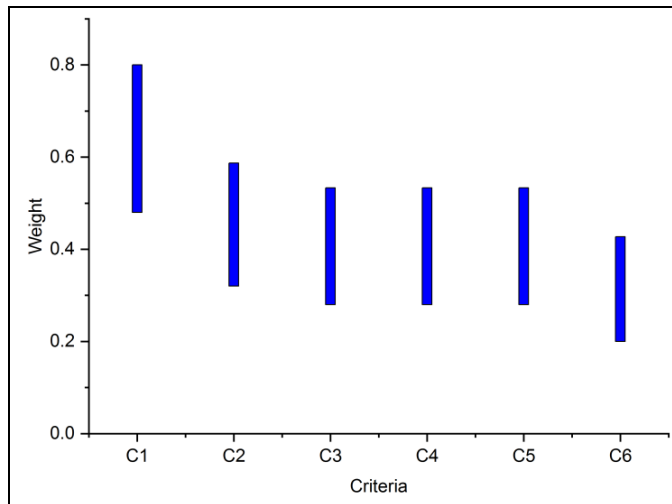
<i>Expert</i>	<i>Supplier</i>	C_1		C_2		C_3		C_4		C_5		C_6	
E_1	S_1	61	70	51	60	21	30	21	30	41	50	41	50
	S_2	51	60	41	50	51	60	21	30	51	60	11	20
	S_3	41	50	51	60	51	60	31	40	31	40	11	20
	S_4	31	40	61	70	51	60	21	30	1	10	1	10
	S_5	61	70	11	20	51	60	41	50	11	20	31	40
	S_6	41	50	51	60	11	20	31	40	41	50	51	60
E_2	<i>Supplier</i>	C_1		C_2		C_3		C_4		C_5		C_6	
	S_1	41	50	51	60	31	40	11	20	51	60	31	40
	S_2	31	40	11	20	41	50	31	40	31	40	1	10
	S_3	61	70	51	60	31	40	41	50	61	70	31	40
	S_4	51	60	41	50	61	70	11	20	21	30	41	50
	S_5	11	20	51	60	41	50	61	70	31	40	51	60
	S_6	41	50	11	20	51	60	61	70	31	40	11	20
E_3	<i>Supplier</i>	C_1		C_2		C_3		C_4		C_5		C_6	
	S_1	51	60	41	50	51	60	31	40	21	30	61	70
	S_2	61	70	31	40	51	60	11	20	41	50	51	60
	S_3	41	50	41	50	31	40	31	40	51	60	61	70
	S_4	61	70	61	70	11	20	21	30	1	10	51	60
	S_5	31	40	51	60	41	50	61	70	51	60	31	40
	S_6	41	50	51	60	61	70	31	40	61	70	11	20

Table 7 Importance of the experts expressed in grey numbers

<i>Expert</i>	<i>Linguistic variable</i>		$\otimes \lambda_k$	
E_1	I		0.6	0.8
E_2	VI		0.8	1.0
E_3	MI		0.4	0.6

Table 8 Aggregated grey criteria weights in grey numbers

<i>Criteria</i>	E_1		E_2		E_3		<i>Aggregated weight</i>	
C_1	0.80	1.00	0.80	1.00	0.80	1.00	0.480	0.800
C_2	0.60	0.80	0.40	0.60	0.60	0.80	0.320	0.587
C_3	0.60	0.80	0.40	0.60	0.40	0.60	0.280	0.533
C_4	0.40	0.60	0.40	0.60	0.60	0.80	0.280	0.533
C_5	0.40	0.60	0.60	0.80	0.40	0.60	0.280	0.533
C_6	0.20	0.40	0.60	0.80	0.20	0.40	0.200	0.427

Figure 2 Relative importance of the considered criteria (see online version for colours)

In the subsequent steps, following the mathematical operations of grey numbers, as shown in Section 3.1, the performance evaluation matrices of the alternatives by the three experts are combined together to formulate a single aggregated decision matrix, as shown in Table 9. As the aggregated decision matrix has not all of its elements in the range of $[0, 1]$, it needs to be normalised depending on the type of the criterion under consideration. Thus, based on the normalisation equations, the corresponding normalised decision matrix is subsequently developed, as depicted in Table 10. The elements of the normalised decision matrix are then multiplied by the predetermined grey criteria weights to frame the weighted normalised decision matrix, as shown in Table 11. In the next step, using equation (19), the corresponding grey BAA matrix is computed, as also exhibited in Table 11. Using the information provided in Table 11, and based on equation (21), the preference index matrix is now developed while measuring the Euclidean distance of the elements of the weighted normalised decision matrix from the grey BAA of each of the criteria against each textile supplier. This preference index matrix is exhibited in Table 12. Row-wise summation of the elements of the preference index matrix provides the final score (S_i) for each textile supplier. In Table 12, when all the competing suppliers are ranked in descending order of their performance scores, it can be revealed that S_3 is the best performing supplier, followed by S_1 . The performance of S_2 is noticed to be the worst.

Table 9 Aggregated decision matrix

Supplier	C_1		C_2		C_3		C_4		C_5		C_6	
S_1	29.933	47.333	29.267	46.000	19.267	33.333	11.267	22.667	24.600	39.333	24.600	40.667
S_2	26.600	43.333	15.267	28.000	27.933	44.667	13.933	25.333	23.933	39.333	9.267	20.667
S_3	29.933	46.667	29.267	46.000	22.600	37.333	21.267	35.333	29.267	46.000	18.600	32.667
S_4	27.933	44.667	31.267	49.333	27.933	43.333	9.933	20.667	5.933	14.667	17.933	31.333
S_5	19.267	33.333	22.600	37.333	26.600	42.667	32.600	50.667	17.267	30.667	23.933	38.667
S_6	24.600	40.000	19.933	34.667	23.933	39.333	26.600	42.000	24.600	40.667	14.600	26.667

Table 10 Normalised decision matrix

<i>Supplier</i>	C_1		C_2		C_3		C_4		C_5		C_6	
S_1	0.632	1.000	0.593	0.932	0.431	0.746	0.222	0.447	0.535	0.855	0.605	1.000
S_2	0.562	0.915	0.309	0.568	0.625	1.000	0.275	0.500	0.520	0.855	0.228	0.508
S_3	0.632	0.986	0.593	0.932	0.506	0.836	0.420	0.697	0.636	1.000	0.457	0.803
S_4	0.590	0.944	0.634	1.000	0.625	0.970	0.196	0.408	0.129	0.319	0.441	0.770
S_5	0.407	0.704	0.458	0.757	0.596	0.955	0.643	1.000	0.375	0.667	0.589	0.951
S_6	0.520	0.845	0.404	0.703	0.536	0.881	0.525	0.829	0.535	0.884	0.359	0.656

Table 11 Weighted normalised decision matrix and grey BAA values

<i>Supplier</i>	C_1		C_2		C_3		C_4		C_5		C_6	
S_1	0.304	0.800	0.190	0.547	0.121	0.398	0.062	0.239	0.150	0.456	0.121	0.427
S_2	0.270	0.732	0.099	0.333	0.175	0.533	0.077	0.267	0.146	0.456	0.046	0.217
S_3	0.304	0.789	0.190	0.547	0.142	0.446	0.118	0.372	0.178	0.533	0.091	0.343
S_4	0.283	0.755	0.203	0.587	0.175	0.517	0.055	0.218	0.036	0.170	0.088	0.329
S_5	0.195	0.563	0.147	0.444	0.167	0.509	0.180	0.533	0.105	0.356	0.118	0.406
S_6	0.249	0.676	0.129	0.412	0.150	0.470	0.147	0.442	0.150	0.471	0.072	0.280
BAA	0.265	0.714	0.155	0.469	0.154	0.477	0.097	0.327	0.114	0.383	0.085	0.325

Table 12 Preference index matrix and final ranking of the textile suppliers

<i>Supplier</i>	C_1	C_2	C_3	C_4	C_5	C_6	S_i	<i>Rank</i>
S_1	0.094	0.085	-0.085	-0.095	0.081	0.108	0.188	2
S_2	0.019	-0.147	0.061	-0.063	0.079	-0.115	-0.167	6
S_3	0.084	0.085	-0.033	0.050	0.163	0.019	0.368	1
S_4	0.045	0.127	0.046	-0.117	-0.227	0.005	-0.121	5
S_5	-0.166	-0.027	0.035	0.223	-0.029	0.087	0.123	3
S_6	-0.041	-0.063	-0.008	0.126	0.095	-0.047	0.062	4

When these suppliers are positioned in Figure 3 considering their performance scores, it can be noticed that there are four suppliers (S_3 , S_1 , S_5 and S_6) in the upper approximation area having superior performance reliably satisfying almost all the requirements of the said textile mill. The location of supplier S_3 in the extreme left corner of the upper approximation area confirms its top position in the derived ranking list. On the contrary, there are two underperforming suppliers (S_2 and S_4) positioned in the lower approximation area. The worst performance of supplier S_2 is validated based on its location in the extreme right corner of the lower approximation area. In Figure 3, clustering of the alternatives in upper and lower approximation areas helps in identifying them as reliable and unreliable suppliers. For adoption of multi-sourcing strategy and undisrupted supply chain, orders may now be proportionally allocated among the reliable suppliers for streamlined production of the considered textile mill. On the other hand, allocation of orders to the unreliable suppliers may be risky with violated contracts, credit damage and delays. Figure 4 plots the relative performance of the suppliers against each

criterion under consideration. It can be interestingly unveiled that the best supplier (S_3) performs excellently with respect to all the evaluation criteria, except delivery criterion (C_3). Although supplier S_2 performs well against criteria C_1 (cost), C_3 (delivery) and C_5 (capability), its performance is notably poor with respect to criteria C_2 (quality), C_4 (flexibility) and C_6 (payment terms). Thus, supplier S_3 can now act as a benchmark to the other underperforming suppliers in increasing efficiency, sales performance and quality, setting clear business goals, better understanding the market competition and identifying areas of continuous improvement.

Figure 3 Positions of the textile suppliers in upper and lower approximation areas (see online version for colours)

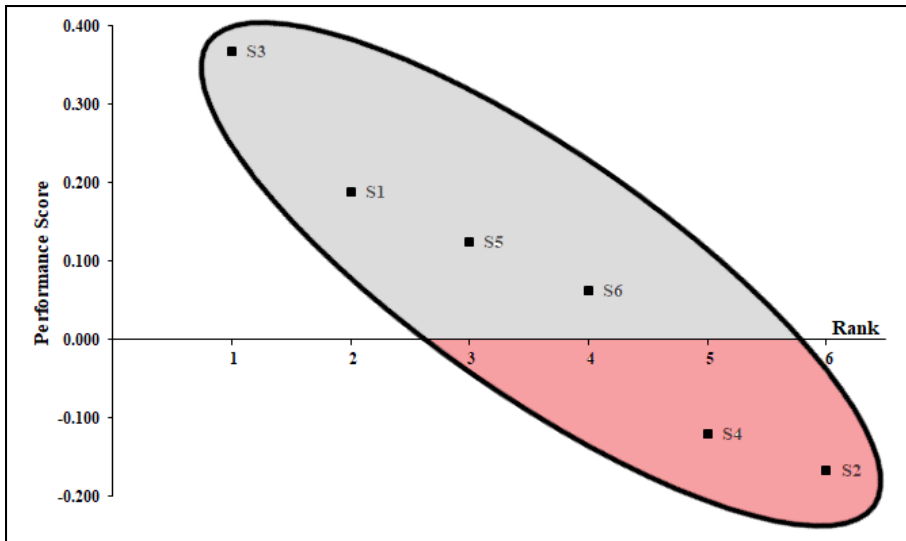
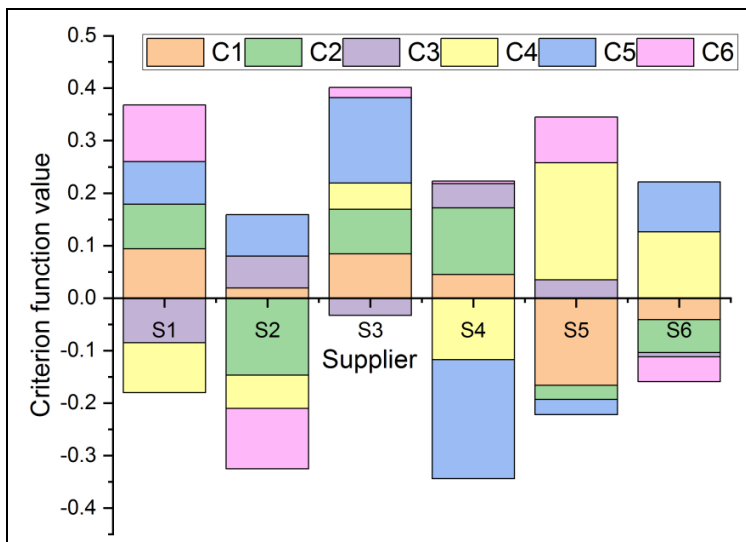


Figure 4 Relative performance of the suppliers with respect to each criterion (see online version for colours)



Finally, the ranking performance of G-MABAC method is contrasted against that of other popular grey-integrated MCDM techniques, like G-WASPAS, G-MOORA, G-TOPSIS and G-VIKOR. It is interestingly noticed that in all the methods, the ranking positions of the best and worst textile suppliers remain unaltered. But, there are significant discrepancies in the intermediate rankings of the considered suppliers which may be attributed to dissimilar mathematical models (mainly normalisation procedure) of the adopted G-MCDM methods.

5 Conclusions

Keeping in mind the independency of grey numbers on exact membership functions, inherent probability distribution and large data, and simplicity of MABAC method, both are integrated in this paper for solving a textile supplier selection problem in a uncertain group decision making framework. The importance of three decision makers, six evaluation criteria and six textile suppliers are first assessed using interval grey numbers. Considering the corresponding aggregated crisp performance scores, application of MABAC partitions the alternative suppliers into upper approximation area (best performing/reliable) and lower approximation area (worst performing/unreliable). It would be helpful to adopt multi-sourcing strategy, thereby avoiding unprecedented disruption in supply chain or overcoming inadequate supply capacity of a single supplier. Acknowledging the best supplier as the benchmark would also assist the underperforming suppliers in better understanding their weaknesses and identifying areas of future improvement to remain competitive in the global textile market. The main limitation of this paper is involvement of lengthy mathematical steps which may be overcome by designing and developing a suitable decision support system for automated decision making with minimum human intervention. Integration of MABAC with other uncertainty models, like interval rough numbers, interval fuzzy numbers, D-numbers etc. for solving textile supplier selection problems may be the future scope of this paper. Future research may also be directed towards exploring effectiveness of G-MABAC method in dealing with green supplier selection problems taking various social, economical, technical and environmental criteria into consideration. It is worthwhile to mention here that as this supplier selection problem is developed considering six generic criteria, i.e., cost, quality, delivery, flexibility, capability and payment terms, it can also be successfully deployed to other industries, like manufacturing, automobile, healthcare etc. with involvement of the concerned experts having sufficient knowledge and experience in those domains.

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Conflicts of interest

No potential conflict of interest was reported by the author(s).

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