SUPPLIER SELECTION IN TEXTILE INDUSTRIES USING INTEGRATED MULTI-CRITERIA DECISION MAKING APPROACHES

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THESIS

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1. INTRODUCTION:

1.1 Overview of Textile Industry and Supplier Selection Problem:

In today's highly competitive global market, supply chain management has emerged out as a major decisive process of efficiently organizing all the activities from the placement of customers' orders to the timely and cost-effective delivery of the end products. It emphasizes on seamless integration of suppliers, producers, distributors, retailers and customers for achieving their goals through transformation of raw materials into quality products (Tayyab & Sarkar, 2021). The basic objective of supply chain management is focused on producing the right product for the right customer in the right amount and at the right time. Supplier evaluation and selection appears to be one of the key determinants for the success of supply chain, influencing the long-term commitment and performance of any manufacturing organization. Suppliers have varying strengths and weaknesses which require careful appraisal before they are ranked based on some specified evaluation criteria. Supplier selection thus deals with short-listing a set of competent suppliers having the highest potential to consistently fulfil the manufacturing organization's needs with an acceptable overall performance. An efficient supplier selection process reduces purchasing risks, ensures uninterrupted production, maximizes overall value for the buyers, develops proximity and long-term relationships between buyers and suppliers, and maximizes benefits by improving the organization's performance. An improper supplier selection decision may have severe detrimental effects, like shortage of raw material inventory, undue interruption in the production process etc. (Amindoust & Saghafinia, 2016; Acar et al., 2016).

The industry is extremely varied, with hand-spun and hand-woven textiles sectors at one end of the spectrum, with the capital-intensive sophisticated mills sector on the other end. The decentralised power looms/ hosiery and knitting sector forms the largest component in the textiles sector. India's textiles industry has around 4.5 crore employed workers including 35.22 lakh handloom workers across the country. Exports of textiles (RMG of all textiles, cotton yarns/fabs/made-ups/handloom products, man-made yarns/fabs/made-ups, handicrafts excluding handmade carpets, carpets and jute mfg. including floor coverings) stood at US$ 29.8 billion between April-December 2021. The Indian textiles market is expected to be worth more than US$ 209 billion by 2029. India is the world's largest producer of cotton. Production stood at 360.13 lakh bales for the crop year October 2021-September 2022. Domestic consumption for the 2021-22 crop year is estimated to be at 335 lakh bales. Production of fibre in India reached 2.40 MT in FY21 (till January 2021), while that for yarn, the production stood at 4,762 million kgs during same period. India's home textile exports grew at a healthy rate of 9% in FY21 despite the pandemic. In the year 2020-21, 1.13 million tonnes of cotton yarn were exported from India. The textiles industry (including dyed and printed) attracted Foreign Direct Investment (FDI) worth US$ 3.93 billion from April 2000-December 2021.

In November 2021, Federico Salas, the Mexican Ambassador to India, visited the Khadi India Pavilion at the India International Trade Fair 2021 and suggested that India and Mexico should come together to promote Khadi globally. Companies in home textile are using technology to optimise the value chain. For example, in October 2021, Welspun India introduced Wel-Trak 2.0—an upgraded, patented end-to-end traceability technology—to track textile raw materials throughout the supply chain. In October 2021, Welspun India collaborated with DuPont Biomaterials to introduce a home textile range and strengthen the company's sustainable textiles business. Indian government has allowed 100% FDI in the sector under the automatic route. The Rs. 10,683 crore (US$ 1.44 billion) PLI scheme is expected to be a major booster for the textile manufacturers. The scheme proposes to incentivise MMF (man-made fibre) apparel, MMF fabrics and 10 segments of technical textiles products. In March 2022, the Bihar government submitted a proposal to the Union Textiles Ministry to set up a mega hub under the PM Mitra Mega Textile Park. In March 2022, Tamil Nadu Chief Minister Mr. MK Stalin announced that the State Industries Promotion Corporation of Tamil Nadu Ltd (SIPCOT) will set up a mega textile park in the Virudhunagar district. Under Union Budget 2022-23, the total allocation for the textile sector was Rs. 12,382 crore (US$ 1.62 billion). Out of this, Rs.133.83 crore (US$ 17.5 million) is for Textile Cluster Development Scheme, Rs. 100 crore (US$ 13.07 million) for National Technical Textiles Mission, and Rs. 15 crore (US$ 1.96 million) each for PM Mega Integrated Textile Region and Apparel parks scheme and the Production Linked Incentive Scheme. For the export of handloom products globally, Handloom Export Promotion Council (HEPC) is participating in various international fairs/events with handloom exporters/weavers to sell their handloom products in the international markets under NHDP. The Ministry of Textiles has also been implementing Handloom Marketing Assistance (HMA), a component of the National Handloom Development Programme (NHDP), all across India. HMA provides a marketing platform to the handloom weavers/agencies to sell their products directly to the consumers, and develop and promote the marketing channel through organizing expos/events in domestic as well as export markets. In November 2021, Union Minister of Textiles, Commerce and Industry, Consumer Affairs & Food and Public Distribution, Mr. Piyush Goyal, stated the desire to target a 3-5x time increase in the export of technical textiles worth US$ 10 billion over the next three years. Union Minister of Textiles, Commerce and Industry, Consumer Affairs & Food and Public Distribution, Mr. Piyush Goyal announced a mega handloom cluster in Manipur and a handloom and handicraft village at Moirang in Bishnupur. The mega cluster will be set up at an estimated cost of Rs. 30 crore (US$ 4.03 million) under the National Handloom Development Programme (NHDP). In October 2021, Union Minister for Commerce and Industry, Textiles, Consumer Affairs, Food & Public Distribution, Mr. Piyush Goyal, announced the creation of 100 textile machinery champions in the country and to promote it in the global market. Through this, the government aims to make India a global player in textiles machinery. In October 2021, the Ministry of Textiles approved continuation of the comprehensive handicrafts cluster development scheme with a total outlay of Rs. 160 crore (US$ 21.39 million).

Through this scheme, the government aims to support domestic SMEs and local artisans. In October 2021, the government introduced SAMARTH training at 75 training centers across the country, to accelerate the scheme's coverage among artisans. The government allocated funds worth Rs. 17,822 crore (US$ 2.38 billion) between FY16 and FY22 for the 'Amended Technology Up-gradation Fund Scheme' (A-TUFS), to boost the Indian textile industry and enable ease of doing business. Techtextil India, a trade fair focused on technical textiles, nonwovens and composites was held from 25th to 27th November 2021 in Mumbai. Tamil Nadu government signed up for Techtextil India 2021 to strengthen indigenous textile production and attract textile investments into the State. The State government promoted technical textile policies through both physical and virtual segments of the hybrid fair organised by Messe Frankfurt Trade Fairs India. In August 2021, Minister of State (MoS), Ministry of Petroleum & Natural Gas and Labour & Employment, Mr. Rameswar Teli launched ONGC-supported Assam handloom project 'Ujjwal Abahan' through the virtual platform. The project will support and train >100 artisans of Bhatiapar of Sivasagar, Assam in Hathkharga handicraft. In August 2021, Flipkart and Himachal Pradesh State Handicrafts and Handloom Corporation Ltd. (HPSHHCL) signed a memorandum of understanding (MoU) to help the state's master craftsmen, weavers and artisans showcase their hallmark products on e-commerce platforms. In July 2021, the government extended the Rebate of State and Central Taxes and Levies (RoSCTL) scheme for exports of apparel/garments and made ups until March 2021. This will help boost exports and enhance competitiveness in the labour-intensive textiles sector. To support the handloom weavers/weaver entrepreneurs, the Weaver MUDRA Scheme was launched to provide margin money assistance at 20% of the loan amount subject to a maximum of Rs. 10,000 (US$ 134.22) per weaver. The loan is provided at an interest rate of 6% with credit guarantee of three years. Gorakhpur is on track to become a major garment manufacturing centre, boosting the economy in eastern Uttar Pradesh. The Gorakhpur Industrial Development Authority (GIDA) will provide four acres of land for construction of a flattened factory and will enable access to entrepreneurs. In March 2021, The Ministry of Textiles favoured limited deal for the India-UK free trade agreement that could boost the garments sector. Effective 1 January 2021, to boost exports, the government has extended the benefit of the Scheme for Remission of Duties and Taxes on Exported Products (RoDTEP) to all exported goods Defence Research and Development Organisation (DRDO) is helping the Indian textile industry to produce yarns and eliminate dependence on import of Chinese and other foreign clothing for military uniforms. Indian defence sector has expressed support towards the Indian technical textile sector. In March 2021, while addressing the 9th edition of TECHNOTEX 2021 organized by FICCI, General Bipin Rawat, Chief of Defence Staff appreciated the innovations in Indian technical textiles and stated that the armed forces will rather reduce imports and instead procure technical textiles from Indian industries as a part of the Atmanirbhar Bharat initiative. Under the Scheme for Integrated Textile Parks (SITP), 59 textile parks were sanctioned, out of which, 22 have been completed.

Sangam India Ltd, one of the foremost producers in PV dyed yarn, cotton and OE yarn and also ready to stitch fabric, has installed two solar power plants of 5 MW that, on average, helps them to bring down their carbon footprint by at least 20% per annum. SIL also plans to increase the use of recycled fibre, leading to lesser consumption of plastic waste by using it as a raw material. India is working on major initiatives, to boost its technical textile industry. Owing to the pandemic, the demand for technical textiles in the form of PPE suits and equipment is on rise. The government is supporting the sector through funding and machinery sponsoring. Top players in the sector are attaining sustainability in their products by manufacturing textiles that use natural recyclable materials. *(Source: Ministry of Textiles, Indian Textile Journal, Department of Industrial Policy and Promotion, Press Information Bureau)*

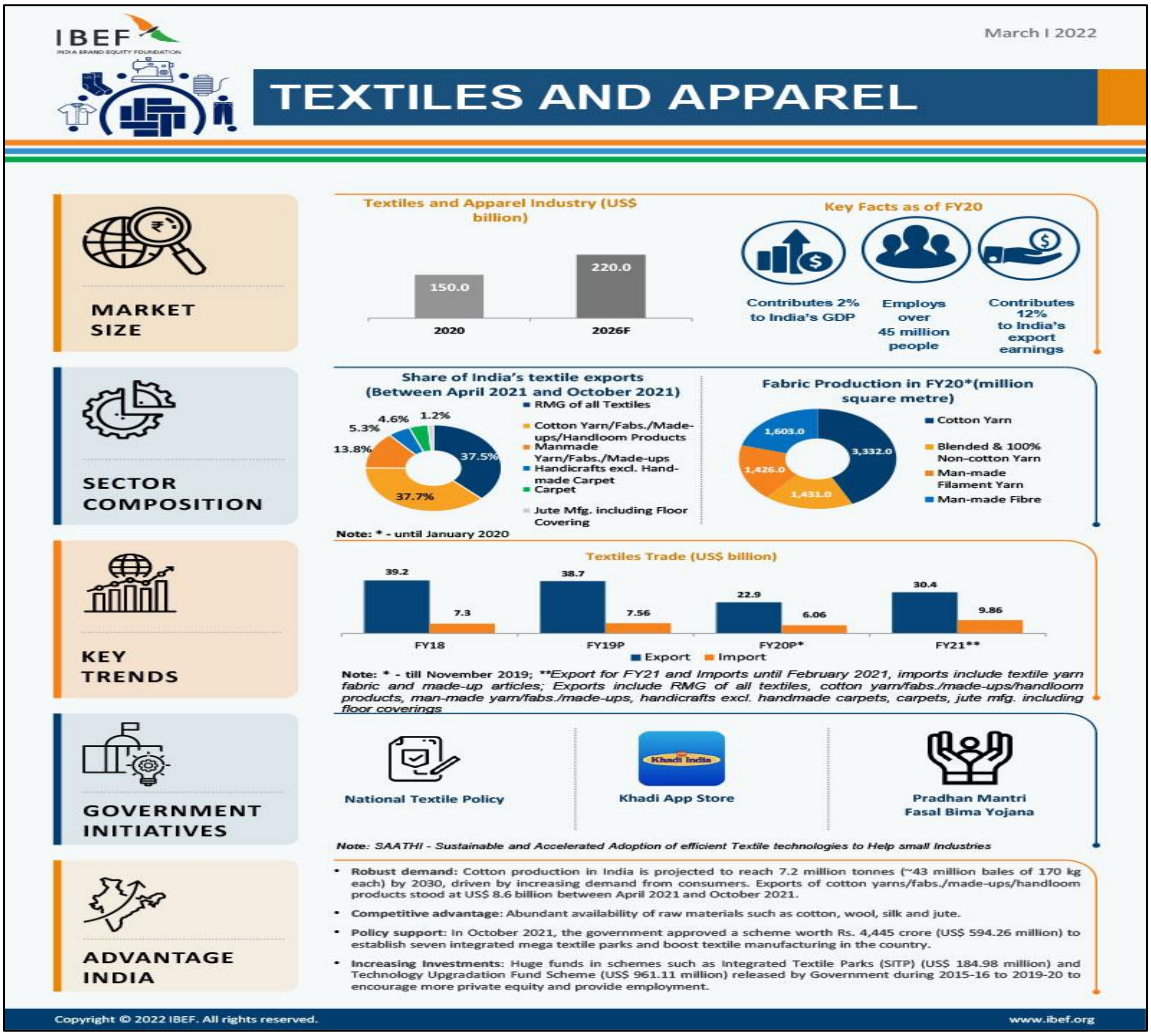
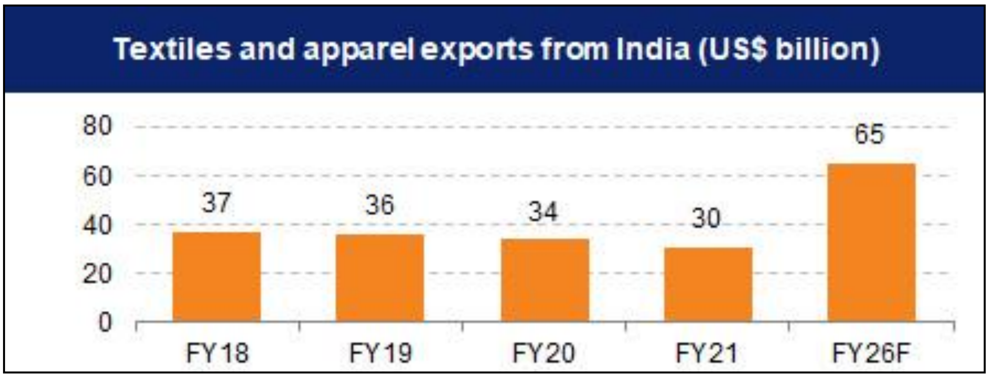


Figure 1.1 Info-graphics of textile industry in India
(Source:https://www.ibef.org/uploads/industry/Infrographics/small/textiles-and-apparel-infographic-feb-22.jpg)



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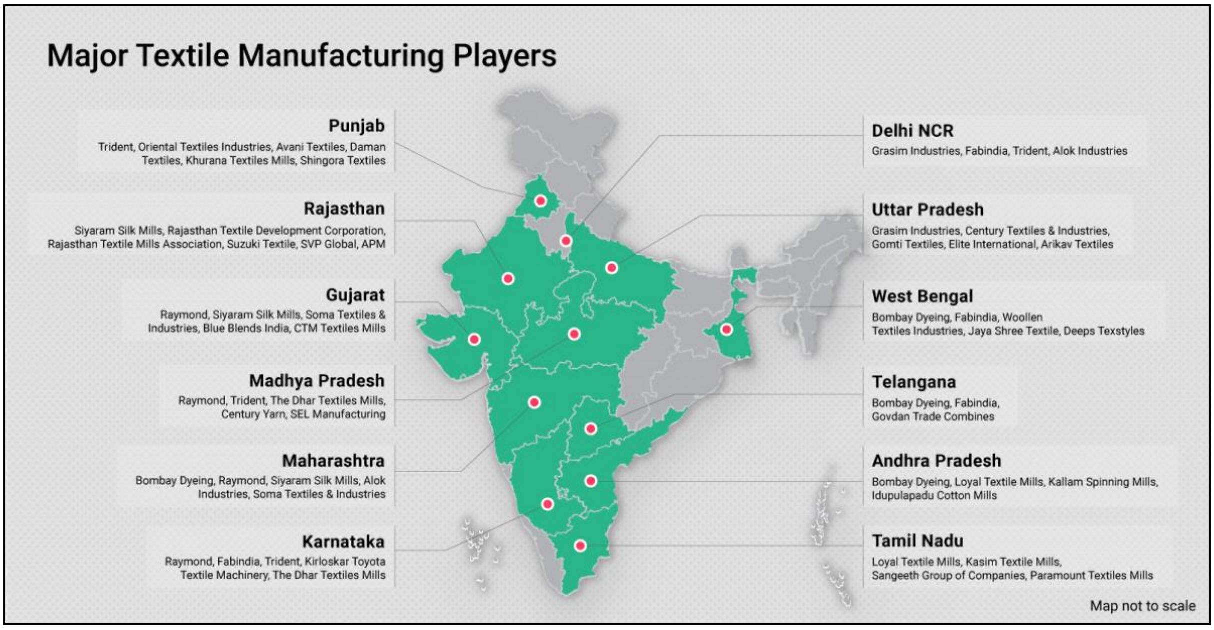
(Source: https://www.ibef.org/assets/images/charts/textile-and-apparel.jpg)



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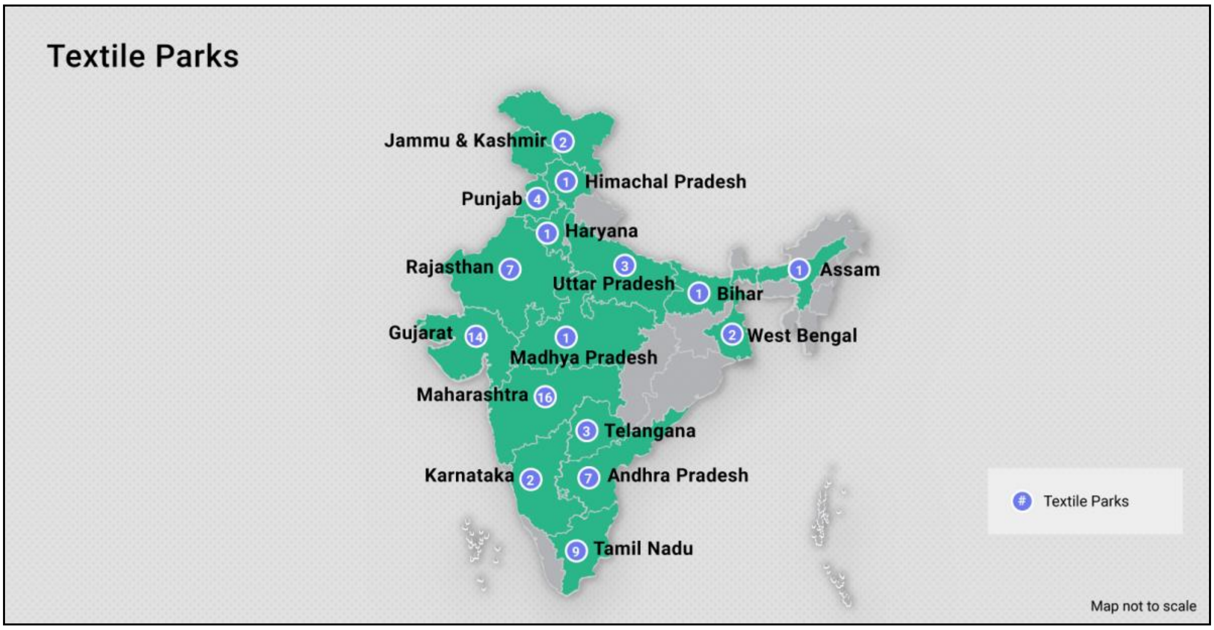
(Source:https://static.investindia.gov.in/s3fs-public/styles/clusters_banner/public/2019-11/Textiles_Cluster-Map.png?itok=DTeaowCP)



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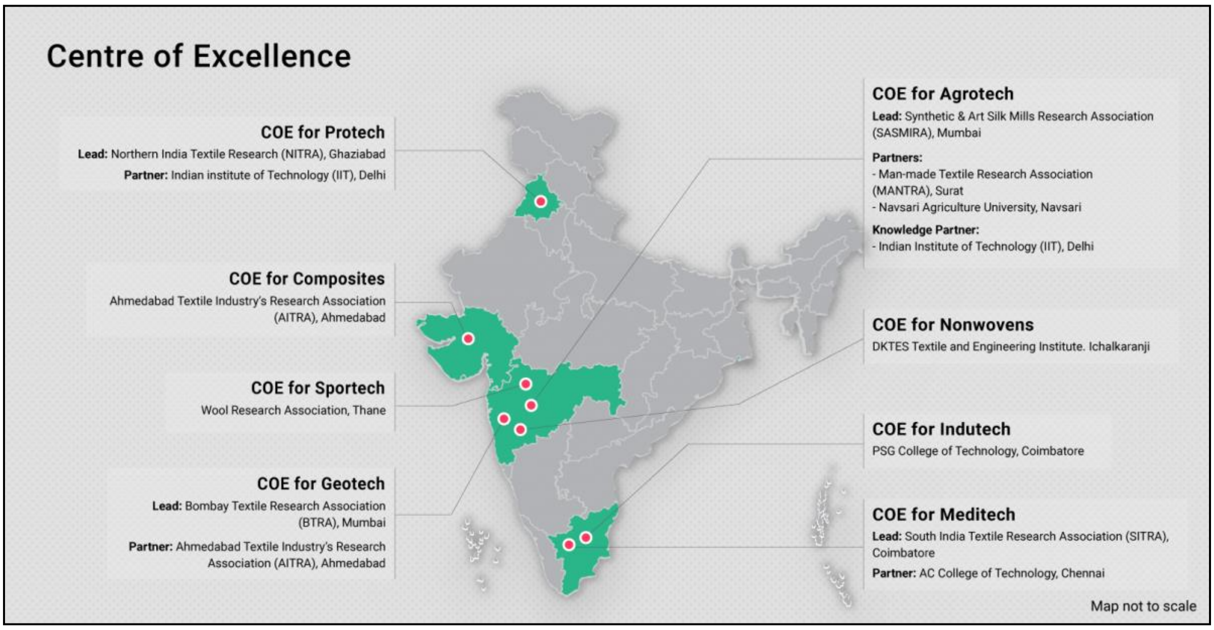
(Source:https://static.investindia.gov.in/s3fs-public/styles/clusters_banner/public/2019-11/Textiles-Park--Map.png?itok=PWhdAaEn)



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(Source:https://static.investindia.gov.in/s3fs-public/styles/clusters_banner/public/2019-11/Centre-of-Excellence.png?itok=ZD4QLX-e)

1.2 Need for Selecting Suppliers in a Textile Industry

Like all other manufacturing industries, evaluation and selection of a set of competent suppliers also plays a key role in timely and cost-effective delivery of raw materials (cotton and other allied fibers, yarn or fabric), chemicals and dyes, machineries, spare parts and other auxiliary components/items in a textile industry. Those suppliers should provide the items that are matched to the textile industry's needs and requirements. Thus, it has now become critical to clearly identify the industry's needs and what it actually wants to procure before selecting a supplier. Selection of suppliers from a large number of candidate choices having varying potentialities and capabilities is a complex task due to involvement of several qualitative and quantitative evaluation criteria (Nong & Ho, 2019). Conflicting nature of the criteria also makes the supplier selection problem more complicated. A supplier supposed to be the best with respect to a particular criterion may poorly perform against another criterion. Also with greater economic globalization, increased marketing competition, diverse client needs, and a changing marketing environment, competition among businesses are gradually shifting into conflicts across different supply chains rather than between businesses themselves (Mattsson, 2003; Johnson, 2006). Supplier selection is an important aspect of supply chain management that should be included in the plan (Huang and Keskar, 2007; Sanayei et al., 2008; Omurca, 2013). Supplier selection is a typical multi-criteria decision-making (MCDM) problem in which a series of indices must be considered and information from these indices must be aggregated in the decision process. MCDM problem is to select a most satisfied alternative from a finite number of feasible alternatives based on the values of each attribute with respect to every alternative. Given the complexity and uncertainty of the supplier selection process, decision makers (DMs) may be unable to express their evaluations in precise numbers, but they may be able to provide some form of approximation using their knowledge and perception. Selection of suppliers from a large number of candidate suppliers having varying potentialities and capabilities is a complex task due to involvement of several qualitative and quantitative evaluation criteria (Nong & Ho, 2019). Conflicting nature of the criteria also makes the supplier selection problem more complicate. A supplier supposed to be the best with respect to a particular criterion may poorly perform against another criterion. The supplier selection problem is having a set of equally compatible suppliers and conflicting evaluation criteria can be treated as a typical multi-criteria decision making (MCDM) problem. In this direction, the past researchers have attempted the applications of several MCDM tools in identifying the most apposite suppliers for textile industries involved on production of varieties of end products (Yıldız & Yayla, 2015; Manucharyan, 2021). Selecting the right supplier may seem like an onerous process for your supply chain. Choosing a good supplier is a critical business decision. If you asked a garment manufacturer 20 years ago how they selected an ingredient supplier, they would have likely said it was based on price, flavor or the supplier location and preference. However, as government and industry put a stronger emphasis on environment protection and ethical, evaluating and selecting the right supplier today has become much more critical and complex.

Selecting the suppliers who can meet your consumers’ demand for higher-quality products may bring some initial costs, but it will pay off over time through consistent, high-quality products. However, the process to find the ideal supplier is often not easy and requires discipline and hard work.

Selecting the right supplier can help you meet the consumer demand for higher-quality ingredients while also meeting high regulatory standards. When selecting the right supplier, manufacturers should remember to:

- Include all key internal stakeholders in the process to agree on important criteria that the supplier should meet.
- Require strong communication between the manufacturer and the supplier. Good communication might not necessarily confirm a successful relationship, but poor communication can almost guarantee a failed relationship.
- Perform audits for the selected supplier, and work with them to address any deficiencies. If the deficiencies are too great, move on to another supplier. Implement adequate monitoring to drive improvement in supplier performance.
- Assess performance through useful metrics and provide the necessary feedback to the supplier.
- Establish an effective certification program and utilize it when the supplier has met its standards.
- Motivate your suppliers to develop strategic partnerships to ensure the greatest opportunity for success for both parties.
- Invest sufficient time, effort and energy early in the relationship to set up for success.

1.3 Literature Review

Zarbini-Sydani et al. (2011) presented the Mazandaran textile factory, one of Iran's largest textile industrial units, is being considered for cotton supplier selection issues. The hierarchical fuzzy TOPSIS model is used to evaluate the effective criteria for ranking the suitable suppliers. According to the findings, cotton quality is regarded as the most important criterion in evaluating cotton suppliers. Furthermore, among different provinces, cotton produced in Golestan is regarded as having the highest quality in the region. Ali-abad cotton factory in Golestan ranked first, which corresponded to Mazandaran textile factory's quality-oriented strategy. Another important criterion is the supplier's ability to meet the customers' regular and emergency needs. Furthermore, flexibility, financial stability and strength, as well as pricing and payment policies, all play important roles in selection of the suppliers.

Yayla et al. (2012) studied the fuzzy TOPSIS method, which was one of the multi-criteria decision making methods, was used to select the most appropriate supplier of garment 'X' operating in Turkey. It was detected through analyses carried out in accordance with the results obtained.

Alehashem et al. (2013) used a questionnaire that was used as an interview to identify and select the best criteria in supplier selection for a specific textile company (Golnesar Textile Manufacturing Company), and then the Analytical Hierarchical Process (AHP) was used to choose the best supplier. Finally, the best supplier for Golnesar textile manufacturing was identified and chosen.

Mokhtari et al. (2013) used fuzzy Delphi, fuzzy AHP and VIKOR under fuzzy environment as a decision tool to supplier selection. They developed a model with high reliability for supplier selection in textile industry. From fuzzy Delphi, they extracted five essential criteria and with fuzzy AHP, they weighted these criteria and with VIKOR under fuzzy environment and choosed the best suppliers. They constructed a questionnaire for fuzzy AHP and VIKOR that it's not needed to notice cost orientation or benefit orientation of criteria. Their finding shows that five criteria; quality, location, cost, trust and delivery are the most effective criteria in textile supplier selection area.

Hlyal et al. (2015) demonstrates that outsourcers and Moroccan manufacturers prioritise schedule compliance as well as the competence and versatility of the production system. Other dimensions, such as quality and human resource development, were included in the formula for calculating overall performance. That should make the contractor selection process easier and more objective.

Sasi and Digalwar (2015) created a methodology for evaluating suppliers in the supply chain cycle that is based on the Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS). They considered some important criteria that affect the process of supplier selection, such as product quality, service quality, delivery time, and price. They calculated the weights for each criterion using the Analytic Hierarchy Process (AHP) and then fed these weights into the TOPSIS method to rank suppliers.

Kara et al. (2016) developed appropriate solutions for a textile firm that is having difficulty determining which supplier is the best and establishing criteria to determine the best option among available alternatives. In that context, the necessary criteria were first defined and classified. Then, using the ANP, which is one of the multi-criteria decision-making techniques, the selection of supplier problem was discussed, solution steps were implemented, and the output was evaluated in the conclusion section.

Shukla (2016) emphasised the significance of the supplier-selection problem and its relationship to supply-chain strategy and business performance in small and medium-sized enterprises such as the garment industry. That presented a model based on the analytical hierarchy process (AHP) that a clothing company can use to select suppliers and develop a supplier relationship management strategy. The performance measurement framework was based on quantitative and qualitative measurements.

Ayvaz and Kuşakcı (2017) applied a trapezoidal type 2 fuzzy multi-criteria decision making method based on TOPSIS to select a convenient supplier in the presence of ambiguous information. The proposed method was used in the supplier selection process of a Turkish textile firm. Furthermore, the same problem was solved using type 1 fuzzy TOPSIS to validate the findings of type 2 fuzzy TOPSIS. A sensitivity analysis was performed to see how the decision changes under various scenarios. The findings indicated that the presented type 2 fuzzy TOPSIS method was more appropriate and effective for dealing with supplier selection in an uncertain environment.

Jing (2018) proposed a procedure for the selection and evaluation of suppliers in supply chain, first, the organization's competitive strategy was defined by analyzing its strengths, weaknesses, opportunities, and threats (SWOT). Supplier selection criteria and indicators are chosen based on competitive strategy in order to establish a framework for selecting suppliers. Following that, potential suppliers were tracked using Data Envelopment Analysis (DEA). Finally, Multi Criteria Decision Making (MCDM) techniques were used to rank suppliers.

Bakhat and Rajaa (2019) implemented the supplier selection problem in a Turkish Textile Company. They used the grey analytical hierarchy process G-AHP model for weighting the set of criteria and the grey weighted aggregated sum product assessment WASPAS-G model for prioritizing suppliers to implement a novel grey integrated multi-criteria approach for improving the supplier procedure within Textile Company.

Guarnieria and Trojan (2019) balanced the social, environmental, and economic criteria, as well as related ethical issues, in the supplier selection process when outsourcing textile industry activities. The model was divided into three stages: i) criteria definition, in which the Copeland method is used to aggregate criteria reported in the literature for a group of decision makers (customers and expert managers); ii) elicitation of decision makers' perceptions about criteria and the definition of weights for these criteria using the AHP method; and iii) multi-criteria supplier classification using the ELECTRE-TRI method.

Burney and Ali (2019) employed a fuzzy analytic hierarchy process (F-AHP) approach for supplier selection in Pakistan's textile industry. Criteria for supplier selection were identified through an informal interview with the purchase manager of a textile manufacturing company. Price and cost, quality, services, delivery time, and payment terms were identified and considered as supplier selection criteria.

Wang et al. (2020) proposed a multi-criteria decision making model (MCDM) for selecting garment and textile suppliers. The supply chain operations reference model (SCOR) and expert opinion are used to define all criteria affecting this process in the first stage. The Fuzzy Analytical Hierarchy Process (FAHP) was used to determine the weight of all potential suppliers, and the preference ranking organization method for enrichment of evaluations (PROMETHEE II) was used to rank the supplier.

Karami et al. (2020) comprehensively developed quantitative and qualitative decision-making criteria to enable the logistician to systematically evaluate and select suppliers. Then, to address the problem of supplier selection and evaluation in the garment industry, a three-step integrated approach is proposed. The criteria are reduced in the first phase by keeping as much information as possible and using principal component analysis. The additive model of data envelopment analysis is enhanced by the resultant principal components in the second phase to determine the efficient suppliers. Finally, in the third phase, efficient suppliers are ranked using the Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method as a compromise ranking approach.

Ersoy and Dogan (2020) studied the performance of 16 common fiber suppliers from five different companies operating in one of the textile sector's subsector, the blanket sector, was measured and evaluated using fuzzy analytic hierarchy process (FAHP) and fuzzy data envelopment analysis (FDEA) methods. Criteria weighted by the FAHP method were chosen as the input and output variables to be used in FDEA.

Ali et al. (2020) focused on the selection of cotton suppliers using a fuzzy soft computing approach integrated into an analytical hierarchy process (AHP). Then, to obtain the best solution, they applied the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Mondragon et al. (2021) looked into the development of a technology and supplier selection approach based on 12 factors influencing manufacturing technology selection in relation to the supply chain. The methodology used identified two competing lamination technologies with advanced development and mechanization: i) full lamination/solvent type; and ii) dot lamination/solvent free. This was followed by the identification of numerous factors influencing manufacturing technology selection in relation to the supply chain, as well as the application of analytical hierarchy process techniques.

Utama et al. (2021) attempted to integrate the Decision Making Trial and Evaluation Laboratory (DEMATEL) and the Analytic Network Process (ANP) for textile supplier selection. DEMATEL was used to assess the relationship between criteria in both methods, which are multi-criteria decision making (MCDM) tools. ANP was also used to evaluate and weight the importance of criteria and suppliers.

Sarıçam and Yilmaz (2021) proposed a comprehensive but feasible integrated framework for supplier selection and overall performance evaluation. The proposed integrated framework tailored for apparel retailers combines the following current techniques with specific capabilities: data envelopment analysis (DEA), analytical hierarchy process (AHP), and order preference by similarity to ideal solution (TOPSIS). DEA was used to evaluate overall performance, while AHP and TOPSIS were used in tandem to provide the quantitative data required by DEA.

Celik et al. (2021) addressed a GSS problem as a multi-criteria decision process. The best worst method (BWM) and TODIM (an acronym for interactive and multi-criteria decision-making in

Portuguese) methods are merged under an improved fuzzy concept of interval type-2 fuzzy sets (IT2FSs). BWM with interval type-2 fuzzy numbers (IT2F-BWM) is used to determine the evaluation criteria for green suppliers. An interval type-2 fuzzy TODIM (IT2F-TODIM) is used to select green suppliers.

1.4 Objective and Scope of the Present Work

In earlier days, evaluation of the suppliers and selection of the best one usually depends on the opinion on a single decision maker associated with the purchasing department of the organization. Although it is a simple, straightforward and less computational intensive task, it may include individual biasness in the decision making process. Nowadays, in order to make this process more scientific and unbiased, decisions from a group of participating experts (from various departments having valued experience) are sought. At the later stage of the evaluation process, judgments of the experts are weighted aggregated to derive a single collective decision. An organization would strive on both individual and group decision making approaches to be successful in the present-day competitive market. Keeping in mind the basic objective of supplier selection, this research first identifies six pivotal criteria, and attempts to express the opinions of experts with respect to the relative significance of the considered criteria and performance of each supplier against each of the criteria. The objective and scope of this research work is as follows:

a) Based on six most significant criteria and involving four experts, an attempt is put forward to integrate interval rough number (IRN) with best worst method (BWM) and evaluation based on distance from average solution (EDAS) method to solve a supplier selection problem for an Indian textile industry. The application of IRN helps in expressing opinions of the experts with respect to relative importance of the considered criteria and performance of the suppliers against each of the criteria using rough boundary intervals under group decision making environment. Later, the criteria weights are determined using IRN-BWM and the alternative suppliers are ranked from the best to the worst employing IRN-EDAS method. The IRN Dombi weighted geometric averaging (IRNDWGA) operator is employed here to aggregate opinions of the participating experts. This integrated approach (IRN-BWM-EDAS) appears to be a useful tool for supplier selection for the considered textile industry engaged in procurement of raw materials in the form of cotton bales. This cotton mill is located in the northern part of India and has a production capacity of around 12,000 tonnes of cotton yarn per year.
b) To examine a novel grey possibility degree technique that is combined with multi-criteria decision making (MCDM) and applied to a supplier selection problem with uncertainty information using a MCDM model. The supplier selection problem is a classic MCDM problem in which data from many indexes must be combined. It is, however, extremely simple for decision-makers to define information under uncertainty as a grey number rather

than a specific number. A unique grey MCDM approach is developed by converting a linguistic scale of grading supplier selection qualities into interval grey values. The steps of the proposed model are described, as well as a novel grey possibility degree method. Finally, the proposed method is demonstrated using a numerical example of supplier selection. The results suggest that the proposed method can handle the challenge of making decisions under uncertainty. The proposed method is demonstrated using a numerical example of supplier selection. The findings suggest that the proposed strategy is effective in gathering information from decision makers in order to select a possible supplier. The method presented in this research can be utilized to solve uncertainty decision-making issues in which a specific value of choice information is unavailable but an interval value set can be defined. Naturally, it can be applied to various MCDM issues. The research is successful in redefining interval grey number, developing a unique interval grey number based MCDM approach, and presenting the suggested approach's solution. It is quite helpful in Supplier selection and has surely improved grey decision-making models.

2. IRN-BWM-EDAS BASED APPROACH TO SUPPLIER SELECTION:

2.1 IRN

Let us assume a textile supplier selection problem involving k experts specifying their preferences in the form of a decision matrix $X = [x_{ij}^{k}]_{m\times n}$ using a scale, where m and n are the numbers of alternative suppliers and criteria respectively, and x_{ij}^{k} represents the preference of k^{th} expert for i^{th} alternative against j^{th} criterion. The preference of k^{th} expert is expressed in the form of RNs as $x_{ij}^{k} = \left(x_{ij}^{k-}, x_{ij}^{k+}\right)$. Thus the initial decision matrix evaluating m alternatives against n criterion by k^{th} expert $(1 \le e \le k)$ in terms of RNs can be expressed as below:

$$X_e = \begin{bmatrix} (x_{11}^{e-}, x_{11}^{e+}) & (x_{12}^{e-}, x_{12}^{e+}) & \dots & (x_{1n}^{e-}, x_{1n}^{e+}) \\ (x_{21}^{e-}, x_{21}^{e+}) & (x_{22}^{e-}, x_{22}^{e+}) & \dots & (x_{2n}^{e-}, x_{2n}^{e+}) \\ \dots & \dots & \dots & \dots \\ (x_{m1}^{e-}, x_{m1}^{e+}) & (x_{m2}^{e-}, x_{m2}^{e+}) & \dots & (x_{mn}^{e-}, x_{mn}^{e+}) \end{bmatrix} \tag{2.1}$$

There is a set of k classes of expert's preferences $x^{-} = \{x_1^{-}, x_2^{-}, ..., x_k^{-}\}$ satisfying the condition $x_1^{-} \le x_2^{-} \le ... \le x_k^{-}\}$. There is also another set of b classes of expert's preferences $x^{+} = \{x_1^{+}, x_2^{+}, ..., x_k^{+}\}$. Now, an interval can be defined in each class $x_i^{+} = [x_i^{L}, x_i^{U}]$; $x_i^{L} \le x_i^{U}$; $1 \le i \le m; x_i^{L}, x_i^{U} \in R,$ where x_i^{L} and x_i^{U} represent the lower and upper boundaries of i^{th} class respectively. Suppose that X is a universe containing all objects and x is an arbitrary object in X. If the lower and upper boundaries are sequenced as follows: $x_1^{L} < x_2^{L} <...,< x_l^{L}; x_1^{U} < x_2^{U} <...,< x_k^{U}$ $(1 \le l,\ k \le m)$, these sequences can then be denoted as two sets: a) a set of lower classes $x^{L} = \{x_1^{L}, x_2^{L}, ..., x_i^{L}\}$, and a set of upper classes $x^{U} = \{x_1^{U}, x_2^{U}, ..., x_i^{U}\}$ $(x_i^{L} \in x^{L}, 1 \le i \le l$ and $x_i^{U} \in x^{U}, 1 \le i \le k)$. The lower and upper approximations of x_i^{L} and x_i^{U} can be described as follows (Chattopadhyay et al., 2022; Ghosh et al., 2022).

a) Lower approximation:

$$\underline{Apr}(x_i^{L}) = \cup\left\{x \in X / x^{L}(x) \le x_i^{L}\right\} \tag{2.2}$$

$$\underline{Apr}(x_i^{U}) = \cup\left\{x \in X / x^{U}(x) \le x_i^{U}\right\} \tag{2.3}$$

b) Upper approximation:

$$\overline{Apr}(x_i^{L}) = \cup\left\{x \in X / x^{L}(x) \ge x_i^{L}\right\} \tag{2.4}$$

$$\overline{Apr}(x_i^{U}) = \cup\left\{x \in X / x^{U}(x) \ge x_i^{U}\right\} \tag{2.5}$$

Now, the lower and upper limit of x_i^{L} and x_i^{U} can be defined as below:

a) Lower limit:

$$\underline{Lim}(x_i^L) = \frac{1}{N_L}\sum_{b=1}^{N_L} x_i^{bL} \Big| x_i^{bL} \in \underline{Apr}(x_i^L) \quad (2.6)$$

$$\underline{Lim}(x_i^U) = \frac{1}{N_L^*}\sum_{b=1}^{N_L^*} x_i^{bU} \Big| x_i^{bU} \in \underline{Apr}(x_i^U) \quad (2.7)$$

b) Upper limit:

$$\overline{Lim}(x_i^L) = \frac{1}{N_U}\sum_{b=1}^{N_U} x_i^{bL} \Big| x_i^{bL} \in \overline{Apr}(x_i^L) \quad (2.8)$$

$$\overline{Lim}(x_i^U) = \frac{1}{N_U^*}\sum_{b=1}^{N_U^*} x_i^{bU} \Big| x_i^{bU} \in \overline{Apr}(x_i^U) \quad (2.9)$$

where N_L and N_L^* are the numbers of objects contained in lower approximations of the classes of objects x_i^L and x_i^U respectively, and N_U and N_U^* are the numbers of objects contained in upper approximations of the classes of objects x_i^L and x_i^U respectively.

Then, the corresponding IRN can be defined using the following expression (Pamučar et al., 2017):

$$IRN(x_i) = \left[RN(x_i^L), RN(x_i^U)\right] = \left[(\underline{L}(x_i^L), \overline{L}(x_i^L)), (\underline{L}(x_i^U), \overline{L}(x_i^U))\right] = \left[(x_i^{L'}, x_i^{U'}), (x_i^L, x_i^U)\right] \quad (2.10)$$

Application of IRNs relieves involvement of the experts while abstracting complex problems, and qualitatively evaluating them based on knowledge and common sense. Use of additional intervals minimizes chances of losing information and provides greater scope to the experts to express their judgements more preciously without making biased decisions. Thus, IRNs can represent both uncertainty and imprecision in a decision making problem. To illustrate the corresponding numerical formulations, let us assume a group decision making situation where three experts require to qualitatively evaluating a specific criterion (attribute) based on a 1-5 scale. Suppose, Expert E_1 assigns a score 3-4, Expert E_2 appraises the importance of that criterion with a score of 4-5 and Expert E_3 assigns a value of 4 to that criterion. Thus, two of the experts (E_1 and E_2) are not sure of their opinions, whereas, the other expert (E_3) perfectly judges the importance of the considered criterion. These experts' preferences on criterion importance can be represented as: $P(E_1) = (3, 4)$, $P(E_2) = (4, 5)$ and $P(E_3) = (4, 4)$. Based on the formulations of IRNs, two classes of objects x_i' and x' are formed as: $x_i' = (3, 4, 4)$ and $x_i = (4, 5, 4)$. These object classes are converted into two rough sequences, $\left(x_i^{L'}, x_i^{U'}\right)$ and $\left(x_i^L, x_i^U\right)$. Thus, for the first class of objects:

$$x_i^{L'}(3) = 3, x_i^{U'}(3) = \frac{1}{3}(3+4+4) = 3.7 \rightarrow x_i'(3) = (3, 3.7), x_i^{L'}(4) = \frac{1}{3}(3+4+4) = 3.7, x_i^{U'}(4) = 4 \rightarrow x_i'(4) = (3.7, 4)$$

Similarly, for the second class of objects:

$$x_i^L(4)=4,\ x_i^U(4)=\frac{1}{3}(4+5+4)=4.3\rightarrow x_i(4)=(4,4.33),\ {}_i^L(5)=\frac{1}{3}(4+5+4)=4.3,\ x_i^U(5)=5\rightarrow x_i(5)=(4.3,5)$$

Thus, the RNs expressing judgments of the three experts are converted into the following IRNs:

IRN (E_1) = [(3, 3.7), (4, 4.3)], *IRN* (E_2) = [(3.7, 4), (4.3, 5)], *IRN* (E_3) = [(3.7, 4), (4, 4.3)]

2.2 IRN-BWM

The BWM, proposed by Rezaei (2015), is a technique for criteria weight measurement, where the expert first identifies the best and the worst criteria, and subsequently develops two pair-wise comparison vectors for the best and the worst criteria. The best criterion is considered to have the most important role in the decision making process, whereas, the worst criterion has the least important role. Using a pre-defined scale (e.g. 1-9), the expert evaluates performance of the best criterion over all other criteria and performance of all other criteria over the worst criterion. These two pair-wise comparison vectors, i.e. best-to-other (BO) and other-to-worst (OW) are treated as the inputs to a linear programming model, which is finally solved to determine the optimal criteria weights. As this method is based on only the best and the worst criteria for pair-wise comparisons, it requires fewer computational steps, while providing a clear understanding of the evaluation process, and more consistent and unbiased results.

In this paper, BWM is integrated with IRNs to deal with uncertainty and ambiguity present while assigning relative importance (weight) to the supplier evaluation criteria in a group decision making environment. Integration of IRNs with BWM protects quality of the existing data by realistically describing expert's preferences with respect to two matrixes, i.e. aggregated BO and OW. To take advantages of BWM, it has already been combined with different uncertainty theories in the literature, like fuzzy BWM (Guo & Zhao, 2017), intuitionistic fuzzy multiplicative BWM (Mou et al., 2016), intuitionistic multiplicative preference BWM (You et al., 2016), intuitionistic preferences relation BWM (Yang et al., 2016), interval-valued fuzzy-rough BWM (Pamučar et al., 2018) and rough BWM (Stević et al., 2017a; Badi & Ballem, 2018). The application of IRN-BWM is illustrated using the following steps:

Step 1: Define a set of criteria for evaluating the alternative suppliers. Suppose there is a group of *e* experts in the decision making process, who defines the set of criteria C = {C_1, C_2,...,C_n}.

Step 2: Define the best (B) and the worst (W) criteria from the set C. The experts arbitrarily choose the B and W criteria.

Step 3: Define the IRNBO vector in which the experts represent their preferences comparing B criterion to other criteria in the set C = {C_1, C_2,...,C_n}. The comparison of criterion B with other criterion in C is expressed through the advantage of criterion B over criterion *j* (*j* = 1,2,...,*n*), i.e. $a_{Bj}^e=(a_{Bj}^{eL},a_{Bj}^{e'U})(1\le e\le k)$. As a result of this comparison, a vector $\mathrm{BO}(A_B^e)$ is obtained, where

$A_B^e = (a_{B1}^{eL}, a_{B1}^{e'U}; a_{B2}^{eL}, a_{B2}^{e'U};...; a_{Bn}^{eL}, a_{Bn}^{e'U})$, a_{Bj}^{eL} and $a_{Bj}^{e'U}$ represent the advantages of criterion B over criterion j, $a_{BB}^{eL} = 1$ and $a_{BB}^{e'U} = 1$. So, for each expert, a BO matrix $A_B^1, A_B^2, ..., A_B^e, ..., A_B^k$ is formed. These individual BO matrixes would be utilized to obtain an aggregated IRNBO matrix (in Step 5).

Step 4: Define the IRNOW vector. Each expert compares j^{th} criterion to W criterion, whereby the advantage of j^{th} criterion over criterion W is represented as $a_{jW}^e = (a_{jW}^{eL}, a_{jW}^{e'U})(1 \le e \le k)$. Thus, a vector $\text{OW}(A_W^e)$ is obtained for each expert, where $A_W^e = (a_{1W}^{eL}, a_{1W}^{e'U}; a_{2W}^{eL}, a_{2W}^{e'U};...; a_{nW}^{eL}, a_{nW}^{e'U})$, a_{jW}^{eL} and $a_{jW}^{e'U}$ denote the advantages of j^{th} criterion over criterion W, $a_{WW}^{eL} = 1$ and $a_{WW}^{e'U} = 1$. Thus, for each expert, a OW matrix $A_W^1, A_W^2, ..., A_W^e, ..., A_W^k$ is framed. Similar to the previous step, the individual OW matrixes are employed to derive an aggregated IRNOW matrix (in Step 6).

Step 5: Define the aggregated IRNBO matrix of the expert's opinions. Based on individual expert's BO matrix $A_B^e = \left[a_{Bj}^{eL}, a_{Bj}^{e'L}\right]_{1\times n}$, two separate matrixes A_B^{*eL} and $A_B^{*e'U}$ are formed in which the expert decisions are aggregated.

$$A_B^{*eL} = \left[a_{B1}^{1L}, a_{B1}^{2L}, ..., a_{B1}^{kL}; a_{B2}^{1L}, a_{B2}^{2L}, ..., a_{B2}^{kL};...; a_{Bn}^{1L}, a_{Bn}^{2L}, ..., a_{Bn}^{kL}\right]_{1\times n} \tag{2.11}$$

$$A_B^{*e'U} = \left[a_{B1}^{1'U}, a_{B1}^{2'U}, ..., a_{B1}^{k'U}; a_{B2}^{1'U}, a_{B2}^{2'U}, ..., a_{B2}^{k'U};...; a_{Bn}^{1'U}, a_{Bn}^{2'U}, ..., a_{Bn}^{k'U}\right]_{1\times n} \tag{2.12}$$

where $a_{Bj}^{eL} = \{a_{Bj}^{1L}, a_{Bj}^{2L}, ..., a_{Bj}^{kL}\}$ and $a_{Bj}^{e'U} = \{a_{Bj}^{1'U}, a_{Bj}^{2'U}, ..., a_{Bj}^{k'U}\}$ represent advantages of criterion B over criterion j.

After forming A_B^{*eL} and $A_B^{*e'U}$ matrixes, each pair of sequences a_{Bj}^{eL} and $a_{Bj}^{e'U}$ is transformed into the corresponding IRN, using Eq. (2.2-2.10), $IRN(a_{Bj}^e) = \left[((\underline{L}(a_{Bj}^{eL-}), (\overline{L}(a_{Bj}^{eU-})), ((\underline{L}(a_{Bj}^{eL+}), (\overline{L}(a_{Bj}^{eU+}))\right]$ where $\underline{L}(a_{Bj}^{eL-})$ and $\overline{L}(a_{Bj}^{eL+})$ represent lower limits, and $\underline{L}(a_{Bj}^{eU-})$ and) $\overline{L}(a_{Bj}^{eU+})$ denote upper limits of $IRN(a_{Bj}^e)$ respectively. So for each sequence $IRN(a_{Bj}^e)$, the corresponding BO matrixes $A_B^1, A_B^2, ..., A_B^e, ... A_B^k$ $(1 \le e \le k)$ are formed. Now, by applying the IRNDWGA operator, the average IRN sequences are obtained (Yazdani et al., 2020). The aggregated IRNBO matrix is expressed in *Eq. (2.13):*

$$\overline{A}_B = \left[IRN(\overline{a}_{B1}), IRN(\overline{a}_{B2}), ..., IRN(\overline{a}_{Bn})\right]_{1\times n} \tag{2.13}$$

Where $IRN(\overline{a}_{Bj}) = \left(\left[\overline{a}_{Bj}^{L-}, \overline{a}_{Bj}^{U-}\right], \left[\overline{a}_{Bj}^{L+}, \overline{a}_{Bj}^{U+}\right]\right)$ presents average IRNs obtained using the following equation:

$$IRNDWGA\{IRN(\varphi_1),\ldots,IRN(\varphi_n)\}=\left[\begin{array}{c}\left\{\dfrac{\sum_{j=1}^{n}\emptyset_j^{L-}}{1+\left\{\sum_{j=1}^{n}w_j\left\{\frac{1-f(\emptyset_j^{L-})}{f(\emptyset_j^{L-})}\right\}^{\rho}\right\}^{1/\rho}},\dfrac{\sum_{j=1}^{n}\emptyset_j^{U-}}{1+\left\{\sum_{j=1}^{n}w_j\left\{\frac{1-f(\emptyset_j^{U-})}{f(\emptyset_j^{U-})}\right\}^{\rho}\right\}^{1/\rho}}\right\}\\ \left\{\dfrac{\sum_{j=1}^{n}\emptyset_j^{L+}}{1+\left\{\sum_{j=1}^{n}w_j\left\{\frac{1-f(\emptyset_j^{L+})}{f(\emptyset_j^{L+})}\right\}^{\rho}\right\}^{1/\rho}},\dfrac{\sum_{j=1}^{n}\emptyset_j^{U+}}{1+\left\{\sum_{j=1}^{n}w_j\left\{\frac{1-f(\emptyset_j^{U+})}{f(\emptyset_j^{U+})}\right\}^{\rho}\right\}^{1/\rho}}\right\}\end{array}\right] \tag{2.14}$$

Step 6: Define the aggregated IRNOW matrix of the expert's opinions. Similar to *step (5),* two separate matrixes A_W^{*eL} and $A_W^{*e'U}$ are formed on the basis of individual expert's OW matrixes $A_W^e=\left[a_{jW}^{eL},a_{jW}^{e'U}\right]_{1\times n}$.

$$A_W^{*eL}=\left[a_{W1}^{1L},a_{W1}^{2L},\ldots,a_{W1}^{mL};a_{W2}^{1L},a_{W2}^{2L},\ldots,a_{W2}^{mL};a_{Wn}^{1L},\ldots,a_{Wn}^{2L},\ldots,a_{Wn}^{mL}\right]_{1\times n} \tag{2.15}$$

$$A_W^{*e'U}=\left[a_{W1}^{1'U},a_{W1}^{2'U},\ldots,a_{W1}^{m'U};a_{W2}^{1'U},a_{W2}^{2'U},\ldots,a_{W2}^{m'U};a_{Wn}^{1'U},\ldots,a_{Wn}^{2'U},\ldots,a_{Wn}^{m'U}\right]_{1\times n} \tag{2.16}$$

where $a_{iW}^{eL}=\{a_{jW}^{1L},a_{jW}^{2L},\ldots,a_{nW}^{mL}\}$ and $a_{jW}^{e'U}=\{a_{jW}^{1'U},a_{jW}^{2'U},\ldots,a_{nW}^{m'U}\}$ denote advantages of criterion j over criterion W. Each pair of sequences a_{jW}^{eL} and $a_{jW}^{e'U}$ is now transformed into $IRN(a_{jW}^e)=\left[((\underline{L}(a_{jW}^{eL-}),(\overline{L}(a_{jW}^{eU-})),((\underline{L}(a_{jW}^{eL+}),(\overline{L}(a_{jW}^{eU+}))\right]$, where $\underline{L}(a_{jW}^{eL-})$ and $\underline{L}(a_{jW}^{eL+})$ signify lower limits, and $\overline{L}(a_{jW}^{eU-})$ and $\overline{L}(a_{jW}^{eU+})$ represent upper limits of $IRN(a_{jW}^e)$, respectively. Thus, for each $IRN(a_{jW}^e)$ sequence, the OW matrixes $A_W^1,A_W^2,\ldots,A_W^e,\ldots,A_W^k\ (1\le e\le k)$ are obtained. As in the previous step, applying IRNDWGA operator, the following aggregated IRNWO matrix is achieved:

$$\overline{A}_W=\left[IRN(\overline{a}_{1W}),IRN(\overline{a}_{2W}),\ldots,IRN(\overline{a}_{nW})\right]_{1\times n} \tag{2.17}$$

Where $IRN(\overline{a}_{jW})=\left(\left[\overline{a}_{jW}^{L-},\overline{a}_{jW}^{U-}\right],\left[\overline{a}_{jW}^{L+},\overline{a}_{jW}^{U+}\right]\right)$ is the average IRNs derived using IRNDWGA operator.

Now, based on the aggregate values of IRNBO and IRNOW matrixes, a nonlinear model for calculating optimal values of weight coefficients is formed, as presented in the next step.

Step 7: Calculate the optimal criteria weights. By solving the following set of equations, the IRN values of criteria weights are derived (Rezaei, 2015).

Min ξ

Subject to

$$\begin{gathered}\left|\frac{w_B^{L-}}{w_j^{U+}}-a_{Bj}^{-U+}\right|\le\xi;\ \left|\frac{w_B^{U-}}{w_j^{L+}}-a_{Bj}^{-L+}\right|\le\xi;\ \left|\frac{w_B^{L+}}{w_j^{U+}}-a_{Bj}^{-U-}\right|\le\xi;\ \left|\frac{w_B^{U+}}{w_j^{L-}}-a_{Bj}^{-L-}\right|\le\xi;\\ \left|\frac{w_j^{L-}}{w_W^{U+}}-a_{jW}^{-U+}\right|\le\xi;\ \left|\frac{w_j^{U-}}{w_{jW}^{L+}}-a_{jW}^{-L+}\right|\le\xi;\ \left|\frac{w_j^{L+}}{w_W^{U+}}-a_{jW}^{-U-}\right|\le\xi;\ \left|\frac{w_j^{U+}}{w_W^{L-}}-a_{jW}^{-L-}\right|\le\xi\\ \sum_{j=1}^{n}w_j^{L-}\le 1,\ \sum_{j=1}^{n}w_j^{L+}\le 1,\ \sum_{j=1}^{n}w_j^{U-}\le 1,\ \sum_{j=1}^{n}w_j^{U+}\le 1,\end{gathered} \tag{2.18}$$

$w_j^{L-} \le w_j^{L+} \le w_j^{U-} \le w_j^{U+},\; w_j^{L-}, w_j^{L+}, w_j^{U-}, w_j^{U+} \ge 0,\; \forall\, j = 1,2,\ldots,n$

Here, $IRN(w_j) = \left[(w_j^{L-}, w_j^{U-}), (w_j^{L+}, w_j^{U+})\right]$ represents the optimal value of criteria weight coefficient, $IRN(\bar{a}_{jW}) = \left(\left[\bar{a}_{jW}^{L-}, \bar{a}_{jW}^{U-}\right], \left[\bar{a}_{jW}^{L+}, \bar{a}_{jW}^{U+}\right]\right)$ and $IRN(\bar{a}_{Bj}) = \left(\left[\bar{a}_{Bj}^{L-}, \bar{a}_{Bj}^{U-}\right], \left[\bar{a}_{Bj}^{L+}, \bar{a}_{BJ}^{U+}\right]\right)$ are the values from IRNOW and IRNBO matrixes respectively.

Step 8: Check the level of consistency for IRN-BWM-based weight coefficients. Since the expert's comparisons captured by IRNBO and IRNOW matrixes are adopted to develop the above model, the consistency of the comparisons needs to be validated. An expression can be defined to represent minimum consistency in the IRN-BWM model. Since, there is a requirement that $\bar{a}_{BW}^{L-} \le \bar{a}_{BW}^{L+} \le \bar{a}_{BW}^{U-} \le \bar{a}_{BW}^{U+}$, the advantage of the best criterion over the worst criterion cannot be greater than $\bar{a}_{BW}^{U+}$. Thus, the upper limit $\bar{a}_{BW}^{U+}$ can be considered to fix the value of consistency index (CI) and all the variables related to $IRN(\bar{a}_{BW})$ can employ CI to calculate the consistency ratio (CR). It can be concluded that the CI which corresponds to $\bar{a}_{BW}^{U+}$ would take the maximum value in the interval [$\bar{a}_{BW}^{L-}$, $\bar{a}_{BW}^{U+}$]. Based on this assumption, *Eq. (2.19)* can be framed to determine the CI value.

$$\xi - (1 + 2\bar{a}_{BW}^{U+})\xi + (\bar{a}_{BW}^{U+2} - \bar{a}_{BW}^{U}) = 0 \tag{2.19}$$

Now, the CR can be expressed using the following equation:

$$CR = \frac{\xi^*}{CI} \tag{2.20}$$

Where CR $\in [0,\, 1]$ and ξ^* is the optimal consistency index.

2.3 IRN-EDAS

The EDAS method (Ghorabaee et al., 2015) belongs to the group of MCDM techniques overcoming some of the drawbacks of the traditional TOPSIS method. In TOPSIS method, the best alternative should be positioned nearest to the ideal solution and farthest from the anti-ideal solution. Identifying the ideal and anti-ideal solutions in a given decision making problem appears to be quite difficult as there may be no alternative having all the best beneficial criteria and worst non-beneficial criteria. On the other hand, the desirability of an alternative in EDAS method is estimated based on its distance from the average solution which is the arithmetic mean of the criterion values for the considered alternatives. This method has higher efficiency, requiring fewer computational steps as compared to other MCDM techniques. In a short time, it has become a popular MCDM technique in solving both engineering and managerial decision making problems. It has also a large number of extensions, like fuzzy EDAS (Ghorabaee et al., 2016), interval grey EDAS (Stanujkic et al., 2017), picture fuzzy EDAS (Zhang et al., 2019), rough EDAS (Stević et al., 2017b), interval-valued Pythagorean fuzzy EDAS (Yanmaz et al., 2020) etc. The procedural steps of IRN-EDAS method are presented as below:

Step 1: Develop the initial decision matrixes based on the judgments of k experts appraising the performance of m alternatives against n criteria in the form of IRNs.

Step 2: Transform the individual decision matrixes into a group IRN matrix.

$$IRN(X_{ij}) = \begin{bmatrix} IRN(x_{11}) & IRN(x_{12}) & \dots & IRN(x_{1n}) \\ IRN(x_{21}) & IRN(x_{22}) & \dots & IRN(x_{2n}) \\ \dots & \dots & \dots & \dots \\ IRN(x_{m1}) & IRN(x_{m2}) & \dots & IRN(x_{mn}) \end{bmatrix} \tag{2.21}$$

Step 3: Calculate the average solution by forming an $IRN(AV_j)$ matrix.

$$IRN(AV_j) = \left[(av_j^L, av_j^U), (av_j^{L'}, av_j^{U'})\right]_{m\times n} \tag{2.22}$$

The values of $IRN(AV_j)$ can be determined applying the following equation:

$$\sum_{i=1}^{m} \frac{IRN(x_{ij})}{m} = \sum_{i=1}^{m} \left[\frac{IRN(x_{ij}^L)}{m}, \frac{IRN(x_{ij}^U)}{m}\right], \left[\frac{IRN(x_{ij}^{L'})}{m}, \frac{IRN(x_{ij}^{U'})}{m}\right] \tag{2.23}$$

Step 4: Formulate the positive distance $IRN(PDA_{ij})$ and negative distance $IRN(NDA_{ij})$ matrixes in relation to the average solution $IRN(AV_j)$ for all criteria.

$$IRN(PDA_{ij}) = \left[pda_j^L, pda_j^U\right], \left[pda_j^{L'}, pda_j^{U'}\right]_{m\times n} \tag{2.24}$$

$$IRN(NDA_{ij}) = \left[nda_j^L, nda_j^U\right], \left[nda_j^{L'}, nda_j^{U'}\right]_{m\times n} \tag{2.25}$$

To obtain elements of these matrixes, it is necessary to take into account the type of criterion (beneficial or non-beneficial) in the supplier selection problem.

$$IRN(PDA_{ij}) = \left[pda_{ij}^L, pda_{ij}^U\right], \left[pda_{ij}^{L'}, pda_{ij}^{U'}\right] = \left[\frac{b_{ij}^L}{av_{ij}^U}, \frac{b_{ij}^U}{av_{ij}^L}\right], \left[\frac{b_{ij}^{L'}}{av_{ij}^U}, \frac{b_{ij}^{U'}}{av_{ij}^L}\right] \text{or} \left[\frac{c_{ij}^L}{av_{ij}^{U'}}, \frac{c_{ij}^U}{av_{ij}^{L'}}\right], \left[\frac{c_{ij}^{L'}}{av_{ij}^U}, \frac{c_{ij}^{U'}}{av_{ij}^L}\right] \tag{2.26}$$

$$IRN(B_{ij}) = \left[b_{ij}^L, b_{ij}^U\right], \left[b_{ij}^{L'}, b_{ij}^{U'}\right] = \max\left(0, \left[x_{ij}^L - av_j^{U'}, x_{ij}^U - av_j^{L'}\right], \left[x_{ij}^{L'} - av_j^U, x_{ij}^{U'} - av_j^L\right]\right) \tag{2.27}$$

$$IRN(C_{ij}) = \left[c_{ij}^L, c_{ij}^U\right], \left[c_{ij}^{L'}, c_{ij}^{U'}\right] = \max\left(0, \left[av_j^L - x_{ij}^{U'}, av_j^U - x_{ij}^{L'}\right], \left[av_j^{L'} - x_{ij}^U, av_j^{U'} - x_{ij}^L\right]\right) \tag{2.28}$$

$$IRN(NDA_{ij}) = \left[nda_{ij}^L, nda_{ij}^U\right], \left[nda_{ij}^{L'}, nda_{ij}^{U'}\right] = \left[\frac{b_{ij}^L}{av_{ij}^{U'}}, \frac{b_{ij}^U}{av_{ij}^{L'}}\right], \left[\frac{b_{ij}^{L'}}{av_{ij}^U}, \frac{b_{ij}^{U'}}{av_{ij}^L}\right] \text{or} \left[\frac{c_{ij}^L}{av_{ij}^{U'}}, \frac{c_{ij}^U}{av_{ij}^{L'}}\right], \left[\frac{c_{ij}^{L'}}{av_{ij}^U}, \frac{c_{ij}^{U'}}{av_{ij}^L}\right] \tag{2.29}$$

$$IRN(B_{ij}) = \left[b_{ij}^L, b_{ij}^U\right], \left[b_{ij}^{L'}, b_{ij}^{U'}\right] = \max\left(0, \left[av_j^L - x_{ij}^{U'}, av_j^U - x_{ij}^{L'}\right], \left[av_j^{L'} - x_{ij}^U, av_j^{U'} - x_{ij}^L\right]\right) \tag{2.30}$$

$$IRN(C_{ij}) = \left[c_{ij}^L, c_{ij}^U\right], \left[c_{ij}^{L'}, c_{ij}^{U'}\right] = \max\left(0, \left[x_{ij}^L - av_j^{U'}, x_{ij}^U - av_j^{L'}\right], \left[x_{ij}^{L'} - av_j^U, x_{ij}^{U'} - av_j^L\right]\right) \tag{2.31}$$

where B_{ij} belongs to the set of beneficial criteria and C_{ij} belongs to the set of non-beneficial criteria.

Step 5: Multiply the IRN matrixes $IRN(PDA_{ij})$ and $IRN(NDA_{ij})$ by the corresponding criteria weights.

$$IRN(VP_{ij}) = \left[vp_j^L, vp_j^U\right], \left[vp_j^{L'}, vp_j^{U'}\right]_{m\times n} = \left[pda_{ij}^L \times w_j^L, pda_{ij}^U \times w_j^U\right], \left[pda_{ij}^{L'} \times w_j^{L'}, pda_{ij}^{U'} \times w_j^{U'}\right] \tag{2.32}$$

$$IRN(VN_{ij}) = \left[vn_j^L, vn_j^U\right], \left[vn_j^{L'}, vn_j^{U'}\right]_{m\times n} = \left[nda_{ij}^L \times w_j^L, nda_{ij}^U \times w_j^U\right], \left[nda_{ij}^{L'} \times w_j^{L'}, nda_{ij}^{U'} \times w_j^{U'}\right] \tag{2.33}$$

Step 6: Calculate sums of the weighted IRN matrixes,

$$IRN(SP_i)=\left[sp_i^{L},sp_i^{U}\right],\left[sp_i^{L'},sp_i^{U'}\right]=\sum_{j=1}^{n}IRN(VP_{ij}) \tag{2.34}$$

$$IRN(SN_i)=\left[sn_i^{L},sn_i^{U}\right],\left[sn_i^{L'},sn_i^{U'}\right]=\sum_{j=1}^{n}IRN(VN_{ij}) \tag{2.35}$$

Step 7: Compute the normalized values for the matrixes.

$$\begin{gathered}IRN\,(NSP_i)=\left[nsp_{ij}^{L},nsp_{ij}^{U}\right],\left[nsp_{ij}^{L'},nsp_{ij}^{U'}\right]=\frac{IRN\,(SP_i)}{\text{Max }IRN(SP)_i}=\\ \left[\frac{sp_i^{L}}{\text{Max }sp_i^{U'}},\frac{sp_i^{U}}{\text{Max }sp_i^{L'}}\right],\left[\frac{sp_i^{L'}}{\text{Max }sp_i^{U}},\frac{sp_i^{U'}}{\text{Max }sp_i^{L}}\right]\end{gathered} \tag{2.36}$$

$$\begin{gathered}IRN\,(NSN_i)=\left[nsn_{ij}^{L},nsn_{ij}^{U}\right],\left[nsn_{ij}^{L'},nsn_{ij}^{U'}\right]=1-\frac{IRN\,(SN_i)}{\text{Max }IRN(SN)_i}=\\ 1-\left[\frac{sn_i^{L}}{\text{Max }sn_i^{U'}},\frac{sn_i^{U}}{\text{Max }sn_i^{L'}}\right],\left[\frac{sn_i^{L'}}{\text{Max }sn_i^{U}},\frac{sn_i^{U'}}{\text{Max }sn_i^{L}}\right]\end{gathered} \tag{2.37}$$

Step 8: Calculate the appraisal scores $IRN(AS_i)$ of all the alternatives.

$$IRN(AS_i)=\left[as_i^{L},as_i^{U}\right],\left[as_i^{L'},as_i^{U'}\right]=\left[\frac{IRN(NSP_i)+IRN(NSN_i)}{2}\right] \tag{2.38}$$

Step 9: Rank the considered alternatives based on the converted crisp values of $IRN(AS_i)$. Any two IRNs, i.e. $IRN(\alpha)=\left([x_i^{L'},x_i^{U'}],[x_i^{L},x_i^{U}]\right)$ and $IRN(\beta)=\left([x_i^{L'},x_i^{U'}],[x_i^{L},x_i^{U}]\right)$ can be ranked using their points of intersection $I(\alpha)$ and $I(\beta)$, while satisfying the following two conditions:

(a) If $I(\alpha) < I(\beta)$, then $IRN(\alpha) < IRN(\beta)$

(b) If $I(\alpha) > I(\beta)$, then $IRN(\alpha) > IRN(\beta)$

For a decision making problem considering four alternatives, the corresponding intersection points can be obtained using the following equations:

$$\mu_\alpha=\frac{RB(\alpha_{ui})}{RB(\alpha_{ui})+RB(\alpha_{li})};RB(\alpha_{ui})=x_i^{U}-x_i^{L};RB(\alpha_{li})=x_i^{U'}-x_i^{L'} \tag{2.39}$$

$$\mu_\beta=\frac{RB(\beta_{ui})}{RB(\beta_{ui})+RB(\beta_{li})};RB(\beta_{ui})=x_i^{U}-x_i^{L};RB(\beta_{li})=x_i^{U'}-x_i^{L'} \tag{2.40}$$

$$\mu_\gamma=\frac{RB(\gamma_{ui})}{RB(\gamma_{ui})+RB(\gamma_{li})};RB(\gamma_{ui})=x_i^{U}-x_i^{L};RB(\gamma_{li})=x_i^{U'}-x_i^{L'} \tag{2.41}$$

$$\mu_\delta=\frac{RB(\delta_{ui})}{RB(\delta_{ui})+RB(\delta_{li})};RB(\delta_{ui})=x_i^{U}-x_i^{L};RB(\delta_{li})=x_i^{U'}-x_i^{L'} \tag{2.42}$$

$$I(\alpha)=\mu_\alpha\times x_i^{L'}+(1-\mu_\alpha)\times x_i^{U} \tag{2.43}$$

$$I(\beta)=\mu_\beta\times x_i^{L'}+(1-\mu_\beta)\times x_i^{U} \tag{2.44}$$

$$I(\gamma)=\mu_\gamma\times x_i^{L'}+(1-\mu_\gamma)\times x_i^{U} \tag{2.45}$$

$$I(\delta)=\mu_\delta \times x_i^{L'} + (1-\mu_\delta)\times x_i^U \tag{2.46}$$

2.4 IRN-BWM-EDAS Based Case Study

This section demonstrates the application of the proposed integrated methodology for selecting the most apposite supplier engaged in providing cotton bales in an Indian textile mill. In this supplier selection process under group decision making environment, involvement of four experts is considered. They are respectively engaged in the purchasing (12 years industrial experience having Master's in Business Administration degree), blowroom (20 years experience with a Bachelor's degree in Textile Technology), spinning (carding, speed frame and ring frame) (10 years experience possessing a Bachelor's degree in Textile Technology) and quality control (8 years of experience with Master's degree in Textile Technology) departments of the said textile mill. The supplier selection problem is solved here-in-under using IRN-BWM-EDAS approach through the adoption of the following steps:

Step 1: Identify the relevant evaluation criteria. Based on the literature review and valued opinions of the participating experts, six evaluation criteria, as provided in *Table 2.1*, are considered for solving this supplier selection problem.

Table 2.1 Evaluation criteria for supplier selection in a textile mill

Criteria	Symbol	Description
Cost	C_1	It is the net price offered by a supplier. The procurement decision is usually made based on the minimum cost for a particular item.
Quality	C_2	It can be defined as the ability of a supplier to consistently meet and maintain the desired quality specifications. Any deviation in the specified quality level may adversely affect the production processes leading to loss of goodwill of the organization.
Delivery	C_3	It is the ability of a supplier to meet the specified delivery schedule. Strict adherence to the delivery schedule is highly recommended to maintain proper inventory level in order to streamline all the production processes.
Technical support	C_4	It can be described as the capability of a supplier to upkeep itself with the advanced technologies to support the procuring organization. The supplier must be aware of all the cutting edge technologies, products and services to meet the ever-changing requirements of the organizations.
Payment terms	C_5	It deals with different payment-related terms, like **payment in advance,** consequences of late payment and delivery, payment disputes etc., to be taken into consideration when a purchase order is placed to a supplier. It also takes into account the ability of a supplier to manage the letter of credit, collection of documents, opening of accounts etc.
Flexibility	C_6	It refers to the capability of a supplier to quickly respond to the changing demands of the buying organization with respect to delivery, volume and product design. It can be treated as a tool to cope with the environmental uncertainties. Besides providing the actual items, a flexible supplier may also be capable to deal with supplying/processing other items.

Step 2: Identification of the best and the worst criteria. After defining the most important evaluation criteria for this problem, all the four experts (E_1, E_2, E_3 and E_4) unanimously decide criterion C_1 (cost) and criterion C_5 (payment terms) as the best (B) and the worst (W) criteria respectively.

Steps 3: Formation of the BO and OW vectors for each of the experts. Based on the identified best and the worst criteria, each of the experts now appraises the relative importance of the remaining criteria with respect to the best and the worst criteria, leading to the formation of BO and OW vectors, as exhibited in *Table 2.2*. These judgments are initially expressed in terms of RNs based on a 1-9 scale to resolve the uncertainty and ambiguity present in the group decision making environment. It is worthwhile to mention here that problem; equal importance is assigned to each of the experts.

Table 2.2 BO and OW vectors

Criteria evaluation					Criteria evaluation				
Best: C_1	E_1	E_2	E_3	E_4	Worst: C_5	E_1	E_2	E_3	E_4
C_2	(3, 4)	(3, 5)	(2, 3)	(4, 5)	C_1	(5, 6)	(5, 7)	(4, 5)	(3, 4)
C_3	(7, 9)	(5, 7)	(6, 7)	(8, 9)	C_2	(8, 9)	(7, 8)	(5, 8)	(7, 9)
C_4	(5, 6)	(5, 7)	(4, 5)	(3, 4)	C_3	(6, 7)	(6, 9)	(5, 6)	(8, 9)
C_5	(6, 7)	(6, 9)	(5, 6)	(8, 9)	C_4	(3, 4)	(3, 5)	(2, 3)	(4, 5)
C_6	(8, 9)	(7, 8)	(5, 8)	(7, 9)	C_6	(7, 9)	(5, 7)	(6, 7)	(8, 9)

Step 4: Based on the mathematical steps, as mentioned in sub-section 2.1, the decisions of the four experts with respect to BO and OW vectors are now transformed into corresponding IRNBO and IRNOW vectors, as depicted in *Table 2.3* and *2.4* respectively. For example, in BO vector for criterion C_3, $P(E_1) = (7, 9)$, $P(E_2) = (5, 7)$, $P(E_3) = (6, 7)$ and $P(E_4) = (8, 9)$, which lead to the formation of two classes of objects x_i' and x' as: $x_i' = (7, 5, 6, 8)$ and $x_i = (9,7,7,9)$. Thus, for the first class of objects:

$$x_i^{L'}(5) = 5, x_i^{U'}(5) = \frac{1}{4}(5+6+7+8) = 6.5 \rightarrow x_i'(5) = (5, 6.5),$$

$$x_i^{L'}(6) = \frac{1}{2}(5+6) = 5.5, x_i^{U'}(6) = \frac{1}{3}(6+7+8) = 7 \rightarrow x_i'(6) = (5.5, 7),$$

$$x_i^{L'}(7) = \frac{1}{3}(5+6+7) = 6, x_i^{U'}(7) = \frac{1}{2}(7+8) = 7.5 \rightarrow x_i'(7) = (6, 7.5)$$

$$x_i^{L'}(8) = \frac{1}{4}(5+6+7+8) = 6.5 = 6, x_i^{U'}(8) = 8 \rightarrow x_i'(8) = (6.5, 8)$$

Similarly, for the second class of objects:

$$x_i^{L}(7) = \frac{1}{2}(7+7) = 7, x_i^{U}(7) = \frac{1}{4}(7+7+9+9) = 8 \rightarrow x_i(7) = (7, 8),$$

$$x_i^{L}(9) = \frac{1}{4}(7+7+9+9) = 8,\ x_i^{U}(9) = \frac{1}{2}(9+9) = 9 \rightarrow x_i(9) = (8, 9).$$

Thus, *IRN*(E_1) = [(6,7.5), (8, 9)], *IRN*(E_2) = [(5,6.5), (7,8)], *IRN*(E_3) = [(5.5,7), (7,8)] and *IRN*(E_4) = [(6.5,8), (8,9)].

Table 2.3 BO vector in terms of IRNs

Best : C_1	E_1	E_2	E_3	E_4
C_2	[(2.67,3.33),(3.50,4.67)]	[(2.67,3.33),(4.5,5.00)]	[(2.00,3.00),(3.00,4.25)]	[(3.00,4.00),(4.5,5.00)]
C_3	[(6.00,7.50),(8.00, 9.00)]	[(5.00,6.50),(7.00,8.00)]	[(5.50,7.00),(7.00,8.00)]	[(6.50,8.00),(8.00,9.00)]
C_4	[(4.25,5.00),(5.00,6.50)]	[(4.25,5.00),(5.50,7.00)]	[(3.50,4.67),(4.50,6.00)]	[(3.00,4.25),(4.00,5.50)]
C_5	[(5.67,6.67),(6.50,8.33)]	[(5.67,6.67),(7.75,9.00)]	[(5.00,6.25),(6.00,7.75)]	[(6.25,8.00),(7.75,9.00)]
C_6	[(6.75,8.00),(8.50,9.00)]	[(6.33,7.33),(8.00,8.50)]	[(5.00,6.75),(8.00,8.50)]	[(6.33,7.33),(8.50,9.00)]

Table 2.4 OW vector in terms of IRNs

Worst: C_5	E_1	E_2	E_3	E_4
C_1	[(4.25,5.00),(5.00,6.50)]	[(4.25,5.00),(5.50,7.00)]	[(3.50,4.67),(4.50,6.00)]	[(3.00,4.25),(4.00,5.50)]
C_2	[(6.75,8.00),(8.50,9.00)]	[(6.33,7.33),(8.00,8.50)]	[(5.00,6.75),(8.00,8.50)]	[(6.33,7.33),(8.50,9.00)]
C_3	[(5.67,6.67),(6.50,8.33)]	[(5.67,6.67),(7.75,9.00)]	[(5.00,6.25),(6.00,7.75)]	[(6.25,8.00),(7.75,9.00)]
C_4	[(2.67,3.33),(3.50,4.67)]	[(2.67,3.33),(4.5,5.00)]	[(2.00,3.00),(3.00,4.25)]	[(3.00,4.00),(4.5,5.00)]
C_6	[(6.00,7.50),(8.00,9.00)]	[(5.00,6.50),(7.00,8.00)]	[(5.50,7.00),(7.00,8.00)]	[(6.50,8.00),(8.00,9.00)]

Step 5: Development of the aggregated IRNBO and IRNOW vectors. Using the IRNDWGA operator of Eq. (14), the IRNBO and IRNOW vectors are aggregated into unique IRN vectors considering equal importance to all the four experts, as shown in *Table 2.5*. The calculation steps to convert the IRNs for criterion C_3 in the BO vector of *Table 2.3* into the corresponding aggregated IRNs are presented as below:

$$IRNDWGA(x_{31}) = \left\{ \begin{array}{l} x_{31}^{L'} = \dfrac{23}{1+\left(0.25\times\left(\dfrac{1-0.26}{0.26}\right)+\ldots+0.25\times\left(\dfrac{1-0.26}{0.26}\right)\right)} = 6.04 \\ x_{31}^{U'} = \dfrac{29}{1+\left(0.25\times\left(\dfrac{1-0.22}{0.22}\right)+\ldots+0.25\times\left(\dfrac{1-0.24}{0.24}\right)\right)} = 6.59 \\ x_{31}^{L} = \dfrac{30}{1+\left(0.25\times\left(\dfrac{1-0.24}{0.24}\right)+\ldots+0.25\times\left(\dfrac{1-0.24}{0.24}\right)\right)} = 7.12 \\ x_{31}^{U} = \dfrac{34}{1+\left(0.25\times\left(\dfrac{1-0.28}{0.28}\right)+\ldots+0.25\times\left(\dfrac{1-0.26}{0.26}\right)\right)} = 9.26 \end{array} \right\}$$

Table 2.5 Aggregated IRN BO and OW vectors

Best : C_1	**IRN BO**	**Worst: C_5**	**IRN OW**
C_2	[(2.51,3.59),(3.21,5.37)]	C_1	[(4.01,5.28),(4.54,5.33)]
C_3	[(6.04,6.59),(7.12,9.26)]	C_2	[(6.48,7.30),(7.55,8.95)]
C_4	[(4.01,5.28),(4.54,5.33)]	C_3	[(5.47,7.11),(6.22,9.43)]
C_5	[(5.47,7.11),(6.22,9.43)]	C_4	[(2.51,3.59),(3.21,5.37)]
C_6	[(6.48,7.30),(7.55,8.95)]	C_6	[(6.04,6.59),(7.12,9.26)]

Step 6: Determine the optimal values of criteria weights. Based on the aggregated IRNBO and IRNOW vectors, the following optimization problem is framed, which is subsequently solved using LINDO 19 software to estimate the optimal criteria weights. The derived IRN-based criteria weights are provided in *Table 2.6.*

Min ξ

Subject to

$$\left|\frac{w_B^{L'}}{w_2^U}-5.37\right|\le\xi;\left|\frac{w_B^{U'}}{w_2^L}-3.21\right|\le\xi;\left|\frac{w_B^L}{w_2^{U'}}-3.59\right|\le\xi;\left|\frac{w_B^U}{w_2^{L'}}-2.51\right|\le\xi;\left|\frac{w_B^{L'}}{w_3^U}-9.26\right|\le\xi;\left|\frac{w_B^{U'}}{w_3^L}-7.12\right|\le\xi;$$

$$\left|\frac{w_B^L}{w_3^{U'}}-6.59\right|\le\xi;\left|\frac{w_B^U}{w_3^{L'}}-6.04\right|\le\xi;\left|\frac{w_B^{L'}}{w_4^U}-5.33\right|\le\xi;\left|\frac{w_B^{U'}}{w_4^L}-4.54\right|\le\xi;\left|\frac{w_B^L}{w_4^{U'}}-5.28\right|\le\xi;\left|\frac{w_B^U}{w_4^{L'}}-4.01\right|\le\xi;$$

$$\left|\frac{w_B^{L'}}{w_5^U}-9.43\right|\le\xi;\left|\frac{w_B^{U'}}{w_5^L}-6.22\right|\le\xi;\left|\frac{w_B^L}{w_5^{U'}}-7.11\right|\le\xi;\left|\frac{w_B^U}{w_5^{L'}}-5.47\right|\le\xi;\left|\frac{w_B^{L'}}{w_6^U}-8.95\right|\le\xi;\left|\frac{w_B^{U'}}{w_6^L}-7.55\right|\le\xi;$$

$$\left|\frac{w_B^L}{w_6^{U'}}-7.30\right|\le\xi;\left|\frac{w_B^U}{w_6^{L'}}-6.48\right|\le\xi;\left|\frac{w_1^{L'}}{w_W^U}-5.33\right|\le\xi;\left|\frac{w_1^{U'}}{w_W^L}-4.54\right|\le\xi;\left|\frac{w_1^L}{w_W^{U'}}-5.28\right|\le\xi;\left|\frac{w_1^U}{w_W^{L'}}-4.01\right|\le\xi;$$

$$\left|\frac{w_2^{L'}}{w_W^U}-8.95\right|\le\xi;\left|\frac{w_2^{U'}}{w_W^L}-7.55\right|\le\xi;\left|\frac{w_2^L}{w_W^{U'}}-7.30\right|\le\xi;\left|\frac{w_2^U}{w_W^{L'}}-6.48\right|\le\xi;\left|\frac{w_3^{L'}}{w_W^U}-9.43\right|\le\xi;\left|\frac{w_3^{U'}}{w_W^L}-6.22\right|\le\xi;$$

$$\left|\frac{w_3^L}{w_W^{U'}}-7.11\right|\le\xi;\left|\frac{w_3^U}{w_W^{L'}}-5.47\right|\le\xi;\left|\frac{w_4^{L'}}{w_W^U}-5.37\right|\le\xi;\left|\frac{w_4^{U'}}{w_W^L}-3.21\right|\le\xi;\left|\frac{w_4^L}{w_W^{U'}}-3.59\right|\le\xi;\left|\frac{w_4^U}{w_W^{L'}}-2.51\right|\le\xi;$$

$$\left|\frac{w_6^{L'}}{w_W^U}-9.26\right|\le\xi;\left|\frac{w_6^{U'}}{w_W^L}-7.12\right|\le\xi;\left|\frac{w_6^L}{w_W^{U'}}-6.59\right|\le\xi;\left|\frac{w_6^U}{w_W^{L'}}-6.04\right|\le\xi;$$

$$\sum_{j=1}^{6} w_j^{L'}\le 1;\sum_{j=1}^{6} w_j^{L}\le 1;\sum_{j=1}^{6} w_j^{U'}\le 1;\sum_{j=1}^{6} w_j^{U}\le 1;$$

$$w_j^{L'}\le w_j^L\le w_j^{U'}\le w_j^U;\; w_j^{L'},w_j^L,w_j^{U'},w_j^U\ge 0,\;\forall\, j=1,2,\ldots,6$$

Table 2.6 Optimal criteria weights

Criteria	IRN weights
C_1	[(0.280, 0.365), (0.220, 0.342)]
C_2	[(0.142, 0.180), (0.140, 0.168)]
C_3	[(0.038, 0.065), (0.028, 0.061)]
C_4	[(0.221, 0.210), (0.202, 0.150)]
C_5	[(0.025, 0.050), (0.015, 0.030)]
C_6	[(0.112, 0.131), (0.110, 0.122)]

Step 7: Appraisal of the relative performance of the competing suppliers with respect to the considered evaluation criteria by each of the experts. As the initial step of IRN-EDAS method, all the four experts now evaluate the performance of the suppliers against each criterion in terms of RNs, as

provided in *Table 2.7*. These RN-based evaluation scores are later converted into IRN-based scores, as shown in *Table 2.8*.

Table 2.7 Individual expert's responses while evaluating alternative suppliers

Expert	Supplier	Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6
E_1	S_1	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)
	S_2	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)
	S_3	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)
	S_4	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
E_2	S_1	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)
	S_2	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
	S_3	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)
	S_4	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)
E_3	S_1	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
	S_2	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)
	S_3	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)
	S_4	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)
E_4	S_1	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)
	S_2	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)
	S_3	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
	S_4	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)

Table 2.8 IRN matrix for IRN-EDAS method

Expert	Supplier	Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6
E_1	S_1	[2.50,5.20], [4.00,6.16]	[2.00,4.67], [3.50,6.60]	[4.00,7.00], [5.60,8.00]	[3.00,5.75], [5.25,7.00]	[4.67,8.00], [6.16,9.00]	[3.50,6.33], [5.25,7.00]
	S_2	[3.60,7.00], [5.60,8.00]	[2.33,5.50], [5.25,7.00]	[3.00,6.33], [5.25,7.00]	[4.33,8.00], [6.16,9.00]	[2.00,4.33], [3.50,6.60]	[2.00,4.33], [4.00,6.16]
	S_3	[2.67,5.50], [5.40,7.25]	[3.25,6.00], [5.40,7.25]	[4.33,7.00], [5.83,8.00]	[2.00,5.00], [3.00,6.60]	[3.80,6.50], [5.40,7.25]	[1.00,4.33], [2.00,5.83]
	S_4	[2.67,4.00], [4.67,6.00]	[3.67,6.00], [5.67,7.00]	[2.00,3.67], [4.67,6.00]	[3.20,4.67], [5.67,7.00]	[2.67,4.00], [4.00,5.67]	[3.20,4.67], [5.00,6.67]
E_2	S_1	[2.67,5.50], [5.40,7.25]	[3.25,6.00], [5.40,7.25]	[4.33,7.00], [5.83,8.00]	[2.00,5.00], [3.00,6.60]	[3.80,6.50], [5.40,7.25]	[1.00,4.33], [2.00,5.83]
	S_2	[2.67,4.00], [4.67,6.00]	[3.67,6.00], [5.67,7.00]	[2.00,3.67], [4.67,6.00]	[3.20,4.67], [5.67,7.00]	[2.67,4.00], [4.00,5.67]	[3.20,4.67], [5.00,6.67]
	S_3	[3.60,7.00], [5.60,8.00]	[2.33,5.50], [5.25,7.00]	[3.00,6.33], [5.25,7.00]	[4.33,8.00], [6.16,9.00]	[2.00,4.33], [3.50,6.60]	[2.00,4.33], [4.00,6.16]
	S_4	[2.50,5.20], [4.00,6.16]	[2.00,4.67], [3.50,6.60]	[4.00,7.00], [5.60,8.00]	[3.00,5.75], [5.25,7.00]	[4.67,8.00], [6.16,9.00]	[3.50,6.33], [5.25,7.00]

Table 2.8 Contd.

	Supplier	Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6
E_3	S_1	[2.67,4.00], [4.67,6.00]	[3.67,6.00], [5.67,7.00]	[2.00,3.67], [4.67,6.00]	[3.20,4.67], [5.67,7.00]	[2.67,4.00], [4.00,5.67]	[3.20,4.67], [5.00,6.67]
	S_2	[2.50,5.20], [4.00,6.16]	[2.00,4.67], [3.50,6.60]	[4.00,7.00], [5.60,8.00]	[3.00,5.75], [5.25,7.00]	[4.67,8.00], [6.16,9.00]	[3.50,6.33], [5.25,7.00]
	S_3	[2.67,5.50], [5.40,7.25]	[3.25,6.00], [5.40,7.25]	[4.33,7.00], [5.83,8.00]	[2.00,5.00], [3.00,6.60]	[3.80,6.50], [5.40,7.25]	[1.00,4.33], [2.00,5.83]
	S_4	[3.60,7.00], [5.60,8.00]	[2.33,5.50], [5.25,7.00]	[3.00,6.33], [5.25,7.00]	[4.33,8.00], [6.16,9.00]	[2.00,4.33], [3.50,6.60]	[2.00,4.33], [4.00,6.16]
	Supplier	Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6
E_4	S_1	[2.50,5.20], [4.00,6.16]	[2.00,4.67], [3.50,6.60]	[4.00,7.00], [5.60,8.00]	[3.00,5.75], [5.25,7.00]	[4.67,8.00], [6.16,9.00]	[3.50,6.33], [5.25,7.00]
	S_2	[3.60,7.00], [5.60,8.00]	[2.33,5.50], [5.25,7.00]	[3.00,6.33], [5.25,7.00]	[4.33,8.00], [6.16,9.00]	[2.00,4.33], [3.50,6.60]	[2.00,4.33], [4.00,6.16]
	S_3	[2.67,4.00], [4.67,6.00]	[3.67,6.00], [5.67,7.00]	[2.00,3.67], [4.67,6.00]	[3.20,4.67], [5.67,7.00]	[2.67,4.00], [4.00,5.67]	[3.20,4.67], [5.00,6.67]
	S_4	[2.67,5.50], [5.40,7.25]	[3.25,6.00], [5.40,7.25]	[4.33,7.00], [5.83,8.00]	[2.00,5.00], [3.00,6.60]	[3.80,6.50], [5.40,7.25]	[1.00,4.33], [2.00,5.83]

Step 8: Formation of the aggregated IRN-EDAS matrix using IRNDWGA operator. The individual decision matrixes for the four participating experts in terms of IRNs are now aggregated using IRNDWGA operator to form the corresponding IRN matrix, as shown in *Table 2.9*.

Table 2.9 Aggregated IRN matrix for IRN-EDAS method

Supplier	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
S_1	[2.49,5.54], [4.26,6.15]	[2.26,6.08], [5.30,5.67]	[3.94,6.98], [3.73,7.47]	[2.98,4.15], [4.99,7.36]	[4.63,6.41], [3.71,9.05]	[3.26,2.94], [4.48,7.71]
S_2	[3.58,4.79], [4.19,8.15]	[2.57,6.26], [4.01,6.87]	[3.07,4.35], [6.14,7.16]	[4.23,5.57], [5.01,9.10]	[2.32,4.44], [6.30,5.70]	[2.29,5.21], [5.47,5.57]
S_3	[2.87,5.43], [5.21,5.97]	[3.18,5.27], [5.53,7.49]	[3.93,5.78], [6.21,5.08]	[2.23,7.79], [3.45,7.40]	[3.61,4.19], [5.39,5.57]	[1.31,4.74], [2.37,7.96]
S_4	[2.47,4.79], [5.95,7.00]	[3.16,4.38], [4.77,7.59]	[2.36,6.76], [5.19,8.41]	[2.91,5.80], [6.55,5.21]	[2.57,7.65], [3.53,7.90]	[2.71,6.22], [3.69,3.84]

Step 9: Calculate the average solution by forming the $IRN(AV_j)$ matrix. Based on the mathematical steps, as highlighted in sub-section 2.3, the average solutions are computed leading to the following matrix:

$$IRN(AV_j)=\begin{bmatrix}[2.85, 5.39], & [4.90, 6.82]\\ [2.79, 5.50], & [4.90, 6.91]\\ [3.32, 5.97], & [5.32, 7.03]\\ [3.09, 5.83], & [5.00, 7.27]\\ [3.28, 5.68], & [4.73, 7.06]\\ [2.39, 4.78], & [4.00, 6.27]\end{bmatrix}$$

The calculations steps of the average solution for criterion C_6 are shown as below:

$$\sum_{i=1}^{m}\frac{IRN(x_{ij})}{m}=\begin{bmatrix}\frac{[3.26+2.29+1.31+2.71]}{4}=2.39\\ \frac{[2.94+5.21+4.74+6.22]}{4}=4.78\\ \frac{[4.48+5.47+2.37+3.69]}{4}=4.00\\ \frac{[7.71+5.57+7.96+3.84]}{4}=6.27\end{bmatrix}$$

Step 10: Formulate the positive distance matrix $IRN(PDA_{ij})$ and negative distance matrix $IRN(NDA_{ij})$ in relation to the average solution $IRN(AV_{ij})$ for all the criteria. An example of calculation of these matrixes for element $IRN(PDA_{46})$ = [0.00, 0.55], [0.00, 0.60] is provided as below:

$$IRN(PDA_{46})=\left[\frac{b_{46}^{L}}{av_{46}^{U'}},\frac{b_{46}^{U}}{av_{46}^{L'}}\right],\left[\frac{b_{46}^{L'}}{av_{46}^{U}},\frac{b_{46}^{U'}}{av_{46}^{L}}\right]=\left[\frac{0.00}{6.27},\frac{2.22}{4.00}\right],\left[\frac{0.00}{4.78},\frac{1.45}{2.39}\right]$$

where

$$IRN(B_{46})=[b_{46}^{L},b_{46}^{U}],[b_{46}^{L'},b_{46}^{U'}]=[0.00, 2.22],[0.00, 1.45]$$

= max(0, [2.71 – 6.27, 6.22 – 4.00], [3.69 – 4.78, 3.84 – 2.39])

Similarly, an example of calculation of these matrixes for element $IRN(NDA_{46})$ = [0.39, 0.08], [0.00, 0.00] is shown as below:

$$IRN(NDA_{46})=\left[\frac{b_{46}^{L}}{av_{46}^{U'}},\frac{b_{46}^{U}}{av_{46}^{L'}}\right],\left[\frac{b_{46}^{L'}}{av_{46}^{U}},\frac{b_{46}^{U'}}{av_{46}^{L}}\right]=\left[\frac{2.43}{6.27},\frac{0.31}{4.00}\right],\left[\frac{0.00}{4.78},\frac{0.00}{2.39}\right]$$

where

$$IRN(B_{46})=[b_{46}^{L},b_{46}^{U}],[b_{46}^{L'},b_{46}^{U'}]=[2.43, 0.31],[0.00, 0.00]$$

= max(0, [6.27 – 3.84,4.00 – 3.69], [4.78 – 6.22, 2.39 – 3.84])

Step 11: Develop the weighted positive distance and negative distance matrixes. Here, $IRN(PDA_{ij})$ and $IRN(NDA_{ij})$ matrixes are multiplied by the corresponding criteria weights. An example of the corresponding calculation steps is provided as below:

$IRN(VP_{46})$ = [0.00, 0.07], [0.00, 0.07] = [0.00×0.112, 0.55×0.131], [0.00×0.110, 0.60×0.122]

$IRN(VN_{46})$ = [0.04, 0.01], [0.00, 0.00] = [0.39×0.112, 0.08×0.131], [0.00×0.110, 0.00×0.122]

Step 12: Compute the sums of the weighted IRN matrixes. An example of these calculation steps is as follows:

$$IRN(SP_{46})=\sum_{j=1}^{6} IRN(VP_{ij})=\begin{bmatrix} 0.05+0.00+0.00+0.07+0.00+0.00=0.12 \\ 0.00+0.00+0.05+0.04+0.03+0.07=0.19 \\ 0.02+0.00+0.00+0.03+0.00+0.00=0.05 \\ 0.50+0.29+0.26+0.10+0.04+0.07=1.26 \end{bmatrix}$$

$$IRN(SN_{46})=\sum_{j=1}^{6} IRN(VN_{ij})=\begin{bmatrix} 0.00+0.00+0.00+0.06+0.00+0.05=0.11 \\ 0.00+0.03+0.00+0.00+0.03+0.01=0.07 \\ 0.00+0.01+0.00+0.01+0.00+0.00=0.02 \\ 0.52+0.00+0.04+0.01+0.03+0.00=0.60 \end{bmatrix}$$

Step 13: Normalize the above matrixes. An example of these calculation steps is exhibited as below:

$$IRN(NSP_4)=[0.08, 3.80],[0.17, 10.50]=\left[\frac{0.12}{1.55},\frac{0.19}{0.05}\right],\left[\frac{0.05}{0.28},\frac{1.26}{0.12}\right]$$

$$IRN\,(NSN_4)=[0.82, 0.125],[0.92, -4.45]=1-\left[\frac{0.11}{0.60},\frac{0.07}{0.08}\right],\left[\frac{0.02}{0.23},\frac{0.60}{0.11}\right]$$

Step 14: Estimate *IRN*(*AS*$_i$) values for all the alternative suppliers. The IRN-EDM method-based calculation of *IRN*(*AS*$_i$) value for the fourth supplier is shown as follows:

$$IRN(AS_4)=[0.45, 1.96],[0.54, 3.03]=\left[\frac{0.08+0.82}{2},\frac{3.80+0.125}{2}\right],\left[\frac{0.17+0.92}{2},\frac{10.50-4.45}{2}\right]$$

The *IRN*(*AS*$_i$) values of all the four competing suppliers are provided in *Table 2.10*. Using *Eq. (2.39-2.46),* these *IRN*(*AS*$_i$) values are now converted into their corresponding crisp values which would lead to developing the condition as $I(\gamma) > I(\delta) > I(\alpha) > I(\beta)$. This analysis reveals that for supplying cotton bales to the considered Indian textile mill, supplier 3 is the most suitable choice, followed by supplier 4.

Table 2.10 Appraisal scores of the alternative suppliers

Supplier	IRN(ASi)	Crisp value	Rank
S1	[0.52, 1.63], [0.41, 3.32]	1.29	3
S2	[0.49, 0.73], [0.37, 4.82]	0.71	4
S3	[0.45, 2.57], [0.44, 3.06]	1.62	1
S4	[0.45, 1.96], [0.54, 3.03]	1.42	2

3. GREY-MABAC BASED APPROACH TO SUPPLIER SELECTION:

3.1 Grey Number

A grey number $\otimes N$ refers to as an interval with defined upper and lower limits and undefined distribution information for N. In the following equation, $\overline{N}$ *and* $\underline{N},$ denote the lower and upper limits of $\otimes N,$ correspondingly:

$$\otimes N = \left[\underline{N}, \overline{N}\right] = \left[N' \in N \middle| \underline{N} \leq N' \leq \overline{N}\right] \tag{3.1}$$

In the following equations, four main grey number mathematical operations are given:

$$Addition: \otimes N_1 + \otimes N_2 = \left[\underline{N_1} + \underline{N_2}, \overline{N_1} + \overline{N_2}\right], \tag{3.2}$$

$$Subtraction: \otimes N_1 - \otimes N_2 = \left[\underline{N_1} - \underline{N_2}, \overline{N_1} - \overline{N_2}\right],$$

$$Division: \otimes N_1 \div \otimes N_2 = \left[\underline{N_1}, \overline{N_1}\right] \times \left[\frac{1}{\overline{N_2}}, \frac{1}{\underline{N_2}}\right], \qquad Multiplication: \otimes N_1 \times \otimes N_2 =$$

$$\begin{bmatrix} min.\left(\underline{N_1 N_2}, \underline{N_2}\overline{N_1}, \overline{N}_2\underline{N_1}\overline{N_1 N_2}\right) \\ max.\left(\underline{N_1 N_2}, \underline{N_2}\overline{N_1}, \overline{N_2 \underline{N_1}}, \overline{N_1 N_2}\right) \end{bmatrix}$$

When it comes to a crisp number, the grey aggregation method is necessary to be applied. In the present work, a "degreying" technique is here after applied with the support of the translating fuzzy data into Crisp Scores (CFCS). Thus, $\otimes N_{ij}^r$ denotes the grey number of a cross functional decision-maker, who will assess the impact of risk i on a risk j where $\underline{N_{ij}^r}$ and $\overline{N_{ij}^r}$ represent the lower and upper grey values of the grey number $\otimes N_{ij}^r$, similarly:

$$\otimes N_{ij}^r = \left[\underline{N_{ij}^r}, \overline{N_{ij}^r}\right] \tag{3.3}$$

The conversion of ambiguous data into crisp scores entails three main steps represented as follows:

Step 1: Normalization

$$\underline{\widetilde{N}_{ij}^r} = \frac{\left(\underline{N_{ij}^r} - min_j \underline{N_{ij}^r}\right)}{\Delta_{min}^{max}}, \overline{\widetilde{\widetilde{N}}}_{ij}^r = \frac{\left(\overline{N}_{ij}^r - min_j \overline{N}_{ij}^r\right)}{\Delta_{max}^{min}}, \tag{3.4}$$

Where,

$$\Delta_{min}^{max} = max_j \overline{N}_{ij}^r - min_j \underline{N_{ij}^r} \tag{3.5}$$

Step 2: Computation of the total normalized crisp values

$$C_{ij}^r = \frac{\left(\underline{\widetilde{N}_{ij}^r}\left(1 - \underline{\widetilde{N}_{ij}^r}\right) + \left(\overline{\widetilde{\widetilde{N}}}_{ij}^r \times \overline{\widetilde{\widetilde{N}}}_{ij}^r\right)\right)}{\left(1 - \underline{\widetilde{N}_{ij}^r} + \overline{\widetilde{\widetilde{N}}}_{ij}^r\right)} \tag{3.6}$$

Step 3: Computation of the crisp values

$$V_{ij}^r = min_j \underline{N_{ij}^r} + C_{ij}^r \Delta_{min}^{max} \tag{3.7}$$

3.2 Grey MABAC Model

The process of applying the grey MABAC model consists of seven main steps as given below:

Step 1: Generating the initial decision matrix ($\hat{T}^k$): the research problem considers m number of alternatives ($A_i, i = 1,2,3,\ldots,m$) and n number of criteria ($C_j, j = 1,2,3,\ldots,n$). Here, $\hat{T}^k = [\otimes t_{ij}^k]_{m\times n}$ denotes the grey decision matrix generated by the decision maker R_k and with the support of *Tables 3.4 – 3.6.*

$$\hat{T}^k = [\otimes t_{ij}^k]_{m\times n} = \begin{bmatrix} [\underline{t}_{11}^k, \overline{t}_{11}^k] & [\underline{t}_{12}^k, \overline{t}_{12}^k] & [\underline{t}_{13}^k, \overline{t}_{13}^k] & \cdots & [\underline{t}_{1n}^k, \overline{t}_{1n}^k] \\ [\underline{t}_{21}^k, \overline{t}_{21}^k] & [\underline{t}_{22}^k, \overline{t}_{22}^k] & [\underline{t}_{23}^k, \overline{t}_{23}^k] & \cdots & [\underline{t}_{2n}^k, \overline{t}_{2n}^k] \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ [\underline{t}_{m1}^k, \overline{t}_{m1}^k] & [\underline{t}_{m2}^k, \overline{t}_{m2}^k] & [\underline{t}_{m3}^k, \overline{t}_{m3}^k] & \cdots & [\underline{t}_{mn}^k, \overline{t}_{mn}^k] \end{bmatrix}_{m\times n} \tag{3.8}$$

Where $\otimes t_{ij}^k$ denotes the performance grade of A_i with respect to criterion C_j according to $R_k (k = 1,2,3,\ldots,K)$**.** Thus, the cross-functional decision-makers K are involved in the evaluation procedure. Each R_s is given equal importance α_k $(where\ \sum_{k=1}^{K} \alpha_k = 1)$. Then, the grey systems theory is applied to handle the fuzziness of the collected data. The linguistic variables and the grey scale for the four risk factors are given in *Tables 3.4 – 3.7.*

Step 2: Formation of the grey decision matrix ($\hat{T}$): the decision matrices are gathered from the cross-functional decision-makers to aggregate the initial decision matrices$\hat{T}^k (k = 1,2,3,\ldots,K)$ into a grey decision matrix set $\hat{T} = [\otimes t_{ij}]_{m\times n}$ as follows:

$$\hat{T} = [\otimes t_{ij}]_{m\times n} = \begin{bmatrix} [\underline{t}_{11}, \overline{t}_{11}] & [\underline{t}_{12}, \overline{t}_{12}] & [\underline{t}_{13}, \overline{t}_{13}] & \cdots & [\underline{t}_{1n}, \overline{t}_{1n}] \\ [\underline{t}_{21}, \overline{t}_{21}] & [\underline{t}_{22}, \overline{t}_{22}] & [\underline{t}_{23}, \overline{t}_{23}] & \cdots & [\underline{t}_{2n}, \overline{t}_{2n}] \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ [\underline{t}_{m1}, \overline{t}_{m1}] & [\underline{t}_{m2}, \overline{t}_{m2}] & [\underline{t}_{m3}, \overline{t}_{m3}] & \cdots & [\underline{t}_{mn}, \overline{t}_{mn}] \end{bmatrix}_{m\times n} \tag{3.9}$$

$$\underline{t}_{ij} = \sum_{k=1}^{K} \alpha_k \times \underline{t}_{ij}^k, \overline{t}_{ij} = \sum_{k=1}^{k} \alpha_k \times \overline{t}_{ij}^k, \tag{3.10}$$

Step 3: Normalization of the elements from the grey aggregated decision matrix ($\hat{P}$): the normalization of the elements of the grey aggregated matrix($\hat{P}$) are identified from the initial matrix ($\hat{T}$) applying the following equation:

$$\otimes P_{ij} = [\underline{P}_{ij}, \overline{P}_{ij}] = \begin{cases} \dfrac{\underline{t}_{ij}}{t_j^+}, \dfrac{\overline{t}_{ij}}{t_j^+} \\ \dfrac{t_j^-}{\overline{t}_{ij}}, \dfrac{t_j^-}{\underline{t}_{ij}} \end{cases} \tag{3.11}$$

where $t_j^+ = max_{1\le i\le m}(t_{ij})$ denotes the benefit category criteria where maximal value of the criterion is required, while $t_j^- = min_{1\le i\le m}(t_{ij})$ indicates the cost category criteria where the minimum value of the criterion is required. Therefore, the normalized grey decision matrix is illustrated as follows:

$$\hat{P} = [\otimes t_{ij}]_{m\times n} = \begin{bmatrix} [\underline{p}_{11}, \overline{p}_{11}] & [\underline{p}_{12}, \overline{p}_{12}] & [\underline{p}_{13}, \overline{p}_{13}] & \cdots & [\underline{p}_{1n}, \overline{p}_{1n}] \\ [\underline{p}_{21}, \overline{p}_{21}] & [\underline{p}_{22}, \overline{p}_{22}] & [\underline{p}_{23}, \overline{p}_{23}] & \cdots & [\underline{p}_{2n}, \overline{p}_{2n}] \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ [\underline{p}_{m1}, \overline{p}_{m1}] & [\underline{p}_{m2}, \overline{p}_{m2}] & [\underline{p}_{m3}, \overline{p}_{m3}] & \cdots & [\underline{p}_{mn}, \overline{p}_{mn}] \end{bmatrix}_{m\times n} \tag{3.12}$$

Step 4: Computation of the elements from the grey weighted decision matrix ($\hat{G}$): the elements of the weighted matrix ($\hat{G}$) are computed based on *eq. (3.13)*. Thus, W_j denotes the weighted coefficients of the criterion j. By applying *eq. (3.14)*, the weighted matrix ($\hat{G}$) is formulated as follows:

$$\otimes g_{ij} = [\underline{g}_{ij}, \overline{g}_{ij}] = W_j \times \otimes p_{ij} = [W_j \times \underline{p}_{11}, W_j \times \overline{p}_{11}], \tag{3.13}$$

$$\hat{G} = [\otimes g_{ij}]_{m\times n} = \begin{bmatrix} [\underline{g}_{11}, \overline{g}_{11}] & [\underline{g}_{12}, \overline{g}_{12}] & [\underline{g}_{13}, \overline{g}_{13}] & \cdots & [\underline{g}_{1n}, \overline{g}_{1n}] \\ [\underline{g}_{21}, \overline{g}_{21}] & [\underline{g}_{22}, \overline{g}_{22}] & [\underline{g}_{23}, \overline{g}_{23}] & \cdots & [\underline{g}_{2n}, \overline{g}_{2n}] \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ [\underline{g}_{m1}, \overline{g}_{m1}] & [\underline{g}_{m2}, \overline{g}_{m2}] & [\underline{g}_{m3}, \overline{g}_{m3}] & \cdots & [\underline{g}_{mn}, \overline{g}_{mn}] \end{bmatrix}_{m\times n} \tag{3.14}$$

Step 5: Calculation of the grey Border Approximation Area (BAA) matrix $(\hat{B})$: the grey Border Approximation Area (BAA) for each criterion is calculated by using *eq. (3.15):*

$$\otimes b_{ij} = [\underline{b}_{ij}, \overline{b}_{ij}] = \left[\left(\prod_{i=1}^{m} \underline{g}_{ij} \right)^{1/m}, \left(\prod_{i=1}^{m} \overline{g}_{ij} \right)^{1/m} \right] \tag{3.15}$$

Thus, $[\underline{g}_{ij}, \overline{g}_{ij}]$ denotes the elements of the weighted matrix ($\hat{G}$) and m indicates the total number of alternatives. Once the grey value $\otimes b_{ij} = [\underline{b}_{ij}, \overline{b}_{ij}]$is calculated for each criterion, a border approximation area vector is generated. However, the BAA is an orientation point for each alternative. Furthermore, the grey vector $\hat{b} = (\otimes g_1, \otimes g_2, \otimes g_3, \ldots, \otimes g_n)_{1\times n}$ is used in the grey Border Approximation Area (BAA) matrix$(\hat{B})$, as rows of the following matrix:

$$\hat{B} = \begin{bmatrix} [\underline{b}_1, \overline{b}_1] & [\underline{b}_2, \overline{b}_2] & \cdots & [\underline{b}_n, \overline{b}_n] \\ [\underline{b}_1, \overline{b}_1] & [\underline{b}_2, \overline{b}_2] & \cdots & [\underline{b}_n, \overline{b}_n] \\ \vdots & \vdots & \ddots & \vdots \\ [\underline{b}_1, \overline{b}_1] & [\underline{b}_2, \overline{b}_2] & \cdots & [\underline{b}_n, \overline{b}_n] \end{bmatrix}_{m\times n} \tag{3.16}$$

Step 6: Computation of the alternatives distance from the BAA matrix for the matrix elements (X): The distance of the alternatives is calculated employing the "Euclidean distance" between the grey numbers $\otimes g_{ij}$ and $\otimes b_j$. Then, the elements matrix X is carried out as follows:

$$X = \hat{G} - \hat{B} = [x_{ij}]_{m\times n} = \begin{bmatrix} \otimes g_{11} - \otimes b_1 & \otimes g_{12} - \otimes b_2 & \cdots & \otimes g_{1n} - \otimes b_n \\ \otimes g_{21} - \otimes b_1 & \otimes g_{22} - \otimes b_2 & \cdots & \otimes g_{2n} - \otimes b_n \\ \vdots & \vdots & \ddots & \vdots \\ \otimes g_{m1} - \otimes b_1 & \otimes g_{m2} - \otimes b_2 & \cdots & \otimes g_{mn} - \otimes b_n \end{bmatrix} \tag{3.17}$$

Where,

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{3.18}$$

The distance of the alternatives from the Border Approximation Area (BAA) of each criterion is defined as the difference between the elements in the grey-weighted matrix $(\hat{G})$ and the value of the border approximation area $(\hat{B})$. Therefore, $\otimes b_j$ denotes the border approximation area of criterion C_j, and $\otimes g_{ij}$ denotes the elements of the grey weighted matrix $(\hat{G})$. The coefficient correlation is carried out as follows:

$$CC(A_i) = \sum_{j=1}^{n} x_{ij}, i = 1, 2, 3, \dots, m, j = 1, 2, 3, \dots, n \tag{3.19}$$

Eq. (3.20) denotes the sum of the distance of the alternatives from the Border Approximation Area (b_{ij}). CC indicates the closeness coefficient of each alternative from the BAA. Alternative $A_i (i = 1, 2, 3, \dots, m)$ belongs to the Border Approximation Area (BAA). There are three main areas and are pined as follows:

$$A_i \in \begin{cases} G^+, & \text{if } x_{ij} > 0, \text{upper approximation area}, \\ G & \text{if } x_{ij} = 0, \text{border approximation area}, \\ G^-, & \text{if } x_{ij} < 0, \text{lower approximation area}, \end{cases} \tag{3.20}$$

where G^+ denotes the upper approximation area for alternatives that are equal or close to the ideal solution, meanwhile G^- denotes the lower approximation area for alternatives that are equal or close to the anti-ideal solution.

Step 7: Ranking the Alternatives: the ranking of the alternatives is performed with the help of the following equation:

$$\hat{R}_i = \sum_{j=1}^{n} x_{ij}, i = 1, 2, 3, \dots, m, j = 1, 2, 3, \dots, n \tag{3.21}$$

3.3 Grey MABAC Model Application

Step 1 and 2: The linguistic terms are translated into a grey number and presented in *Table 3.5 & 3.6.* The aggregated grey decision matrix is obtained by applying equations (8)–(10).

Step 3: The aggregated grey decision matrix $(\hat{T})$ is converted into the normalized grey decision matrix $(\hat{P})$ by using *eq (3.11) and (3.12). Table 3.7* illustrates the normalized grey decision matrix $(\hat{P})$.

Step 4: The weighted grey decision matrix $(\hat{G})$ is computed by using the weight vector and *eq. (3.9) and (3.10)*. However, the weighted matrix is given as presented in *Table 3.8.*

Step 5: This step considers the calculation of the Border Appoximation Area (BAA) by applying *eq. (3.15) and (3.16).* The latter is calculated with the help of the geometric average as per shown in *Table 3.9.*

Step 6: The preference index matrix (X) is calculated by utilizing *eq. (3.17)* as per viewed in *Table 3.10.*

Step 7: The closeness coefficients for each failure mode (CC) are calculated by applying *eq. (3.19)* and given in *Table 3.11*. Furthermore, the suppliers are ranked to the descending order (from the upper value to the lowest value).

Table 3.1 List of Criteria

C1	Cost
C2	Quality
C3	Delivery
C4	Technical Support
C5	Payment Terms
C6	Flexibility

Table 3.2 Grey model linguistic terms and grey weights

Linguistic weights	**Grey weights**
Absolute important (AI)	[7, 9]
More important (MI)	[5, 7]
Important (I)	[3, 5]
Moderately important (DI)	[1,3]
Equal important (EI)	[1,1]

Table 3.3 Linguistic terms and the evaluation scale

Scale	**Grey Value**
Very poor (VP)	[0, 1]
Poor (P)	[1, 3]
Medium poor (MP)	[3, 4]
Fair (F)	[4, 5]
Medium good (MG)	[5, 6]
Good (G)	[6, 9]
Very good (VG)	[9, 10]

Table 3.4 Performance rating of the decision-makers.

	C1			C2			C3		
	DM1	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**
S1	G	MG	F	MP	MG	G	MG	VP	P
S2	MP	F	G	MG	VP	P	G	G	VG
S3	VP	P	F	G	G	MG	G	MG	F
S4	VG	MG	P	F	P	G	VP	P	F
S5	G	G	VG	G	VG	F	F	MP	MG
S6	F	MP	MG	MP	MG	P	MG	VP	P

Table 3.4 Contd.

	C4			C5			C6		
	DM1	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**
S1	G	G	MG	P	G	G	P	G	G
S2	G	VG	F	VP	P	F	VG	P	F
S3	MG	VP	P	P	F	G	VG	F	VP
S4	G	G	VG	P	F	P	P	P	F
S5	MP	MG	G	VG	F	F	P	F	P
S6	VP	P	F	MP	MG	MP	G	MG	F

Table 3.5 Grey decision matrix ($\widehat{T}^k$).

	C1			C2			C3		
	DM1	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**
S1	[6, 9]	[5, 6]	[4, 5]	[3, 4]	[5, 6]	[6, 9]	[5, 6]	[0, 1]	[1, 3]
S2	[3, 4]	[4, 5]	[6, 9]	[5, 6]	[0, 1]	[1, 3]	[6, 9]	[6, 9]	[9, 10]
S3	[0, 1]	[1, 3]	[4, 5]	[6, 9]	[6, 9]	[5, 6]	[6, 9]	[5, 6]	[4, 5]
S4	[9, 10]	[5, 6]	[1, 3]	[4, 5]	[1, 3]	[6, 9]	[0, 1]	[1, 3]	[4, 5]
S5	[6, 9]	[6, 9]	[9, 10]	[6, 9]	[9, 10]	[4, 5]	[4, 5]	[3, 4]	[5, 6]
S6	[4, 5]	[3, 4]	[5, 6]	[3, 4]	[5, 6]	[1, 3]	[5, 6]	[0, 1]	[1, 3]

Table 3.5 Contd

	C4			C5			C6		
	DM1	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**
S1	[6, 9]	[6, 9]	[5, 6]	[1, 3]	[6, 9]	[6, 9]	[1, 3]	[6, 9]	[6, 9]
S2	[6, 9]	[9, 10]	[4, 5]	[0, 1]	[1, 3]	[4, 5]	[9, 10]	[1, 3]	[4, 5]
S3	[5, 6]	[0, 1]	[1, 3]	[1, 3]	[4, 5]	[6, 9]	[9, 10]	[4, 5]	[0, 1]
S4	[6, 9]	[6, 9]	[9, 10]	[1, 3]	[4, 5]	[1, 3]	[1, 3]	[1, 3]	[4, 5]
S5	[3, 4]	[5, 6]	[6, 9]	[9, 10]	[4, 5]	[4, 5]	[1, 3]	[4, 5]	[1, 3]
S6	[0, 1]	[1, 3]	[4, 5]	[3, 4]	[5, 6]	[3, 4]	[6, 9]	[5, 6]	[4, 5]

Table 3.6 Average grey decision matrix ($\widehat{T}$).

	C1	C2	C3	C4	C5	C6
S1	[5.0, 6.7]	[4.7, 6.3]	[2.0, 3.3]	[5.7, 8.0]	[5.3, 7.0]	[4.3, 7.0]
S2	[4.3, 6.0]	[2.0, 3.3]	[7.0, 9.3]	[6.3, 8.0]	[2.0, 3.0]	[4.7, 6.0]
S3	[1.7, 3.0]	[5.7, 8.0]	[5.0, 6.7]	[2.0, 8.3]	[4.7, 5.7]	[4.3, 5.3]
S4	[5.0, 6.3]	[3.7, 5.7]	[1.7, 3.0]	[7.0, 9.3]	[2.7, 3.7]	[2.0, 3.7]
S5	[7.0, 9.3]	[6.3, 8.0]	[4.0, 5.0]	[4.7, 6.3]	[6.0, 6.7]	[2.0, 3.7]
S6	[4.0, 5.0]	[3.0, 4.3]	[2.0, 3.3]	[1.7, 3.0]	[4.0, 4.7]	[5.0, 6.7]

Table 3.7 Normalized grey decision matrix ($\widehat{P}$).

	C1	C2	C3	C4	C5	C6
S1	[0.25, 0.60]	[0.75, 0.79]	[0.29, 0.36]	[0.81, 0.36]	[0.29, 0.56]	[0.87, 1.00]
S2	[0.28, 0.70]	[0.32, 0.41]	[1.00, 1.00]	[0.90, 0.86]	[0.67, 1.50]	[0.93, 0.86]
S3	[0.57, 1.76]	[0.90, 1.00]	[0.71, 0.71]	[0.29, 0.36]	[0.35, 0.60]	[0.87, 0.76]
S4	[0.27, 0.60]	[0.59, 0.71]	[0.24, 0.32]	[1.00, 1.00]	[0.55, 1.13]	[0.40, 0.52]
S5	[0.18, 0.43]	[1.00, 1.00]	[0.54, 0.57]	[0.67, 0.68]	[0.30, 0.50]	[0.40, 0.52]
S6	[0.34, 0.67]	[0.48, 0.54]	[0.29, 0.36]	[0.24, 0.38]	[0.43, 0.75]	[1.00, 0.95]

Table 3.8 Weighted grey decision matrix ($\widehat{G}$).

	C1	C2	C3	C4	C5	C6
S1	[1.78, 5.40]	[3.73, 5.51]	[0.86, 1.79]	[0.81, 2.57]	[0.29, 0.56]	[0.87, 3.00]
S2	[1.98, 6.28]	[1.59, 2.89	[3.00, 5.00]	[0.90, 2.57]	[0.67, 1.50]	[0.93, 2.57]
S3	[3.97, 15.88]	[4.52, 7.00]	[2.14, 3.57]	[0.29, 1.07]	[0.35, 0.64]	[0.87, 2.29]
S4	[1.89, 5.40]	[2.94, 4.99]	[0.71, 1.61]	[1.00, 3.00]	[0.55, 1.13]	[0.40, 1.57]
S5	[1.28, 6.00]	[5.00, 7.00]	[1.71, 2.68]	[0.67, 2.04]	[0.30, 0.50]	[1.00, 2.86]
S6	[2.38, 5.00]	[2.38, 3.76]	[0.86, 1.79]	[0.24, 0.96]	[0.43, 0.75]	[1.28, 1.55]

Table 3.9 Grey BAA matrix ($\widehat{B}$).

	C1	C2	C3	C4	C5	C6
BAA	[1.54, 1.87]	[1.65, 1.77]	[1.45, 1.59]	[1.25, 1.52]	[1.17, 1.31]	[1.28, 1.55]

Table 3.10 Preference index matrix ($\widehat{X}$).

	C1	C2	C3	C4	C5	C6
S1	[0.24, 3.53]	[2.08, 3.74]	[-0.59, 0.19]	[-0.45, 1.05]	[-0.89, -0.75]	[-0.42, 1.45]
S2	[0.44, 4.41]	[-0.06, 1.11]	[1.55, 3.41]	[-0.35, 1.05]	[-0.50, 0.19]	[1.02, 11.92]
S3	[2.43, 14.01]	[2.87, 5.23]	[0.69, 1.98]	[-0.97, -0.45]	[-0.82, -0.67]	[0.74, 24.63]
S4	[0.35, 3.53]	[1.29, 3.21]	[-0.74, 0.01]	[-0.25, 1.48]	[-0.63, -0.19]	[0.02, 7.21]
S5	[-0.26, 1.99]	[3.35, 5.23]	[0.26, 1.08]	[-0.59, 0.52]	[-0.87, -0.81]	[0.02, 9.04]
S6	[0.84, 4.83]	[0.73, 1.99]	[-0.59, 0.19]	[-1.02, -0.55]	[-0.74, -0.56]	[1.31, 5.44]

Table 3.11 Closeness coefficient (CC) and ranking of the Suppliers.

Supplier	CC	Rank
S1	9.19	3
S2	11.92	2
S3	24.63	1
S4	7.21	5
S5	9.04	4
S6	5.44	6

4. CONCLUSION

This research work conducts a detailed study of the application of MCDM techniques in supplier selection problem in an Indian textile mill. In this study, two integrated techniques, namely, IRN-BWM-EDAS and Grey-MABAC are employed for ranking the suppliers. The following are the findings of each of the studies.

a) In First analysis, an integrated approach combining IRN, BWM and EDAS methods for solving a supplier selection problem is employed for an Indian textile mill. For this purpose, six evaluation criteria, i.e. cost, quality, delivery, technical support, payment terms and flexibility, four alternative suppliers and four experts engaged in the purchasing, blowroom, spinning and quality control departments of the said mill are considered. At first, the relative importance assigned to different criteria by the experts is expressed in terms of IRNs which are aggregated together to estimate the corresponding optimal criteria weights using BWM. Similarly, the performance of each of the competing suppliers with respect to the considered evaluation criteria is also expressed using IRNs. The aggregated IRNs for supplier performance evaluation are the inputs to EDAS method which would finally help in ranking those suppliers. Based on this integrated approach, supplier 3 emerges out as the most apposite choice, followed by supplier 4. Although it is a computationally extensive method, but it leads to more accurate and reliable solution while providing unbiased decision reducing the chances of losing information. The accuracy of the derived ranking results may be contrasted against other existing integrated MCDM approaches, like rough BWM-MAIRCA, rough-MABAC-DoE, IRN-SWARA-MABAC etc.

b) In second, an integrated approach combining IGN and MABAC methods for solving a supplier selection problem is employed. For this purpose, again six evaluation criteria used before, i.e. cost, quality, delivery, technical support, payment terms and flexibility, six alternative suppliers and three experts engaged in the different departments of the said mill are considered. At first, the relative importance assigned to different criteria by the experts is expressed in terms of IGNs by using a linguistic table. Similarly, the performance of each of the competing suppliers with respect to the considered evaluation criteria is also expressed using IGNs. The aggregated IGNs for supplier performance evaluation are the inputs to MABAC method which would finally help in ranking those suppliers. Based on this integrated approach, supplier 3 emerges out as the most apposite choice, followed by supplier 2. This research work contributes to the field of supplier selection in a number of ways. Grey systems theory (GST) is seen as a helpful tool for dealing with the fuzziness and uncertainty that comes with bad data. As a result, it is able to drive and address unclear data processing risk factors and alternatives in a systematic manner in this work. In comparison to other MCDM approaches, the Grey MABAC model has a significant advantage. It demonstrates how to take a methodical approach to aggregating decision-makers' judgments. It allowed us to categorise the criteria as beneficial or non-beneficial. It takes into account the calculation of the proximity coefficient values (CCi) and divides them into three categories (positive upper approximation area, zero border approximation area, and negative lower approximation area).

To ease out the computational steps involved in the approach, a decision support framework may be developed as a future scope for the research.

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