Decision Making: Applications in Management and Engineering
Vol. 5, Issue 2, 2022, pp. 219-240.
ISSN: 2560-6018
eISSN: 2620-0104
DOI:_ https://doi.org/10.31181/dmame0307102022p

AN INTEGRATED IRN-BWM-EDAS METHOD FOR SUPPLIER SELECTION IN A TEXTILE INDUSTRY

Vivek Kumar Paul[1], Santonab Chakraborty[2] and Shankar Chakraborty[1*]

[1] Department of Production Engineering, Jadavpur University, Kolkata, West Bengal, India
[2] National Institute of Industrial Engineering, Mumbai, India

Received: 6 June 2022;
Accepted: 11 September 2022;
Available online: 7 October 2022.

Original scientific paper

Abstract: *Like all other manufacturing industries, supplier selection also plays a pivotal role in a textile industry with respect to timely and cost-effective delivery of raw materials (cotton, yarn or fabric), chemicals and dyes, machineries, spare parts and other auxiliary parts/items. An appropriately selected supplier would help the textile industry in seamless production of final or semi-finished products leading to effective deployment of supply chain management concept. Due to involvement of many competing suppliers and a set of conflicting criteria, supplier selection is often treated as a typical multi-criteria decision making problem. The process of choosing the right supplier for a given item often becomes more difficult due to presence of both quantitative and qualitative evaluation criteria. In this paper, based on six most significant criteria, 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 a textile industry. The application of IRN helps in expressing opinions of the decision makers 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. An IRN Dombi weighted geometric averaging (IRNDWGA) technique is considered to aggregate the opinions of the decision makers. This integrated approach identifies alternative 3 as the most apposite supplier for the textile industry under consideration.*

Key words: *Supplier selection, textile industry, rough numbers, BWM, EDAS, MCDM, ranking.*

1. Introduction

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 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 shortlisting a set of

* Corresponding author.
E-mail addresses: kumarpaulvivek@gmail.com (V.K. Paul), santonabchakraborty@gmail.com (Santonab Chakraborty), s_chakraborty00@yahoo.co.in (Shankar Chakraborty)

competent suppliers having the highest potential to consistently fulfill the manufacturing organization's needs with an acceptable overall performance. An efficient supplier selection process would reduce purchasing risks, ensure uninterrupted production, maximize overall value for the buyers, develop proximity and long-term relationships between buyers and suppliers, and maximize 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).

In India, textile industry plays an increasingly important role in the national economy, not only by meeting the growing and diverse requirements of the people, but also generating huge job opportunities, making a major contribution in promoting economic development. The Indian textile industry contributes 5% to the country's GDP, 7% to the industry output in value terms, 12% to the country's export earnings, and 5% to the global trade in textiles and apparel. The growth rate of Indian textile industry was estimated to be 8.7% during 2015-2020, increased from about 7% from 2010-2015. India ranks as the world's sixth largest textile and clothing exporter, and is also the major cotton and jute producer. It is also the second largest silk producer and 95% of the world's hand-woven fabric comes from India. The Indian technical textiles sector is estimated at USD 16 billion, approximately 6% of the global market. The textile and apparel industry in India is the second largest employer in the country providing direct employment to 45 million people and 100 million people in allied industries. The domestic technical textile market for synthetic polymer was valued at USD 7.1 billion in 2020 and is projected to reach USD 11.6 billion by 2027, growing at a CAGR of 7.2%, while the technical textile market for woven fabrics is expected to grow at a CAGR of 7.4% to USD 15.7 billion by 2027, up from USD 9.5 billion in 2020. Investment in the Indian textile industry has witnessed an erroneous growth of almost 69%, increasing from USD 1.41 million in 2010 to USD 2.38 billion in 2019. By 2029, the Indian textiles market is expected to be worth more than USD 209 billion.

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 (fiber, yarn or fabric), chemicals and dyes, machineries, spare parts and other auxiliary parts/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 suppliers having varying potentialities and capabilities is a complex task due to involvement of several qualitative and quantitative evaluation criteria (Nhu-Mai Thi & 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. The supplier selection problem having a set of equally compatible suppliers and conflicting evaluation criteria can be treated as a typical MCDM problem (Chakraborty & Chakraborty, 2022; Chakraborty et al., 2023). In this direction, the past researchers have attempted the applications of several MCDM tools in identifying the most apposite suppliers for textile industries involved in production of varieties of end products (Yıldız & Yayla, 2015; Manucharyan, 2021).

In earlier days, evaluation of the suppliers and selection of the best one usually depend 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 paper first identifies six pivotal criteria, and attempts to express the opinions of four experts with respect to the relative significance of the considered criteria and performance of each supplier against each of the criteria using IRNs. The weights of the six evaluation criteria are determined using IRN-BWM approach and the competing suppliers are ranked from the best to the worst based on IRN-EDAS method. This integrated approach (IRN-BWM-EDAS) appears to be a useful tool for supplier selection in a given textile industry engaged in procurement of raw materials in the form of cotton bales.

This paper is structured as follows: Section 2 provides a concise literature review of different MCDM methods employed for solving supplier selection problems in textile industries. The mathematical details of IRN, IRN-BWM and IRN-EDAS are presented in Section 3. A demonstrative example consisting of four suppliers is solved in Section 4 using the proposed approach and conclusions are drawn in Section 5.

2. Literature review

It has already been mentioned that the supplier selection process can often be treated as an MCDM problem with an aim to select the most apposite supplier fulfilling the requirements of a textile industry. Table 1 presents a concise review of supplier selection problems in textile industries taking into account the number of suppliers, evaluation criteria, MCDM tool(s) applied and integration of MCDM techniques with other methods. It can be interestingly noticed that AHP has been mainly employed for criteria weight measurement, followed by ANP. Unlike AHP, ANP considers inter-dependencies between the criteria and it has not a strictly hierarchical structure. On the other hand, TOPSIS, MOORA, WASPAS and VIKOR have been the other popular tools used for evaluation and ranking of the suppliers. Fuzzy theory and grey theory have been integrated with the MCDM tools to evaluate relative importance of the criteria under uncertain decision making environment. In the similar direction, DEA has been applied for shortlisting the efficient suppliers through an initial screening process, PCA has been adopted for criteria weight measurement and data dimensionality reduction, and DEMATEL has been employed to segregate the evaluation criteria into cause and effect groups with development of the corresponding causal diagrams.

Ali et al. (2020) developed a fuzzy-AHP-TOPSIS-based decision support system for solving a cotton supplier selection problem in a Pakistani textile industry. The weights of five evaluation criteria, i.e. cost, quality, service, delivery and payment terms were first estimated using fuzzy-AHP method and TOPSIS was later applied to rank the candidate suppliers. Utama et al. (2021a) integrated AHP method with MOORA to solve a green supplier selection problem in a textile industry. The weights of eight evaluation criteria were estimated using AHP and the considered suppliers were ranked based on MOORA appraisal scores. Product price was identified as the most important criterion affecting the supplier selection decision. While assessing the performance of apparel retailers, Sarıçam and Yilmaz (2021) presented the combined application of DEA, AHP and TOPSIS methods. AHP was employed to determine the criteria and sub-criteria weights and the apparel retailers were initially ranked using TOPSIS method. A set of feasible and most efficient retailers was finally identified based on the application of DEA. Celik et al. (2021) first estimated weights of the considered evaluation criteria using BWM and interval type-2 fuzzy numbers, and later ranked the green suppliers for a textile industry based on TODIM and interval type-2 fuzzy numbers. Product design and pattern suitability, purchase cost, dye and print quality, profit, and variation in price were identified as the most significant sub-criteria.

Based on this literature review of the applications of different MCDM techniques in solving textile supplier selection problems, it can be noticed that the past researchers have endeavored to mainly integrate fuzzy theory and grey theory with different MCDM tools to rank the suppliers from the best to the worst under uncertain decision making environment. This paper proposes an integrated approach combining IRN, BWM and EDAS methods for solving a supplier selection problem in an Indian textile mill. To the best of the authors' knowledge, till date, there has been no application of IRN-BWM-EDAS method for solving supplier selection problems in textile industries.

Table 1: Literature review on MCDM-based supplier selection in textile industries

Author(s)	No. of suppliers	Criteria	MCDM tool(s)	Other tool(s)
Hlyal et al. (2015)	5	Cost, quality, logistics efficiency, production capacity, social climate, versatility	AHP	
Sasi and Digalwar (2015)	2	Quality, labor and pollution rules, product variety, transportation facility, raw material cost, labor cost, counterpart flexibility, research background, export cost, degree of specialization, international relation, flexibility in production, number of production centers, dependency on import	AHP, TOPSIS	
Kara et al. (2016)	3	Basic requirements, performance requirement, attractive service requirement	ANP	
Shukla (2016)	3	Cost, quality, reliability, delivery, flexibility	AHP	
Ayvaz and Kuşakcı (2017)	4	Cost, delivery performance, customer relationships, payment options, technical capability	TOPSIS	Fuzzy theory

Table 1: Contd.

		R&D rate, productivity, gross profit rate,		

Jing (2018)	12	quantity discount, inventory turnover ratio, return rate, discount rate, operating expense rate	TOPSIS	Fuzzy theory, DEA
Bakhat and Rajaa (2019)	7	Quality, cost, technological capability, technical support, delivery, flexibility, supplier reputation, discount opportunities	AHP, WASPAS	Grey theory
Guarnieria and Trojan (2019)	10	Ability to fulfil customers' requirements, quality, on-time delivery, technological capacity, accordance with the law, continuous improvement, environmental impact, managing hazardous waste, environmental management	ELECTRE	Copeland method, AHP
Burney and Ali (2019)	4	Cost, quality, service, delivery, payment terms	AHP	Fuzzy theory
Wang et al. (2020)	10	Reliability, responsiveness, flexibility, cost, assets	PROMETHEE-II, AHP	Fuzzy theory
Karami et al. (2020)	12	Quality, price, location, lead time, monetary position, financial position, on-time delivery, ability to product change, support and service, technical capacity	VIKOR	PCA, DEA
Ersoy and Dogan (2020)	16	Price, quality, delivery, reliability, inventory availability, flexibility, pollution rate of the raw material	AHP	Fuzzy theory, DEA
Ali et al. (2020)	5	Cost, quality, service, delivery, payment terms	AHP, TOPSIS	Fuzzy theory
Mondragon et al. (2021)	1	Technology used by the suppliers, technology used by the customers, automation, rapid manufacturing, capacity, reduced cycle time, cost, ROI, supply chain performance, on-time delivery, skill, environmental impact	AHP	Fuzzy theory
Utama et al. (2021a)	8	Company profile, quality, cost, delivery, service, environment	MOORA	AHP
Sarıçam and Yilmaz (2021)	4	Management and organization, usage of up-to-date technology and equipment, quality system and certification, geographical location, product price, seamless production, product quality, follow up, lead time, technical capability, accuracy, reliability	AHP, TOPSIS	DEA
Celik et al. (2021)	3	Environmental, social, quality, risk, cost/price, capability, business structure	BWM, TODIM	Interval type-2 fuzzy number
Utama et al. (2021b)	3	Price, quality, conformance to specifications, on-time delivery, appropriateness of quantities, replacement of damaged goods, performance history, flexibility, eco-friendly material, permittance, delivery cost, mode of transportation, capability, environmental certificate, payment method	ANP	DEMATEL
This paper	4	Cost, quality, delivery, technical support, payment terms, flexibility	EDAS	IRN, BWM

3. Methods

3.1 IRN

Let us assume a 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 predefined 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} decision maker ($1 \le e \le k$) can be expressed as below:

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

There is a set of k classes of expert's preferences $x^- = \{x_1^-, x_2^-, \dots, x_k^-\}$ satisfying the condition $\{x_1^- \le x_2^- \le \dots \le x_k^-\}$. There is also another set of k classes of expert's preferences $x^+ = \{x_1^+, x_2^+, \dots, x_k^+\}$. 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 interval limits are sequenced as follows: $x_1^L < x_2^L <\dots,< x_l^L; x_1^U < x_2^U <\dots,< x_k^U$ ($1 \le l, k \le m$), the above sequences can then be denoted as two sets: a) a set of lower classes $x^L = \{x_1^L, x_2^L, \dots, x_i^L\}$, and a set of upper classes $x^U = \{x_1^U, x_2^U, \dots, x_i^U\}$ ($x_i^L \in x^L, 1 \le i \le l$ 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:

$$\underline{Apr}(x_i^L) = \cup \left\{x \in X / x^L(x) \le x_i^L\right\} \tag{2}$$

$$\underline{Apr}(x_i^U) = \cup \left\{x \in X / x^U(x) \le x_i^U\right\} \tag{3}$$

b) Upper approximation:

$$\overline{Apr}(x_i^L) = \cup \left\{x \in X / x^L(x) \ge x_i^L\right\} \tag{4}$$

$$\overline{Apr}(x_i^U) = \cup \left\{x \in X / x^U(x) \ge x_i^U\right\} \tag{5}$$

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

a) Lower limit:

$$\underline{Lim}(x_i^L) = \frac{1}{N_L} \sum_{b=1}^{N_L} x_i^{bL} \left| x_i^{bL} \in \underline{Apr}(x_i^L) \right. \tag{6}$$

$$\underline{Lim}(x_i^U) = \frac{1}{N_L^*} \sum_{b=1}^{N_L^*} x_i^{bU} \left| x_i^{bU} \in \underline{Apr}(x_i^U) \right. \tag{7}$$

b) Upper limit:

$$\overline{Lim}(x_i^L) = \frac{1}{N_U} \sum_{b=1}^{N_U} x_i^{bL} \left| x_i^{bL} \in \overline{Apr}(x_i^L) \right. \tag{8}$$

$$\overline{Lim}(x_i^U) = \frac{1}{N_U^*} \sum_{b=1}^{N_U^*} x_i^{bU} \left| x_i^{bU} \in \overline{Apr}(x_i^U) \right. \tag{9}$$

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 where 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):

$$IRN(x_i)=\left[RN(x_i^L),RN(x_i^U)\right]$$
$$=\left[\left(\underline{L}(x_i^L),\overline{L}(x_i^L)\right),\left(\underline{L}(x_i^U),\overline{L}(x_i^U)\right)\right]=\left[\left(x_i^{L'},x_i^{U'}\right),\left(x_i^L,x_i^U\right)\right] \tag{10}$$

Thus, IRNs can effectively represent both uncertainty and imprecision in a decision making process. To illustrate its numerical formulations, let us assume a group decision making situation where three experts require to qualitatively evaluate 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 now 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_i are formed as: x_i' = (3, 4, 4) and x_i = (4, 5, 4). These object classes are now 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:

$$x_i^L(4)=\frac{1}{3}(3+4+4)=3.7, x_i^U(3)=4 \rightarrow x_i(4)=(3.7,4),$$
$$x_i^L(4)=4,\ x_i^U(4)=\frac{1}{3}(4+4+5)=4.3 \rightarrow x_i(4)=(4,4.33), x_i^L(5)=\frac{1}{3}(4+4+5)=4.3,$$
$$x_i^U(5)=5 \rightarrow x_i(5)=(4.3,5)$$

Thus, the RNs expressing the 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)]

Application of IRNs relieves involvement of the decision makers 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 decision makers to express their judgments more preciously without making biased decisions (Yazdani et al., 2020).

3.2 IRN-BWM

The BWM, proposed by Rezaei (2015), is an MCDM technique for criteria weight measurement, where the decision maker 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 reverse role. Using a pre-defined scale (e.g. 1-9), the decision maker evaluates the performance of the best criterion over all other criteria and the performance of all other criteria over the worst criterion. These two pair-wise comparison vectors (i.e. BO and OW) are treated as the inputs to a linear programming model, which is finally solved to determine the optimal criteria weight values. 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 (Sadjadi & Karimi, 2018; Pamučar et al., 2020; Khan et al., 2021; Rodríguez-Gutiérrez et al., 2021; Hasan et al., 2022; Srdjevic et al., 2022).

In this paper, BWM is combined with IRNs to deal with uncertainty and ambiguity present while assigning the relative importance (weight) to the considered supplier selection 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 best-to-other (BO) and other-to-worst (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 the proposed IRN-BWM is illustrated using the following steps:

Step 1: Define a set of criteria for evaluating the alternatives. 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} (where *n* is the total number of criteria).

Step 2: Define the best (B) and 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 the 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 advantage of criterion B over criterion *j*, $a_{BB}^{eL}=1$ and $a_{BB}^{e'U}=1$. So, for each e^{th} expert, a BO matrix $A_B^1,A_B^2,\ldots,A_B^e,\ldots,A_B^k$ is formed. These individual expert 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 $\mathrm{O}W(A_W^e)$ is obtained for e^{th} 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 advantage of j^{th} criterion over criterion *W*, $a_{WW}^{eL}=1$ and $a_{WW}^{e'U}=1$. Thus, for each expert, a OW matrix $A_W^1,A_W^2,\ldots,A_W^e,\ldots,A_W^k$ 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 $A_B^{*e'L}$ are formed in which the expert decisions are aggregated:

$$A_B^{*eL}=\left[a_{B1}^{1L},a_{B1}^{2L},\ldots,a_{B1}^{kL};a_{B2}^{1L},a_{B2}^{2L},\ldots,a_{B2}^{kL};a_{Bn}^{1L},a_{Bn}^{2L},\ldots,a_{Bn}^{kL}\right]_{1\times n} \tag{11}$$

$$A_B^{*e'U}=\left[a_{B1}^{1'U},a_{B1}^{2'U},\ldots,a_{B1}^{k'U};a_{B2}^{1'U},a_{B2}^{2'U},\ldots,a_{B2}^{k'U};a_{Bn}^{1'U},a_{Bn}^{2'U},\ldots,a_{Bn}^{k'U}\right]_{1\times n} \tag{12}$$

where $a_{Bj}^{eL}=\{a_{Bj}^{1L},a_{Bj}^{2L},\ldots,a_{Bj}^{kL}\}$ and $a_{Bj}^{e'U}=\{a_{Bj}^{1'U},a_{Bj}^{2'U},\ldots,a_{Bj}^{k'U}\}$ represent advantage 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 IRNs, using Eqs. (2)-(10), $IRN(a_{Bj}^e)=\left[((L(a_{Bj}^{eL-}),(L(a_{Bj}^{eU-})),((L(a_{Bj}^{eL+}),(L(a_{Bj}^{eU+}))\right]$ where $L(a_{Bj}^{eL-})$ and $L(a_{Bj}^{eL+})$ represent lower limits, and $L(a_{Bj}^{eU-})$ and) $L(a_{Bj}^{eU+})$ denote upper limits of $IRN(a_{Bj}^e)$ respectively. So for each sequence $IRN(a_{Bj}^e)$, the corresponding BO matrixes $A_B^1,A_B^2,\ldots,A_B^e,\ldots A_B^k$ $(1\le e\le k)$ are formed. Now, by applying the IRNDWGA operator, the average IRN sequence is obtained. The aggregated IRNBO matrix is expressed in Eq. (13):

$$\overline{A}_B=\left[IRN(\overline{a}_{B1}),IRN(\overline{a}_{B2}),\ldots,IRN(\overline{a}_{Bn})\right]_{1\times n} \tag{13}$$

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:

$$IRNDWGA\{IRN(\varphi_1),\ldots,IRN(\varphi_n)\} = \left[\begin{array}{c}\left\{\dfrac{\sum_{j=1}^{n}\emptyset_j^{L-}}{1+\left\{\sum_{j=1}^{n} w_j\left\{\frac{1-f(\emptyset_j^{L-})}{f(\emptyset_j^{L-})}\right\}^{\rho}\right\}^{1/\rho}}, \dfrac{\sum_{j=1}^{n}\emptyset_j^{U-}}{1+\left\{\sum_{j=1}^{n} w_j\left\{\frac{1-f(\emptyset_j^{U-})}{f(\emptyset_j^{U-})}\right\}^{\rho}\right\}^{1/\rho}}\right\} \\ \left\{\dfrac{\sum_{j=1}^{n}\emptyset_j^{L+}}{1+\left\{\sum_{j=1}^{n} w_j\left\{\frac{1-f(\emptyset_j^{L+})}{f(\emptyset_j^{L+})}\right\}^{\rho}\right\}^{1/\rho}}, \dfrac{\sum_{j=1}^{n}\emptyset_j^{U+}}{1+\left\{\sum_{j=1}^{n} w_j\left\{\frac{1-f(\emptyset_j^{U+})}{f(\emptyset_j^{U+})}\right\}^{\rho}\right\}^{1/\rho}}\right\}\end{array}\right] \tag{14}$$

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 $A_W^e = \left[a_{jW}^{eL}, a_{jW}^{e'U}\right]_{1\times n}$.

$$A_W^{*eL} = \left[a_{W1}^{1L}, a_{W1}^{2L},\ldots,a_{W1}^{mL}; a_{W2}^{1L}, a_{W2}^{2L},\ldots,a_{W2}^{mL}; a_{Wn}^{1L}, a_{Wn}^{2L},\ldots,a_{Wn}^{mL}\right]_{1\times n} \tag{15}$$

$$A_W^{*e'U} = \left[a_{W1}^{1'U}, a_{W1}^{2'U},\ldots,a_{W1}^{m'U}; a_{W2}^{1'U}, a_{W2}^{2'U},\ldots,a_{W2}^{m'U}; a_{Wn}^{1'U}, a_{Wn}^{2'U},\ldots,a_{Wn}^{m'U}\right]_{1\times n} \tag{16}$$

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 advantage of criterion j over criterion W. By applying Eqs. (2)-(10), each pair of sequences a_{jW}^{eL} and $a_{jW}^{e'U}$ is transformed into:

$IRN(a_{jW}^{e}) = \left[((\underline{L}(a_{iW}^{eL-}), (\overline{L}(a_{iW}^{eU-})), ((\underline{L}(a_{iW}^{eL+}), (\overline{L}(a_{iW}^{eU+}))\right]$sequence, where $\underline{L}(a_{jW}^{eL-})$ and $\underline{L}(a_{jW}^{eL+})$ represent lower limits, while $\overline{L}(a_{jW}^{eU-})$ and $\overline{L}(a_{jW}^{eU+})$ represent upper limits of $IRN(a_{jW}^{e})$ sequence, respectively. So, 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 IRN sequences are achieved:

$$\overline{A}_W = \left[IRN(\overline{a}_{1W}), IRN(\overline{a}_{2W}),\ldots,IRN(\overline{a}_{nW})\right]_{1\times n} \tag{17}$$

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 obtained using IRNDWGA operator.

Now, based on the aggregate values of IRNBO and IRNOW matrixes, a nonlinear model for calculating optimal values of the weight coefficients is formed, as presented in the next step. The IRNDWGA operator is chosen in this paper due to its minimum number of operational parameters and flexibility against changing values of those parameters.

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

Min ξ

subject to

$$\begin{aligned} &\left|\frac{w_B^{L-}}{w_j^{U+}} - a_{Bj}^{-U+}\right| \le \xi;\ \left|\frac{w_B^{U-}}{w_j^{L+}} - a_{Bj}^{-L+}\right| \le \xi;\ \left|\frac{w_B^{L+}}{w_j^{U+}} - a_{Bj}^{-U-}\right| \le \xi;\ \left|\frac{w_B^{U+}}{w_j^{L-}} - a_{Bj}^{-L-}\right| \le \xi; \\ &\left|\frac{w_j^{L-}}{w_W^{U+}} - a_{jW}^{-U+}\right| \le \xi;\ \left|\frac{w_j^{U-}}{w_{jW}^{L+}} - a_{jW}^{-L+}\right| \le \xi;\ \left|\frac{w_j^{L+}}{w_W^{U+}} - a_{jW}^{-U-}\right| \le \xi;\ \left|\frac{w_j^{U+}}{w_W^{L-}} - a_{jW}^{-L-}\right| \le \xi \\ &\sum_{j=1}^{n} w_j^{L-} \le 1,\ \sum_{j=1}^{n} w_j^{L+} \le 1,\ \sum_{j=1}^{n} w_j^{U-} \le 1,\ \sum_{j=1}^{n} w_j^{U+} \le 1, \\ &w_j^{L-} \le w_j^{L+} \le w_j^{U-} \le w_j^{U+},\ w_j^{L-}, w_j^{L+}, w_j^{U-}, w_j^{U+} \ge 0,\ \forall\, j = 1,2,\ldots,n \end{aligned} \tag{18}$$

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

Step 8: Check the level of consistency for IRN-BWM method-based weight coefficients. Since the expert's comparisons captured by IRNBO and IRNOW matrixes are adopted to define the above model, a check is required for consistency of the comparisons. It also represents validation of the criteria weight coefficients. 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). Thus, 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. (19) can be framed to determine the CI value.

$$\xi - (1+2\bar{a}_{BW}^{U+})\xi + (\bar{a}_{BW}^{U+2} - \bar{a}_{BW}^{U}) = 0 \tag{19}$$

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

$$CR = \frac{\xi^*}{CI} \tag{20}$$

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

3.3 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 of its 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 criteria values for the considered alternatives. This method has excellent efficiency, requiring fewer computational steps as compared to other MCDM techniques. In a short time, it has become a popular technique in solving both engineering and managerial decision making problems, like machine selection (Ulutaş, 2017), materials selection (Chatterjee et al., 2018; Dhanalakshmi et al., 2022), evaluation of the performance of steam boilers (Kundakcı, 2019), selection of cotton fabrics (Mitra, 2022), grading of jute fibres (Mitra, 2021), industrial robot selection (Rashid et al., 2021), parametric optimization of a wire electrical discharge machining process (Okponyia & Oke, 2021), evaluation of alternative facility locations (El-Araby et al., 2022) etc. 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.

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

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

$$IRN(AV_j) = \left[(av_j^L, av_j^U), (av_j^{L'}, av_j^{U'})\right]_{m\times n} \tag{22}$$

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

$$\sum_{i-1}^{m} \frac{IRN(x_{ij})}{m} = \sum_{i=1}^{m} \left[\frac{IRN(x_{ij}^L)}{m}, \frac{IRN(x_{ij}^U)}{m}\right], \left[\frac{IRN(x_{ij}^{L'})}{m}, \frac{IRN(x_{ij}^{U'})}{m}\right] \tag{23}$$

Step 4: Calculate 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.

$$IRN(PDA_{ij}) = \left[pda_j^L, pda_j^U\right], \left[pda_j^{L'}, pda_j^{U'}\right]_{m\times n} \tag{24}$$

$$IRN(NDA_{ij}) = \left[nda_j^L, nda_j^U\right], \left[nda_j^{L'}, nda_j^{U'}\right]_{m\times n} \tag{25}$$

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.

$$IRN(PDA_{ij}) = \left[pda_{ij}^L, pda_{ij}^U\right], \left[pda_{ij}^{L'}, pda_{ij}^{U'}\right] = \left[\frac{b_{ij}^L}{av_{ij}^U}, \frac{b_{ij}^U}{av_{ij}^L}\right], \left[\frac{b_{ij}^{L'}}{av_{ij}^U}, \frac{b_{ij}^{U'}}{av_{ij}^L}\right] \text{or} \left[\frac{c_{ij}^L}{av_{ij}^{U'}}, \frac{c_{ij}^U}{av_{ij}^{L'}}\right], \left[\frac{c_{ij}^{L'}}{av_{ij}^U}, \frac{c_{ij}^{U'}}{av_{ij}^L}\right] \tag{26}$$

$$IRN(B_{ij}) = \left[b_{ij}^L, b_{ij}^U\right], \left[b_{ij}^{L'}, b_{ij}^{U'}\right] = \max\left(0, \left[x_{ij}^L - av_j^{U'}, x_{ij}^U - av_j^{L'}\right], \left[x_{ij}^{L'} - av_j^U, x_{ij}^{U'} - av_j^L\right]\right) \tag{27}$$

$$IRN(C_{ij}) = \left[c_{ij}^L, c_{ij}^U\right], \left[c_{ij}^{L'}, c_{ij}^{U'}\right] = \max\left(0, \left[av_j^L - x_{ij}^{U'}, av_j^U - x_{ij}^{L'}\right], \left[av_j^{L'} - x_{ij}^U, av_j^{U'} - x_{ij}^L\right]\right) \tag{28}$$

$$IRN(NDA_{ij}) = \left[nda_{ij}^L, nda_{ij}^U\right], \left[nda_{ij}^{L'}, nda_{ij}^{U'}\right] = \left[\frac{b_{ij}^L}{av_{ij}^{U'}}, \frac{b_{ij}^U}{av_{ij}^{L'}}\right], \left[\frac{b_{ij}^{L'}}{av_{ij}^U}, \frac{b_{ij}^{U'}}{av_{ij}^L}\right] \text{or} \left[\frac{c_{ij}^L}{av_{ij}^{U'}}, \frac{c_{ij}^U}{av_{ij}^{L'}}\right], \left[\frac{c_{ij}^{L'}}{av_{ij}^U}, \frac{c_{ij}^{U'}}{av_{ij}^L}\right] \tag{29}$$

$$IRN(B_{ij}) = \left[b_{ij}^L, b_{ij}^U\right], \left[b_{ij}^{L'}, b_{ij}^{U'}\right] = \max\left(0, \left[av_j^L - x_{ij}^{U'}, av_j^U - x_{ij}^{L'}\right], \left[av_j^{L'} - x_{ij}^U, av_j^{U'} - x_{ij}^L\right]\right) \tag{30}$$

$$IRN(C_{ij}) = \left[c_{ij}^L, c_{ij}^U\right], \left[c_{ij}^{L'}, c_{ij}^{U'}\right] = \max\left(0, \left[x_{ij}^L - av_j^{U'}, x_{ij}^U - av_j^{L'}\right], \left[x_{ij}^{L'} - av_j^U, x_{ij}^{U'} - av_j^L\right]\right) \tag{31}$$

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*(*PDAij*) and *IRN*(*NDAij*) by the corresponding criteria weights.

$$IRN(VP_{ij}) = \left[vp_j^L, vp_j^U\right], \left[vp_j^{L'}, vp_j^{U'}\right]_{m\times n} = \left[pda_{ij}^L \times w_j^L, pda_{ij}^U \times w_j^U\right], \left[pda_{ij}^{L'} \times w_j^{L'}, pda_{ij}^{U'} \times w_j^{U'}\right] \tag{32}$$

$$IRN(VN_{ij}) = \left[vn_j^L, vn_j^U\right], \left[vn_j^{L'}, vn_j^{U'}\right]_{m\times n} = \left[nda_{ij}^L \times w_j^L, nda_{ij}^U \times w_j^U\right], \left[nda_{ij}^{L'} \times w_j^{L'}, nda_{ij}^{U'} \times w_j^{U'}\right] \tag{33}$$

Step 6: Calculate sums of the weighted IRN matrixes,

$$IRN(SP_i) = \left[sp_i^L, sp_i^U\right], \left[sp_i^{L'}, sp_i^{U'}\right] = \sum_{i=1}^{n} IRN(VP_{ij}) \tag{34}$$

$$IRN(SN_i) = \left[sn_i^L, sn_i^U\right], \left[sn_i^{L'}, sn_i^{U'}\right] = \sum_{i=1}^{n} IRN(VN_{ij}) \tag{35}$$

Step 7: Calculate the normalized values for the matrixes.

$$IRN(NSP_i) = \left[nsp_{ij}^L, nsp_{ij}^U\right], \left[nsp_{ij}^{L'}, nsp_{ij}^{U'}\right] = \frac{IRN(SP_i)}{\text{Max } IRN(SP)_i} = \left[\frac{sp_i^L}{\text{Max } sp_i^{U'}}, \frac{sp_i^U}{\text{Max } sp_i^{L'}}\right], \left[\frac{sp_i^{L'}}{\text{Max } sp_i^U}, \frac{sp_i^{U'}}{\text{Max } sp_i^L}\right] \tag{36}$$

$$IRN(NSN_i) = \left[nsn_{ij}^L, nsn_{ij}^U\right], \left[nsn_{ij}^{L'}, nsn_{ij}^{U'}\right] = 1 - \frac{IRN(SN_i)}{\text{Max } IRN(SN)_i} = 1 - \left[\frac{sn_i^L}{\text{Max } sn_i^{U'}}, \frac{sn_i^U}{\text{Max } sn_i^{L'}}\right], \left[\frac{sn_i^{L'}}{\text{Max } sn_i^U}, \frac{sn_i^{U'}}{\text{Max } sn_i^L}\right] \tag{37}$$

Step 8: Calculate the appraisal scores *IRN*(*ASi*) of all the alternatives.

$$IRN(AS_i) = \left[as_i^L, as_i^U\right], \left[as_i^{L'}, as_i^{U'}\right] = \left[\frac{IRN(NSP_i) + IRN(NSN_i)}{2}\right] \tag{38}$$

Step 9: Rank the considered alternatives based on the converted crisp values of IRN(*ASi*). 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:

$$\mu_\alpha = \frac{RB(\alpha_{ui})}{RB(\alpha_{ui}) + RB(\alpha_{li})}; RB(\alpha_{ui}) = x_i^U - x_i^L; RB(\alpha_{li}) = x_i^{U'} - x_i^{L'} \quad (39)$$

$$\mu_\beta = \frac{RB(\beta_{ui})}{RB(\beta_{ui}) + RB(\beta_{li})}; RB(\beta_{ui}) = x_i^U - x_i^L; RB(\beta_{li}) = x_i^{U'} - x_i^{L'} \quad (40)$$

$$\mu_\gamma = \frac{RB(\gamma_{ui})}{RB(\gamma_{ui}) + RB(\gamma_{li})}; RB(\gamma_{ui}) = x_i^U - x_i^L; RB(\gamma_{li}) = x_i^{U'} - x_i^{L'} \quad (41)$$

$$\mu_\delta = \frac{RB(\delta_{ui})}{RB(\delta_{ui}) + RB(\delta_{li})}; RB(\delta_{ui}) = x_i^U - x_i^L; RB(\delta_{li}) = x_i^{U'} - x_i^{L'} \quad (42)$$

$$I(\alpha) = \mu_\alpha \times x_i^{L'} + (1 - \mu_\alpha) \times x_i^U \quad (43)$$

$$I(\beta) = \mu_\beta \times x_i^{L'} + (1 - \mu_\beta) \times x_i^U \quad (44)$$

$$I(\gamma) = \mu_\gamma \times x_i^{L'} + (1 - \mu_\gamma) \times x_i^U \quad (45)$$

$$I(\delta) = \mu_\delta \times x_i^{L'} + (1 - \mu_\delta) \times x_i^U \quad (46)$$

4. IRN-BWM-EDAS-based supplier selection for an Indian textile industry

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 (Table 1) and valued opinions of the participating experts, six evaluation criteria, as provided in Table 2, are considered for solving this supplier selection problem.

Table 2: 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 price for a particular item.
Quality	C_2	It can be defined as the ability of a supplier to consistently meet and maintain the 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. If there are discrepancies in opinions among the experts with respect to identification of the best and the worst criteria, separate BO and OW vectors would be formed leading to different weight information of the considered criteria. These varying weights expressed in the form of IRNs would later be aggregated together using a suitable operator to derive a common criteria weight set for its subsequent application.

Step 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 3. 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 in this problem, equal importance is assigned to each of the experts.

Table 3: 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 3.1, 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 Tables 4 and 5 respectively. For example, in BO vector for criterion C_3, P(E1) = (7, 9), P(E2) = (5, 7), P(E3) = (6, 7) and P(E4) = (8, 9), which lead to the formation of two classes of objects x_i' and x_i as: x_i' = (7,5,6,8) and x_i = (9,7,7,9). Thus, for the first class of objects:

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

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

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

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

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 4: 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 5: 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 6. The calculation steps to convert the IRNs for criterion C_3 in the BO vector of Table 4 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 6: 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 7. While solving this problem, the ξ^* value is attained as 0.18 and the corresponding CI for n = 6

is 3.00 (Rezaei, 2015). Thus, the CR value becomes 0.18/3.00 = 0.06 symbolizing excellent consistency in the derived criteria weights.

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 7: 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 8. These RN-based evaluation scores are later converted into IRN-based scores, as shown in Table 9.

Table 8: Individual expert's responses while evaluating the suppliers

	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)

	Supplier	Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6

E2	S1	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)
	S2	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
	S3	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)
	S4	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)

	Supplier	Criteria					
		C1	C2	C3	C4	C5	C6
E3	S1	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
	S2	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)
	S3	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)
	S4	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)

	Supplier	Criteria					
		C1	C2	C3	C4	C5	C6
E4	S1	(3, 4)	(2, 5)	(6, 7)	(4, 6)	(8, 9)	(5, 6)
	S2	(6, 7)	(3, 6)	(5, 6)	(8, 9)	(2, 5)	(2, 4)
	S3	(3, 5)	(6, 7)	(2, 5)	(4, 7)	(3, 4)	(4, 6)
	S4	(4, 7)	(5, 7)	(7, 8)	(3, 4)	(6, 7)	(1, 2)

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 10.

Table 9: IRN matrix for IRN-EDAS method

	Supplier	Criteria					
		C1	C2	C3	C4	C5	C6
E1	S1	[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]
	S2	[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]
	S3	[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]
	S4	[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]

	Supplier	Criteria					
		C1	C2	C3	C4	C5	C6
E2	S1	[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]
	S2	[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]
	S3	[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]
	S4	[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]

	Supplier	Criteria					
		C1	C2	C3	C4	C5	C6
E3	S1	[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]
	S2	[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]

S3	[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]
S4	[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					
		C1	C2	C3	C4	C5	C6
E4	S1	[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]
	S2	[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]
	S3	[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]
	S4	[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]

Table 10: IRN matrix for IRN-EDAS method

Supplier	Criteria					
	C1	C2	C3	C4	C5	C6
S1	[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]
S2	[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]
S3	[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]
S4	[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 3.3, 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 of all the alternative suppliers. The IRN-EDAS 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 11. Using Eqs. (39)-(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. In order to validate the performance of this integrated approach, the derived rank order of the considered suppliers is compared with that of other popular MCDM methods, like IRN-BWM-WASPAS, IRN-BWM-MOORA, IRN-BWM-TOPSIS and IRN-BWM-VIKOR. It can be interestingly noticed that in all the considered integrated approaches, supplier 3 appears to be the best choice, while there are alternations in the positions of the remaining suppliers in the derived ranking lists.

Table 11: Appraisal scores of the alternative suppliers

Supplier	$IRN(AS_i)$	Crisp value	Rank
S_1	[0.52, 1.63], [0.41, 3.32]	1.29	3
S_2	[0.49, 0.73], [0.37, 4.82]	0.71	4

S_3	[0.45, 2.57], [0.44, 3.06]	1.62	1
S_4	[0.45, 1.96], [0.54, 3.03]	1.42	2

5. Conclusions

This paper proposes an integrated approach combining IRN, BWM and EDAS methods for solving a supplier selection problem 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. One main limitation of this paper is that it does not consider effects of the changing values of different operational parameters in IRNDWGA operator on the final solutions. 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. To ease out the computational steps involved in the approach, a decision support framework may be developed as a future scope of this paper.

List of abbreviations

AHP	Analytic Hierarchy Process	ANP	Analytic Network Process
BWM	Best Worst Method	CAGR	Compound annual growth rate
DEA	Data Envelopment Analysis	DEMATEL	Decision Making Trial and Evaluation Laboratory
DoE	Design of experiments	EDAS	Evaluation based on Distance from Average Solution
ELECTRE	Elimination Et Choice Translating Reality	IRN	Interval rough number
IRNDWGA	IRN Dombi weighted geometric averaging	MABAC	Multi-Attributive Border Approximation area Comparison
MAIRCA	Multi-Attributive Real-Ideal Comparative Analysis	MCDM	Multi-Criteria Decision Making
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis	PCA	Principal Component Analysis
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation	RN	Rough number
ROI	Return on investment	SWARA	Step-wise Weight Assessment Ratio Analysis
TODIM	TOmada de Decisao Interativa Multicriterio	TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VIekriterijumsko KOmpromisno Rangiranje	WASPAS	Weighted Aggregated Sum Product Assessment

Author Contributions: Conceptualization, V.K.P. and Santonab Chakraborty; data collection and analysis, V.K.P; draft and calculations, Santonab Chakraborty; literature review and editing, Shankar Chakraborty

Funding: This research received no external funding.

Data Availability Statement: This paper has not used any data repository.

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

References

Acar, A. Z., Önden, İ., & Gürel, Ö. (2016). Evaluation of the parameters of the green supplier selection decision in textile industry. Fibres & Textiles in Eastern Europe, 24(5), 8-14.

Ali, S.M., Burney, S.M.A., & Khan, S.Y. (2020). Fuzzy-AHP-TOPSIS: An integrated multi-criteria decision support system for supplier selection in Pakistan's textile industry. International Journal of Computer Science and Network Security, 20(4), 91-99.

Amindoust, A., & Saghafinia, A. (2016). Textile supplier selection in sustainable supply chain using a modular fuzzy inference system model. Journal of the Textile Institute, 108(7), 1250-1258.

Ayvaz, B., & Kuşakcı, A. O. (2017). A trapezoidal type-2 fuzzy multi-criteria decision making method based on TOPSIS for supplier selection. Pamukkale University Journal of Engineering Sciences, 23(1), 71-80.

Badi, I., & Ballem, M. (2018). Supplier selection using the rough BWM-MAIRCA model: A case study in pharmaceutical supplying in Libya. Decision Making: Applications in Management and Engineering, 1(2), 16-33.

Bakhat, R., & Rajaa, M. (2019). Developing a novel grey integrated multi-criteria approach for enhancing the supplier selection procedure: A real-world case of textile company. Decision Science Letters, 8, 211-224.

Burney, S. M. A., & Ali, S. M. (2019). Fuzzy multi-criteria based decision support system for supplier selection in textile industry. International Journal of Computer Science and Network Security, 19(1), 239-244.

Celik, E., Yucesan, M., & Gul, M. (2021). Green supplier selection for textile industry: a case study using BWM-TODIM integration under interval type-2 fuzzy sets. Environmental Science and Pollution Research, 28, 64793-64817.

Chakraborty, S., & Chakraborty, S. (2022). A scoping review on the applications of MCDM techniques for parametric optimization of machining processes. Archives of Computational Methods in Engineering, 29, 4165-4186.

Chakraborty, S., Chatterjee, P., & Das, P. P. (2023). Multi-criteria Decision Making in Manufacturing Environment: Models and Applications. CRC Press, India.

Chatterjee, P., Banerjee, A., Mondal, S., Boral, S., & Chakraborty, S. (2018). Development of a hybrid meta-model for material selection using design of experiments and EDAS method. Engineering Transactions, 66(2), 187-207.

Chattopadhyay, R., Das, P. P., & Chakraborty, S. (2022). Development of a rough-MABAC-DoE-based metamodel for supplier selection in an iron and steel industry. Operational Research in Engineering Sciences: Theory and Applications, 5(1), 20-40.

Dhanalakshmi, C. S., Madhu, P., Karthick, A., Mathew, M., & Kumar, R.V. (2022). A comprehensive MCDM-based approach using TOPSIS and EDAS as an auxiliary tool for pyrolysis material selection and its application. Biomass Conversion and Biorefinery, 1-16. https://doi.org/10.1007/s13399-020-01009-0.

El-Araby, A., Sabry, I., & El-Assal, A. (2022). A comparative study of using MCDM methods integrated with entropy weight method for evaluating facility location. Operational Research in Engineering Sciences: Theory and Applications, 5(1), 121-138.

Ersoy, Y., & Dogan, N. Ö. (2020). An integrated model of fuzzy AHP/Fuzzy DEA for measurement of supplier performance: A case study in textile sector. International Journal of Supply and Operations Management, 7(1), 17-38.

Ghosh, S., Chakraborty, S., & Chakraborty, S. (2022). An integrated IRN-SWARA-MABAC-based approach for evaluation of tourism websites of the Indian states. OPSEARCH, 59(3), 974-1017. https://doi.org/10.1007/s12597-022-00583-3

Ghorabaee, M. K., Zavadskas, E. K., Olfat, L., & Turskis, Z. (2015). Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). Informatica, 26(3), 435-451.

Ghorabaee, M. K., Zavadskas, E. K., Amiri, M., & Turskis, Z. (2016). Extended EDAS method for fuzzy multi-criteria decision-making: an application to supplier selection. International Journal of Computers Communications & Control, 11(3), 358-371.

Guarnieria, P., & Trojan, F. (2019). Decision making on supplier selection based on social, ethical, and environmental criteria: A study in the textile industry. Resources, Conservation & Recycling, 141, 347-361.

Guo, S., & Zhao, H. (2017). Fuzzy best-worst multi-criteria decision-making method and its applications. Knowledge-Based Systems, 121, 23-31.

Hasan, M. G., Ashraf, Z., & Khan, M. F. (2022). Multi-choice best-worst multi-criteria decision-making method and its applications. International Journal of Intelligent Systems, 37(2), 1129-1156.

Hlyal, M., Chahid, M. T., Soulhi, A., Alami, J., & Alami, N. (2015). Supplier's selection for the Moroccan textile sector by using performance measurement system. Modern Applied Science, 9(3), 102-116.

Jing, S. L. (2018). Supplier selection ranking using MCDM approach in the textile industries. International Journal of Applied Optimization Studies, 1(1), 25-38.

Kara, K., Koleoglu, N., & Gürol, P. (2016). Analytic network process (ANP) in supplier selection: A case study in textile sector. International Journal of Business and Social Science, 7(5), 241-257.

Karahan, K. A. R. A., KOLEOGLU, N., & GÜROL, P. (2016). Analytic network process (ANP) in supplier selection: A case study in textile sector. International Journal of Business and Social Science, 7(5).

Karami, S., Yaghin, R. G., & Mousazadegan, F. (2020). Supplier selection and evaluation in the garment supply chain: an integrated DEA-PCA-VIKOR approach. Journal of the Textile Institute, 112(4), 578-595.

Khan, S. A., Kusi-Sarpong, S., Naim, I., Ahmadi, H. B., & Oyedijo, A. (2022). A best-worst-method-based performance evaluation framework for manufacturing industry. Kybernetes, 51(10), 2938-2963.

Kundakcı, N. (2019). An integrated method using MACBETH and EDAS methods for evaluating steam boiler alternatives. Journal of Multi-Criteria Decision Analysis, 26, 27-34.

Manucharyan, H. (2021). Multi-criteria decision making for supplier selection: A literature critique. Independent Journal of Management & Production, 12(1), 329-352.

Mitra, A. (2021). Gradation of raw jute fibres using evaluation based on distance from average solution (EDAS) method. Journal of Institution of Engineers: Series E, 102(1), 25-32.

Mitra, A. (2022). Selection of cotton fabrics using EDAS method. Journal of Natural Fibers, 19(7), 2706-2718. https://doi.org/10.1080/15440478.2020.1821289.

Mondragon, A. E. C., Mastrocinque, E., Tsai, J. F., & Hogg, P. J. (2019). An AHP and fuzzy AHP multifactor decision making approach for technology and supplier selection in the high-functionality textile industry. IEEE Transactions on Engineering Management, 68(4), 1112-1125.

Mou, Q., Xu, Z., & Liao, H. (2016). An intuitionistic fuzzy multiplicative best-worst method for multi-criteria group decision making. Information Sciences, 374, 224-239.

Nhu-Mai Thi, N. O. N. G., & HO, P. T. (2019). Criteria for Supplier Selection in Textile and Apparel Industry. The Journal of Asian Finance, Economics and Business (JAFEB), 6(2), 213-221.

Okponyia, K. O., & Oke, S. A. (2021). Novel EDAS-Taguchi and EDAS-Taguchi-Pareto methods for wire EDM process parametric selection of Ni55.8Ti (Nitinol) shape memory alloy. International Journal of Industrial Engineering and Engineering Management, 3(2), 105-122.

Pamučar, D., Mihajlović, M., Obradović, R., & Atanasković, P. (2017). Novel approach to group multi-criteria decision making based on interval rough numbers: Hybrid DEMATEL-ANP-MAIRCA model. Expert Systems with Applications, 88, 58-80.

Pamučar, D., Petrović, I., & Ćirović, G. (2018). Modification of the best-worst and MABAC methods: A novel approach based on interval-valued fuzzy-rough numbers. Expert Systems with Applications, 91, 89-106.

Pamučar, D., Ecer, F., Cirovic, G., & Arlasheedi, M. A. (2020). Application of improved best worst method (BWM) in real-world problems. Mathematics, 8(8), 1342.

Rashid, T., Ali, A., & Chu, Y-M. (2021). Hybrid BW-EDAS MCDM methodology for optimal industrial robot selection. PLoS One, 16(2), e0246738.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. Omega, 53, 49-57.

Rodríguez-Gutiérrez, P., Guerrero-Baena, M.D., Luque-Vílchez, M., & Castilla-Polo, F. (2021). An approach to using the best-worst method for supporting sustainability reporting decision-making in SMEs. Journal of Environmental Planning and Management, 64(14), 2618-2640.

Sadjadi, S. J., & Karimi, M. (2018). Best-worst multi-criteria decision-making method: A robust approach. Decision Science Letters, 7(4), 323-340.

Sarıçam, C., & Yilmaz, S. M. (2021). An integrated framework for supplier selection and performance evaluation for apparel retail industry. Textile Research Journal, 92(17-18), 2947-2965. https://doi.org/10.1177/0040517521992353.

Sasi, J. C., & Digalwar, A. K. (2015). Application of AHP and TOPSIS method for supplier selection between India & China in textile industry. International Research Journal of Engineering and Technology, 2(4), 1730-1738.

Shukla, M. K. (2016). Supplier evaluation and selection criteria in business performance of small and medium scale enterprise. International Research Journal of Engineering and Technology, 3(6), 70-76.

Srdjevic, B., Srdjevic, Z., Reynolds, K. M., Lakicevic, M., & Zdero, S. (2022). Using analytic hierarchy process and best–worst method in group evaluation of urban park quality. Forests, 13(2), 290.

Stanujkic, D., Zavadskas, E. K., Ghorabaee, M. K., & Turskis, Z. (2017). An extension of the EDAS method based on the use of interval grey numbers. Studies in Informatics and Control, 26(1), 5-12.

Stević, Ž., Pamučar, D., Zavadskas, E. K., Ćirović, G., & Prentkovskis, O. (2017a). The selection of wagons for the internal transport of a logistics company: A novel approach based on rough BWM and rough SAW methods. Symmetry, 9(11), 264.

Stević, Ž., Pamučar, D., Vasiljević, M., Stojić, G., & Korica, S. (2017b). Novel integrated multi-criteria model for supplier selection: Case study construction company. Symmetry, 9(11), 279.

Tayyab, M., & Sarkar, B. (2021). An interactive fuzzy programming approach for a sustainable supplier selection under textile supply chain management. Computers & Industrial Engineering, 155, 107164.

Ulutaş, A. (2017). Sewing machine selection for a textile workshop by using EDAS method. Journal of Business Research, 9(2), 169-183.

Utama, D.M., Asrofi, M.S., & Amallynda, I. (2021a). Integration of AHP-MOORA algorithm in green supplier selection in the Indonesian textile industry. Journal of Physics: Conference Series, 1933, 012058.

Utama, D.M., Maharani, B., & Amallynda, I. (2021b). Integration Dematel and ANP for the supplier selection in the textile industry: A case study. JURNAL ILMIAH TEKNIK INDUSTRI, 20(1), 119-130.

Wang, C. N., Viet, V. T. H., Ho, T. P., Nguyen, V. T., & Nguyen, V. T. (2020). Multi-criteria decision model for the selection of suppliers in the textile industry. Symmetry, 12(6), 979.

Yang, Q., Zhang, Z., You, X., & Chen, T. (2016). Evaluation and classification of overseas talents in China based on the BWM for intuitionistic relations. Symmetry, 8(11), 137.

Yanmaz, O., Turgut, Y., Can, E. N., & Kahraman, C. (2020). Interval-valued Pythagorean fuzzy EDAS method: an application to car selection problem. Journal of Intelligent & Fuzzy Systems, 38(4), 4061-4077.

Yazdani, M., Chatterjee, P., Pamucar, D., & Chakraborty, S. (2020). Development of an integrated decision making model for location selection of logistics centers in the Spanish autonomous communities. Expert Systems with Applications, 148, 113208.

Yıldız, A., & Yayla, A. Y. (2015). Multi-criteria decision-making methods for supplier selection: A literature review. South African Journal of Industrial Engineering, 26(2), 158-177.

You, X., Chen, T., & Yang, Q. (2016). Approach to multi-criteria group decision-making problems based on the best-worst-method and electre method. Symmetry, 8(9), 95.

Zhang, S., Wei, G., Gao, H., Wei, C., & Wei, Y. (2019). EDAS method for multiple criteria group decision making with picture fuzzy information and its application to green suppliers selections. Technological and Economic Development of Economy, 25(6), 1123-1138.