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Supplier selection for aerospace & defense industry through MCDM methods

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ABSTRACT

This paper utilized the leverage of three Multi-Criteria Decision Making (MCDM) methods, namely AHP, TOPSIS, and SECA, in the supplier selection process in the context of an Aerospace & Defense (A&D) company to simplify, supplement, and standardize their ongoing practice. First, we identified and recommended additional criteria, the companies might include in their present supplier selection process with justification. Second, we employ the SECA and Fuzzy-TOPSIS methods; and compare the raking with and without additional criteria to explore the critical difference and its afterword effect on the company's performance. Third, for easy implementation and process standardization, we utilize the functionalities of Text Shell software ESTA so that the decision makers can understand the impact of the inclusion of criteria such as sustainability and technology within the operation and identify the possibility for significant improvements or expected loss. Finally, a case study is considered by benchmarking the current practice. The results reflect that adding other criteria, such as sustainability or delivery time, can utterly change the ongoing practice. We found that the company that needs to work in close proximity to the government and deal with the next generation of technologies can face significant barriers when they include additional criteria in the selection process. Moreover, it is not easy to comply without a drastic change in their whole process to ensure quality, sustainability, and financial stability simultaneously. Most importantly, how standardizing the entire process is a critical challenge in the aerospace and defense industry.

1. Introduction

The supplier selection problem to assist green transition must be discussed and evaluated from a more holistic and strategic view and adapted based on which section the company is operating within (Hamdan and Cheaitou, 2017). An ideal solution for designing a specific supplier selection process is impossible since it is complex due to the diversity in the factors affecting the stakeholders' perspectives. Therefore, there is no one-size-fits-all solution (Taherdoost and Brard, 2019). Due to the involvement of various criteria from various stakeholders, researchers and practitioners use Multi-Criteria Decision Making (MCDM) methods to resolve the conflict. However, the number of criteria to incorporate in the MCDM methods is a complex problem since the decision makers (DMs) have to consider various criteria to choose the most appropriate suppliers, which might depend on context and internal protocols in implementing the state of art technology solutions (Massa, 2022).

Noticeably, the number of criteria and their characteristics have unique merits and limitations. For example, researchers and policymakers are recommended to consider sustainability, technology, and R&D investment, among others, as critical criteria to support the green transition. However, direct costs, such as labor and materials, development and integration of new technology, and indirect costs, such as quality control, lead time, and poor delivery, might prove crucial for companies. In such a scenario, DMs can rely on various MCDM methods in the supplier selection process. Furthermore, the decision in practice is sometimes dichotomous. For example, a set of suppliers that satisfies the AS9100 ISO standard should only be considered. This means that the sponsor Aerospace & Defense (A&D) company only collaborates with suppliers with innovative knowledge and process technologies. In that scenario, some existing suppliers might fail to comply with those standards and face product compliance challenges in an ever-changing regulatory landscape. In addition, it is paramount that the security, economic, social, and environmental perspectives are well integrated and aligned to achieve sustainable development. Each aspect can indirectly impact the overall sustainable development goal, and all aspects

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must work together to achieve it. Therefore, implementing MCDM methods for finding a final recommendation needs standardization. Setting weight for each criterion (performance indicator) directly influences the definitive ranking of the MCDM method, and those can be defined objectively or subjectively. Subjective weights can be assigned based on the experiences of the experts, and objective weights can be used through mathematical analysis based on attributes of the data set. Therefore, it is not easy to support the MCDM integration without developing a scenario analysis and problem-solving expertise. Additionally, it is impossible to ascertain which MCDM techniques are the best in practical use since each method has its own merits and demerits. The researcher recommends that more than one MCDM technique be used to obtain a trustworthy decision (Bahrami and Rastegar, 2022). Analyzing the ranking based on multiple MCDM methods is considered helpful insight, even though rankings are usually not concurrent. Therefore, over the years, several MCDM methods such as TOPSIS (Hwang and Yoon, 1981), VIKOR (Duckstein and Opricovic, 1980), Extended VIKOR (Sayadi et al., 2009), AHP (Saaty, 1988), MARCOS (Stević et al., 2020), MOORA(Brauers and Zavadskas, 2006) and ELECTRE (Roy, 1968) are used in the supplier selection process. Additionally, several authors used fuzzy logic to consider incomplete/imprecise information, both normal fuzzy number (Sun, 2010) and interval type-2 fuzzy number (Bera et al., 2020) in the context of supplier selection.

This study uses three MCDM methods: AHP, TOPSIS, and SECA. TOPSIS, developed by Hwang and Yoon in 1981, is one of the simple MCDM ranking methods used extensively to solve real-world decision problems in diverse application areas (Yoon and Hwang, 1995). We used a similar approach by Nkuna et al. (2022) while implementing the AHP and TOPSIS methods. However, the SECA method was developed recently by Keshavarz-Ghorabaee et al. (2018), and two key advantages of the method are: first, there is no need to set weights separately, and second, the method is developed in such a way that it can assign weights for each criterion and generate final ranking by solving a multiobjective non-linear programming model to minimize bias. This method has also gained popularity in quickly solving real-life conflicting decision-making problems due to its easy application (Wang et al., 2020). AHP, as developed by T.L. Saaty in 1981, is a structured method in group decision-making to rank decisions based on relative importance. The objective of using three methods by benchmarking their current practice is to ensure higher reliability and acceptance to the case company and its operators, who is responsible for selecting suppliers for the company.

We aim to develop a system that can help DMs obtain a flexible overview and provide them with an easily applicable system to standardize the process and reduce their environmental footprint. Therefore, first, we explore the company's key criterion. Next, we integrate some possible criteria, the higher management would like to incorporate in the future and support green transition. In the literature, the comparative evaluation between the existing practice and the new preference after the inclusion of the new criterion is still missing. Consequently, we want to explore the possible changes and affect that can bring the inclusion of additional criteria and employ two MCDM methods. We found a strong correlation between the Fuzzy approach and the SECA, while those are implemented for the supplier selection process based on the criterion used in excising practice and criteria that would likely be integrated in the future. This finding is also supported by Bahrami and Rastegar (2022), who encountered the same when the SECA method was evaluated with others. The analysis demonstrates that SECA is closely correlated to all fuzzy approaches the authors investigated. We utilize both the TOPSIS and SECA models in software to include what the authors expect is a big issue within companies in their supplier selection process, variety. We showcased in a practical setting to support flexible, sustainable supplier selection through the ESTA software. Developing such module software aims to provide higher explainability, insight, and flexibility to conduct sensitivity for the DMs, significantly improving their operation semi-autonomously. The paper is organized as follows: The next section presents a review of the supplier selection and corresponding criterion. Section 3 offers an overview of MCDM techniques in the form of AHP, Fuzzy TOPSIS, and SECA. In Section 4, we present the results and the proposed implementation of MCDM methods, while Section 5 highlights the implications and feasibility of the study. And finally, we provide concluding remarks in Section 6.

2. Literature review

Businesses continuously seek to create competitive advantages to maintain or increase their market share. Supplier selection is a well-established and well-acknowledged strategic area directly affecting the company's success (Rouyendegh et al., 2020). The process can impact profitability by reducing costs and improving performance, thus directly affecting competitiveness (Taherdoost and Brard, 2019). However, the DMs must have a wide range of criteria to select a specific supplier with certainty. Multiple criteria provide a practical framework for benchmarking, but the complexity for the DMs is to choose the most appropriate supplier that meets all the requirements (Rouyendegh et al., 2020). In this context, a criterion means a parameter that impacts whether a supplier is selected among alternatives. In the following subsection, we suggest possible supplier criteria for the sponsor company with additional criteria to include that will further support proper standardization.

2.1. Criteria

The analysis of identifying the best criteria to measure the performance of suppliers has been the focus of many researchers and purchasing practitioners during the last couple of decades (Benyoucef et al., 2003). We refer to the work by Deshmukh and Chaudhari (2011), where the authors analyzed 49 articles published between 1992 and 2007 to summarize the criterion used in the supplier selection process. In this study, we update the list as shown in Table 1.

Table 1 indicates that the current literature suggests a wide variety of potential criteria to be used for supplier selection in different industrial contexts. However, including additional criteria brings implementation and interpretation complexities and proves to be challenging from a data-handling perspective. Additionally, allocating weights for each criterion is also an issue. Therefore, we introduce the SECA method to avoid such complexity and develop a software prototype for easy implementation. Next, we focus on the company's current practice with four criteria and a new extended criterion list.

3. Methods

3.1. Analytic hierarchy process

The AHP analysis follows a relative, subjective comparison of the chosen criteria (Papathanasiou et al., 2018). The analyses are conducted based on semi-structured interviews with the company representatives. The following steps are defined for AHP implementation to showcase how the investigation is conducted.

Step 1. Establishment of the pair-wise comparison matrix.

The first step is to define the evaluated criteria. A pair-wise comparison matrix (A is an n $\times$ n matrix), where n is the number of criteria and the element of the matrix $a_{ij} = 1 \forall i = j$, is constructed to get the criteria priority value (CPV). This is done using the 1–9 preference scale (1 equal importance of both elements and nine absolute primacy of one aspect over another). The scores illustrate the importance of each alternative. The pair-wise comparison must be developed carefully and with limited use of extremely small or enormous preference scales.

Table 1
Various criteria used in the literature.

Criteria	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}
Cost	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Quality	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Delivery	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Worker safety and health	x		x			x	x	x	x					x		x
Technology		x	x		x	x	x	x	x	x	x		x	x	x	x
Flexibility		x						x	x	x		x	x	x	x	x
Environmental Affairs		x	x	x			x		x	x				x	x	x
Financial Stability		x				x			x	x	x	x	x	x	x	x
Reliability		x	x					x		x		x	x	x	x	x
Risk		x	x					x						x	x	
Packaging and Transport Quality		x			x	x	x	x		x	x					
Production capacity		x	x					x						x	x	
Location		x	x		x	x			x	x			x		x	x
Communication System		x	x				x	x		x		x	x		x	x
Repair Service			x		x	x		x		x				x		x
R&D								x	x	x				x	x	x
Service		x	x	x				x		x	x			x	x	x
Repair Service			x		x	x				x	x			x	x	x
Market Position					x				x			x	x	x		
Warranty/Claims		x	x			x	x									
EMS	x								x							
Green Supply Chain	x								x	x					x	x
Suppliers of supplier	x														x	x
Worker Dismissal	x		x													
Response Speed		x						x								
Lead Time		x						x					x			x
Past Experience		x						x								
Reputation		x	x					x		x			x			
Building And Facility		x			x	x										
Relationship		x											x	x		x
Expiration Date		x														
Regulatory Compliance		x			x	x										
Payment Terms		x											x	x	x	x
Waste Management		x								x						x
Waste Handling		x								x						x
Efficient Material Handling		x			x											
Supplier Capacity		x						x				x			x	
Management and Organisation		x	x													
Attitude			x		x	x					x					
Commercial Plans			x													
Process Improvement			x													
Product Development			x													
Professionalism			x		x	x	x									
Green Manufacturing System				x					x							x
Green Image				x					x							x
Cooperation				x	x			x					x			
Performance History					x			x				x				
Training Aids					x	x										
Electronic Data Interchange (EDI)							x	x								
Culture							x	x								
Trade Restriction							x	x								
Skill level of staff								x				x	x			
Self-audits								x								
IT Standards							x	x								
Emergency orders										x			x			
Order cycle time										x			x			
Sales Support													x			

A_1 = (Arabsheybani et al., 2018), A_2 = (Stević, 2017), A_3 = (Taherdoost and Brard, 2019), A_4 = (Rouyendegh et al., 2020), A_5 = (Mohammed et al., 2019), A_6 = (Weber et al., 1991), A_7 = (Kar and Pani, 2014), A_8 = (Ho et al., 2010), A_9 = (Utama, 2021), A_{10} = (Stević et al., 2020), A_{11} = (Deng and Chan, 2011), A_{12} = (Wu et al., 2022), A_{13} = (Hamdan and Cheaitou, 2017), A_{14} = (Scott et al., 2015), A_{15} = (Fagundes et al., 2021), A_{16} = (Fallahpour et al., 2017).

Step 2. Eigenvector

This step includes computing the priority vector of criteria to identify the numerical weights (w_1, w_2, … …, w_n) of the alternatives, where $\sum_{i=1}^{n} w_i = 1$.

Step 3. Consistency test

A consistency test is conducted to ensure that the calculated values and criteria weights are consistent. The first step is to identify λ_{max} which is treated as an eigenvalue problem. The closer λ_{max} is to n, the more consistent the relationship matrix. λ_{max} equals the individual sum of the vectors for each weight in the relationship matrix. The Consistency Ratio is calculated as $CR = \frac{Consistency\ Index\ (CI)}{Random\ consistency\ index\ (RCI)}$ where $CI = \frac{\lambda_{max} - n}{n-1}$ and $RCI = \frac{1.98(n-2)}{n}$. If $CR \leq 0.10$, the matrix is considered consistent. If not, the DMs will need to revise the relationship matrix.

3.2. Combined F-AHP analysis

To ease the assessment, a Fuzzy AHP analysis is conducted. The DMs will only need to relate to linguistic variables, which is beneficial in this case due to a lack of understanding. The linguistic terminology is seen in Appendix Table B1. To aggregate the decision, we translated the decision matrix into fuzzy numbers, as suggested by (Sun, 2010), we used the following relation: $\widetilde{a}_{ij} = (\widetilde{x}^1_{ij} \oplus \widetilde{x}^2_{ij} \oplus \ldots \oplus \widetilde{x}^n_{ij})$. To calculate the fuzzy geometric mean, we used: $\widetilde{r}_{ij} = (\widetilde{a}^1_{i1} \oplus \widetilde{a}^2_{i2} \oplus \ldots \oplus \widetilde{a}^n_{in})$, which is translated to the fuzzy weights through the following relation: $\widetilde{w}_i = (\widetilde{r}_{i1} \oplus \widetilde{r}_{i2} \oplus \ldots \oplus \widetilde{r}_{in})^{-1}$

In this study, we conduct two sets of analysis: (i) based on the present practice of the case company by considering the following four criteria: Quality (C_5); Cost (C_7); Relationship (C_8); Lead Time (C_9), and (ii) by considering the following nine criteria: Flexibility (C_1); Financial Stability (C_2); Sustainability (C_3); Technology (C_4); Quality (C_5); Delivery (C_6); Cost (C_7); Relationship (C_8); and Lead-Time (C_9) based on the discussion with sponsor company employees, which is also supported by literature from Table 1.

3.3. Fuzzy technique for order of preference by similarity to ideal solution (TOPSIS)

A Fuzzy TOPSIS analysis is incorporated to rank alternatives based on the AHP analysis criteria as the supplier selection engine. The Fuzzy TOPSIS analysis makes sense as it compares the alternatives by integrating incomplete and uncertain information and using qualitative assessments in a matter where the ideal solution is considered. In supplier selection, everything is a trade-off, and the ability to create weights that challenges the ideal solutions seems a great fit (Altintas and Utlu, 2021). Similar to F-AHP, each criterion is evaluated in a linguistic, qualitative manner, conducted through interviews. According to linguistic terminology, the fuzzy set is presented in Appendix Table B2. This paper follows the methodology from Sun (2010) to interlink AHP with TOPSIS. Such integration of F-AHP methods with other MCDM methods such as MOORA is also familiar in the literature (Singh et al., 2022). Some steps are aggregated for simplicity, but the overall approach remains identical. The decision matrix is the resulting Fuzzy ratings from a workshop where the purpose was to establish the current performance of suppliers. The steps are as follows:

1. **Determine the weighting of criteria** is where DMs assess the weighting of evaluation criteria in relation to the linguistic terminology.
2. **Construct decision matrix** is where the decision matrix is determined based on the linguistic, triangular set and aggregates the answers from different DMs.$\widetilde{x_{ij}} = \frac{1}{k}(\widetilde{x}_{ij_1} \oplus \widetilde{x}_{ij_k} \oplus \ldots \widetilde{x_{ij_K}})$, where $\widetilde{x}_{ij_k}$ equals the performance rating for the k th expert for the j_c criteria as $\widetilde{x}_{ij_k} = (\widetilde{l}_{ij_k}, \widetilde{m}_{ij,k} \widetilde{u}_{ij_k})$.
3. **Normalization of the decision matrix** is the max/min normalization of criteria ratings. From the decision matrix (R), we determine the normalized decision matrix as: $\widetilde{R} = [\widetilde{r}_{ij}]_{m\times n}, i = 1, 2\ldots, n;\ j = 1, 2\ldots, n$ where $r_{ij} = \left(\frac{l_y}{u_j^+}, \frac{m_y}{u_j^+}, \frac{u_y}{u_j^+}\right)$ and $u_j^+ = max_i\{u_{ij} | i = 1, 2, \ldots, n\}$. For the weighted, normalized decision matrix ($\widetilde{V}$), the formula is: $\widetilde{V} = [\widetilde{v}_{ij}]_{m\times n}, i = 1, 2, ..., m; j = 1, 2, \ldots, n$ where $\widetilde{v}_{ij} = \widetilde{r}_{ij} \oplus \widetilde{w}_i$.
4. **The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)** is the calculation of the best possible outcome for each (FPIS A^+) and the negative counterpart (FNIS A^-). We define them as: $A^+ = (\widetilde{v}_l^+, \widetilde{v}_j^+, \ldots, \widetilde{v}_n^+)$ and $A^- = (\widetilde{v}_l^-, \widetilde{v}_j^-, \ldots, \widetilde{v}_n^-)$.
5. **Distance to ideal solution** calculates the distance from each criterion to the best and worst outcomes. These distances ($\widetilde{d}_i^+$ and $\widetilde{d}_i^-$) from each alternative is calculated as: $\widetilde{d}_i^+ = \sum_{j=1}^n d(\widetilde{v}_{ij}, \widetilde{v}_j^+), i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$ and $\widetilde{d}_i^- = \sum_{j=1}^n d(\widetilde{v}_{ij}, \widetilde{v}_j^-), i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$
6. **Obtain Closeness Coefficient (CC)** is a measure from which the ranking can be derived when minimizing the distance to the FPIS while maximizing the distance to the FNIS, such that: $\widetilde{CC}_i = \frac{\widetilde{d}_i^-}{\widetilde{d}_i^+ + \widetilde{d}_i^-}, i = 1, 2, \ldots, m.$

3.4. Simultaneous evaluation of criteria and alternatives (SECA)

SECA method is not dependent on qualitative input in the weighing of criteria and hence remains unbiased in the weight determination. The method evaluates the scenarios through a multiobjective non-linear programming model and determines the weights based on the standard deviation and correlation in a decision matrix (Das et al., 2022).

Step 1. We start with the decision matrix $X = (x_{ij})_{m\times n}$ and all the criteria are divided into two subcategories: beneficial criterion (BC) and non-beneficial (NC). BCs have a positive effect, and growth in their values leads to the improvement of the decision-making function, whereas NC has a negative effect, and growth in their values has a reverse effect on the objective function. Note that all the criteria used in our model are BC. However, the normalized decision matrix (X^N) is determined by using the following formula:

$$X^N = \left(x_{ij}^N\right)_{m\times n},$$

$$\text{where, } x_{ij}^N = \begin{cases} \dfrac{x_{ij}}{max_k x_{kj}} \ if\ j \in BC \\ \dfrac{min_k x_{kj}}{x_{kj}} \ if\ j \in BC \end{cases}$$

The elements of the weighted normalized matrix for the SECA method are presented in Tables C1 and C.2.

Step 2: Determine the correlation between each pair of criteria (π_{jk}) and the standard deviation ($\sigma_j, j = 1, 2, \ldots, n$) for each criterion to obtain the variation information within and in between criteria (see Tables C3 for correlation coefficient and Tables C4 for standard deviations).

Step 3: Compute the conflict between each criterion against other criteria (π_j), where $\pi_j = \sum_{j=1}^n (1 - \pi_{jk})$. Note that an increase in the variation within the criterion intensifies the objective importance of that criterion.

Step 4: Normalized the σ and π_j as the reference points by using the following relations:

$$\begin{cases} \sigma_j^N = \dfrac{\sigma_j}{\sum_{k=1}^n \sigma_k} \\ \pi_j^N = \dfrac{\pi_j}{\sum_{k=1}^n \pi_k} \end{cases} \tag{1}$$

We refer to Tables C5 and C.6 for the detail.

Step 5: Finally, the weights (w_j) are determined by solving the following non-linear optimization problem

$$\begin{cases} Max\ Z = \lambda_a - \beta(\lambda_b + \lambda_c) \\ s.t. \\ \lambda_a \le S_i, where\ S_i = \sum_{j=1}^n \omega_j x_{ij}^N \forall\forall i \in \{1, 2, \ldots, m\} \\ \lambda_b = \sum_{j=1}^n \left(\omega_j - \sigma_j^n\right)^2 \forall i \in \{1, 2, \ldots, n\} \\ \lambda_c = \sum_{j=1}^n \left(\omega_j - \pi_j^n\right)^2 \forall i \in \{1, 2, \ldots, n\} \\ \sum_{j=1}^n \omega_j = 1, \varepsilon \le \omega_j \le 1, \forall j \in \{1, 2, \ldots n\} \end{cases} \tag{2}$$

In Equation (2), the objective is to maximize the performance of each criterion by considering the effects of the overall performance score of each alternative criterion (λ_a), and variation within and between criteria through (λ_b) and (λ_c), respectively. Through the process, the coefficient for aggregation β ($\beta \geq 0$) for all three measures (λ_a, λ_b, and λ_c) is used. Note that the constraint introduced for weights ensures that the sum of weights should be equal to a unit, and a lower non-negative bound ($\varepsilon = 0.001$) is used for a lower limit of each criterion. We determine the optimal value of β through sensitivity analysis, as shown in Tables C7.

4. Results

Currently, the criteria used at the company are Cost, Relationship, Lead-Time, and Quality. The relationship, defined as the individual preference of a purchaser as a result of their relationship with any given supplier, is deemed the most important. This is because the DMs will disregard a small cost, quality, and lead time difference in selecting the preferred supplier. The relationship matrix is derived from company interviews and presented in Table A1. This relationship matrix yields a CI of **0.014** < 0.1, i.e., the relationship is consistent. The final weights are obtained as follows: Lead Time- 9.8%, Quality-16.5%, Cost- 33.7%; and Relationship- 40.0%. The corresponding ranking is presented in Table 2. Similarly, we compute the ranking for the supplier based on Fuzzy-TOPSIS and SECA methods based on nine criteria. We refer to Appendices B and C, respectively, for the step-wise detail of obtaining the final ranking for both methods. Note that while we determine weights, both methods lead to different outcomes, as presented in Table 2.

Clearly, MCDM selects a better supplier. This is primarily due to S_2 performing much better in what the literature suggests to be essential criteria. It is found that the rankings change depending on the weights, but not enough to disregard performance. This indicates a healthy sensitivity in the model(s). S_2 would be the preferred supplier of both MCDM models, while the company's preferred supplier would be S_8.

Table 2
The CCi and final ranks for each method.

	Fuzzy-TOPSIS		SECA	AS-IS	
	CC_i	Rank	CC_i Rank	CC_i	Rank
S_1	0.641	4	0.609 3	0.672	2
S_2	0.792	1	0.711 1	0.589	4
S_3	0.728	3	0.676 2	0.396	10
S_4	0.595	7	0.495 8	0.671	3
S_5	0.618	5	0.512 7	0.429	9
S_6	0.562	8	0.542 6	0.485	7
S_7	0.752	2	0.558 5	0.473	8
S_8	0.614	6	0.600 4	0.687	1
S_9	0.553	9	0.426 10	0.554	5
S_{10}	0.470	10	0.433 9	0.530	6

Note that we compute the Spearman correlation coefficient (SCC) to investigate the difference among ranks (Akoglu, 2018). The correlation coefficient between the TOPSIS and SECA is obtained as $\rho_{\{\text{Fuzzy, SECA}\}} = 0.84$. Therefore, it indicates a strong correlation. This seems like a positive effect of working with performance data and only changing weights, as the decision matrix remains a potent and decisive factor. Considering the same performance data, the mismatch between the analyses and the company AHP looks profound. It is found that $\rho_{\{\text{TOPSIS, Company}\}} = -0.139$ and $\rho_{\{\text{SECA, Company}\}} = 0.055$. This means that even though it is applied to the same performance data, the company selects significantly different than the MCDM methods recommended. Therefore, this supports the study hypothesis that the company's current setup/practice needs to be evaluated further. For both the TOPSIS and SECA methods, S_2 gets a higher preference, whereas, for the sponsored company, it is S_8. From Table 3, presented below, we quantify the performance of suppliers with respect to the criterion before applying the MCDM methods; then, we can see the importance of weight setting for the newly included criterion.

4.1. Practical implementation

While MCDM and supplier selection is a much-visited territory in academia, the practical implementations of such are not. Authors seem to infer that existing analyses of MCDM application for supplier selection are relatively less concerned about how companies might utilize these methods in a practical setting. Definitely, the supplier selection process is context-dependent, and extracting structured data is a real problem. More specifically, defining sustainability and quantifying such measures is still missing in the A&D sectors. Therefore, we emphasize how DMs could use MCDM in the supplier selection process with little to no knowledge about the process through prototype software. The functionalities will be showcased through a constraint-based software called Expert System Shell for Text Automation, or ESTA (He et al., 2019). The intent of ESTA is to aid DMs by establishing a knowledge base and an expert system. The constraint-based nature of the software allows for easy implementation of intended functionalities with other software. The system operators are sent in any appropriate direction based on their previous selections due to the current situation. This is why ESTA makes sense in this application, as MCDM requires a knowledge base that ESTA can mimic. An assumption in MCDM methods, weight establishment, is that the weights are static, which is not the case in a real-world environment. Purchasers might encounter various situations where they must deviate from the standard set of weights, creating the need for dynamic weight determination. An example could be a rush order, where the lead time is to be prioritized. Notably, the fuzzy approach allows much freedom in the designation of weights, thus allowing for the development and alignment of weights for individual scenarios. For rush orders, the DMs should be able to select a model where the weight of lead time is high, at the trade-off of other criteria. The intended scenarios, weights, and results are depicted in Table 4.

When comparing the result in Table 4 to the decision matrix in Table B6, it is apparent that the manipulation of weights works as intended and thus can be included in the proposed software to account for sensitivity analysis of highlighting possible options in a dynamic setting. The intention is to create a database that interconnects suppliers and their ability to deliver specific part numbers with performance data, to select the best supplier. This database should be connected to front-end software, which should be developed. The decision tree and proposed software functionality through ESTA can be seen in Fig. 1.

As an illustration of the functionalities, a decision tree is constructed to the left in Fig. 1. The decision tree represents the functionalities of the software. Each step represents a choice in ESTA software, which is showcased to the right (Fig. 1b). The system recognizes suppliers' parts, scenarios, and performance to calculate the CC and ranks suppliers accordingly. This allows DMs to utilize the system while not having to consider MCDM methods in detail and thus will enable managers to control how the process is conducted.

4.2. Managerial implications

While the previous section regards a possible solution, it is also important to investigate how such developments would need to be implemented. As mentioned, several prerequisites exist for successfully implementing and using these methods. This implementation will be split into system prerequisites and human interaction. System prerequisites in this context mean what needs to be done for the proposed system to work properly. The authors suggest a step-wise implementation to test the waters and then scale to the rest of the suppliers. These considerations will be based on Karandikar and Nidamarthi (2007), where the authors investigated how to implement standardization initiatives successfully. Our view on how to adapt the line of thinking to the sponsor company is presented below:

1. Create consensus on internal benefits and customer value

Table 3
Linguistic ratings of supplier performance.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
S_1	Goo	Poor	Good	Good	Fair	Fair	Good	Good	Good
S_2	Fair	Good	Good	Fair	Good	Very Good	Very Good	Good	Fair
S_3	Good	Good	Good	Very Good	Good	Good	Fair	Very Good	Poor
S_4	Good	Very Poor	Poor	Poor	Very Good	Fair	Fair	Good	Good
S_5	Good	Poor	Fair	Good	Very Good	Fair	Poor	Good	Fair
S_6	Very Good	Very Poor	Poor	Fair	Poor	Very Good	Good	Fair	Good
S_7	Good	Good	Fair	Very Good	Very Good	Very Poor	Very Good	Fair	Fair
S_8	Very Poor	Very Good	Very Good	Good	Good	Fair	Poor	Good	Very Good
S_9	Very Poor	Fair	Fair	Fair	Poor	Fair	Good	Very Good	Fair
S_{10}	Fair	Very Poor	Poor	Very Poor	Fair	Very Good	Poor	Good	Good

Table 4
The scenarios, weights, and results. The results are shown as CC_i (Rank).

Criteria	Lead-Time	Exceptional Quality	Low Cost	Sustainability
C_1	5.0%	5.0%	5.0%	5.0%
C_2	5.0%	5.0%	5.0%	60.0%
C_3	5.0%	5.0%	5.0%	5.0%
C_4	5.0%	15.0%	5.0%	5.0%
C_5	5.0%	50.0%	5.0%	5.0%
C_6	25.0%	5.0%	5.0%	5.0%
C_7	5.0%	5.0%	60.0%	5.0%
C_8	5.0%	5.0%	5.0%	5.0%
C_9	40.0%	5.0%	5.0%	5.0%
Alternatives	**Lead-Time**	**Exceptional Quality**	**Low Cost**	**Sustainability**
S_1	0.630 (5)	0.533 (7)	0.685 (3)	0.369 (6)
S_2	0.665 (3)	0.698 (5)	0.861 (1)	0.759 (2)
S_3	0.497 (7)	0.757 (2)	0.527 (6)	0.759 (3)
S_4	0.561 (6)	0.657 (6)	0.412 (7)	0.187 (9)
S_5	0.468 (8)	0.757 (2)	0.242 (9)	0.332 (7)
S_6	0.688 (2)	0.278 (9)	0.624 (4)	0.198 (8)
S_7	0.399 (10)	0.828 (1)	0.824 (2)	0.727 (4)
S_8	0.717 (1)	0.698 (4)	0.291 (8)	0.845 (1)
S_9	0.422 (9)	0.249 (10)	0.594 (5)	0.465 (5)
S_{10}	0.630 (4)	0.320 (8)	0.164 (10)	0.144 (10)

This paper seeks to validate that the current process is inefficient and that utilizing MCDM as a flexible standardization tool will reduce hidden costs. The next step is for the case company to adapt to this thinking line and establish a business case. Therefore, the first step would be understanding the value and verifying the potential based on the data.

2. Agree on guiding principles

These guiding principles could roughly be translated to the models, criteria, and weights in MCDM. Managers within the case company must agree and align the criteria, weights, performance data, and models that the proposed revamped process should use.

3. Create sales strategy

Standardization is primarily an internal benefit. However, the case company started early in the process, and the standardization would enable them to create documentation on the process that could ultimately become an order winner in the A&D industry. Therefore, they should investigate how implementing this standardization could benefit them from a sales point of view.

4. Technical implementation

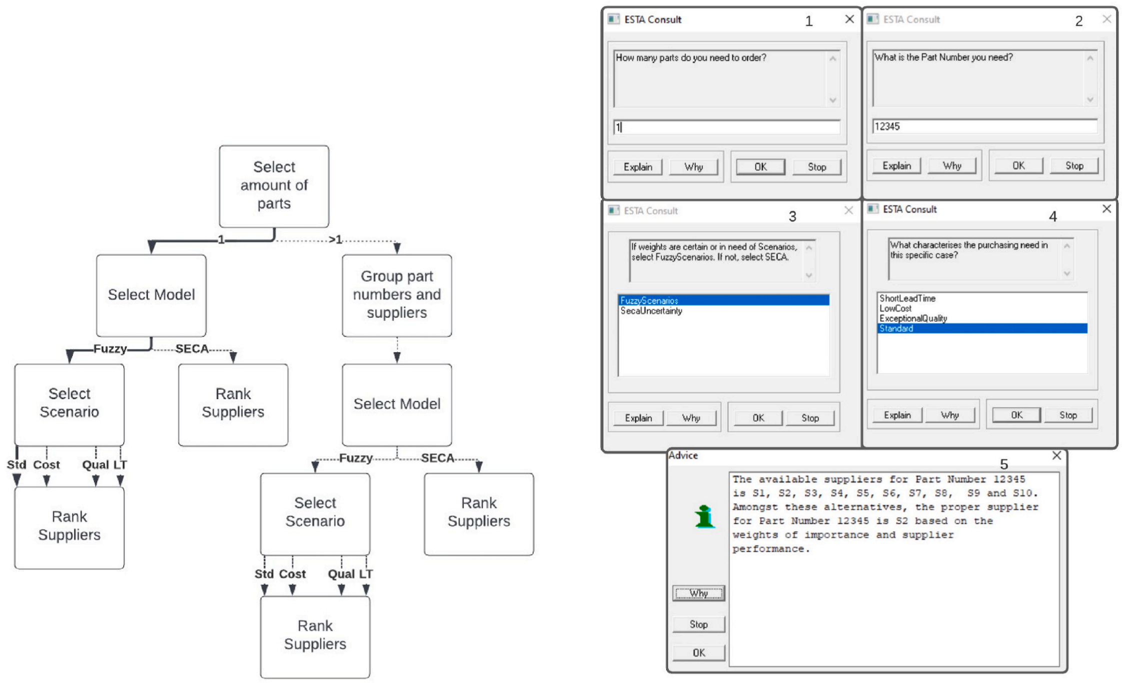
This is where the sponsor company implements the proposed software prototype and integrates it into its present system before defining functionalities clearly to the DMs.

The other aspect is humans. The DMs that currently select the suppliers would need to adapt to a new system. To do so, they will need training, and the Case Company would probably need to initiate change management initiatives to make the purchasers own the new process. Cameron and Green (2015) suggested that solid leadership communication will help the purchasers own the changes and early preparation and incorporation in the change.

5. Discussion

The literature on the association between sustainability and the defense industry is often neglected and sometimes not compatible with the Environmental, Social, and Governance criteria used to define sustainability in the context of other sectors. The technology integration or production of defense material represents a great responsibility and investment; and is subject to strict regulations and financial constraints. It is phenomenal that many financial institutions are reluctant to support defense activities; they sometimes implement their own internal policies that limit cooperation with the defense industry. Therefore, the debate about sustainable finance often lumps together with some suppliers' categories, severely affecting competitiveness and financial viability (Massa, 2022). Note that supplier selection criteria and Total Cost of Ownership (TCO) are interlinked. TCO provides many benefits such as it helps clarify and define supplier performance expectations both in the manufacturer and supplier over time (Ellram, 1995). The perspective of selecting the proper supplier is to mitigate the total direct and indirect costs associated with purchasing a part rather than just the acquisition cost (Dogan and Aydin, 2011). As we found in Table 4, there are somehow links between the ranking of SECA, TOPSIS, and TCO, and the assessment of whether an increase happens from selecting the proposed supplier is possible. For example, one key factor that affects defense bids is the relationship (Emmanuel-Ebikake et al., 2014). Results also reflect the effect.

In addition, a standardized approach to sustainable supplier selection is achieved by incorporating flexibility in weights to account for real-life variety (Fallahpour et al., 2017). The proposed software functionalities will enable the purchasers to utilize MCDM methods in practice without having to conduct a new MCDM analysis at each purchasing scenario. Managerial implications of this implementation boil down to system prerequisites and human interaction to aid the case company in proper, verified implementation. However, there are some risks in utilizing this approach. For the Fuzzy TOPSIS, the inherent risk is the information bias in assigning weights. For SECA, an inherent risk is data and lack of flexibility. The inherent risk for the sponsor company to keep its current process is the lack of a standardized and high TCO. The point is that either way, sustainable supplier selection is a process of high risk and possibly high reward (Arabsheybani et al., 2018). Therefore, a standardized, data-driven approach is beneficial. The risks of not aligning and standardizing, meaning keeping the current process by excluding the criterion such as Sustainability (C1) or Financial Stability (C2), are much riskier than the one of utilizing a unified strategy with an additional amount of criterion. In this direction, since there is no possible way to calculate the actual savings, it adds additional risk as the solutions might be redundant (Ershadi et al., 2021). In addition, the



(a) The decision tree (b) The software implementation through ESTA

Fig. 1. Implementation of ESTA

overall impact of implementation across all suppliers and part numbers remains unquantifiable with respect to the sponsor company. Therefore, we conduct a qualitative analysis based on the present situation at the company and the ranking recommended by two MCDM methods. The results reflect that our recommendation also brings direct benefit to in perspective of TCO.

Optimizing supplier selection allows the selection of the greener supplier and optimizes the selection process. A better process requires minimum resources; thus, companies will gain the optimum outcome with fewer resources. This is also a sustainability improvement, which inevitably becomes more achievable by incorporating sustainable MCDM supplier selection. The reason is that MCDM supplier selection allows for blending sustainability measures and criteria without compromising business objectives or profitability more than absolutely required. This should translate into companies being more willing to adapt to the green agenda in the future, with the added benefit of being front-runners in the worldwide sustainability race and the advantages that follow, at a cost minimum.

In a recent report by Bowcott et al. (2021), it is estimated that the armed forces, and more specifically, the defense departments, are generating almost 50% of the greenhouse gas emissions of the public sector. Therefore, the industry cannot be excluded from the green transition. In this study, our key focus is sustainable supplier selection. The components suppliers for the defense industry also need to ensure precise emissions standards in producing and shipment of such components. The sponsored company must incorporate those measures to comply with its strategies' green and sustainable policies, standards, and procedures. Historically, the defense industry remains one of the key contributors to technological innovation (Bellais, 2013). However, the dynamic nature of quality standard, contracts and past performance are the key in this industry (Emmanuel-Ebikake et al., 2014). As included in the UN Sustainable Development Goal (SDG) number 16: peace, security, and strong institutions are the key to the prosperity of our countries and societies and so implicitly, thanks to the defense industry. Now, the defense industry can enable the green transition mainly through developing new systems and technologies and supporting the standardization of tasks by paying attention to the factors such as the digitalization of paper works, the design of energy consumption management policies, and others. To address this chllanging task, the Defense industry should divert a significant number of resources to "green R&D". Technological innovation is the keyway to making the green transition possible, not only in the military but in all industrial areas sectors (Massa, 2022).

As a result of the current global situation, sustainability will inevitably become a deciding factor in tomorrow's supply chains. That is, sustainability might be the deciding variable in whether companies thrive or diminish. The Case Company is in the A&D sector, closely linked to governments and their sustainability goals. Thus, it is even more critical. But how should companies cope? The authors would argue that sustainable supplier selection is an ideal place to start, as every decision regarding product supply significantly impacts emissions. For the Case Company, this means that they will have a direct negative impact on the buyer's Sustainable Development Goals (SDGs) if they do not take action. This does not mean that companies would need to focus only on sustainability, but it should be included in the decision to secure future endeavors. MCDM is an ideal process to balance sustainability with the organization's internal goals, which is what the proposed solutions seek to do (Stević et al., 2020). The barriers to the adaptation of sustainability in the context of the A&D industry are many. McKinsey (Bowcott et al., 2021) argue that the priority of having mission-critical capabilities, long equipment life cycles, and increased focus on high-emission niches will prove significant challenges in future A&D sustainability endeavors. When operating in the defense industry, there are lives at stake. Revamping processes to favor sustainability might jeopardize a fully functional system that might cost lives. Therefore, a vast barrier is a need to reduce emissions without making unacceptable trade-offs.

6. Conclusions

Supplier selection is generally a highly complex problem due to the sheer number of alternatives and criteria. This paper proposes a method to identify a preference for alternative suppliers through two MCDM methods. The sponsor company's AS-IS selection is based on four criteria considered as a benchmark to compare the performance of the two methods. To investigate the impact of utilizing this approach on the supplier selection process, a supplier base of 10 individual suppliers is established from the sponsor company. The rankings of these suppliers are identified through the application of the AHP weights in a TOPSIS engine based on a supplier performance-based decision matrix. These rankings are supported by the SECA method, which is incorporated to validate the use of MCDM models concerning the sponsor company. The result shows a powerful correlation between the two MCDM models and little-to-no correlation between the MCDM models and the current state. Clearly, this indicates a potential opportunity for process optimization. Considerations of enabling a dynamic environment to account for real-life variety are established, and a prototype system (ESTA) is constructed to showcase the proposed functionalities of practical implementation. The results reflect that the relationship remains a critical criterion in the defense industry. The sponsor company is willing to incorporate criteria such as sustainability or technology, but the inclusion can significantly affect the current practice. In fact, during our discussion also, the authorities are much more concerned with such changes and their effect on the total cost of ownership and building long-term resilience. To continue the green transition, a lot of resources are needed for R&D to develop new systems and technologies that will shape the future shift toward a greener and Yazdani more sustainable world. In this regard, the prototype we developed can support the evaluation of alternatives and be a concrete technological solution for supplier selection. The authors found for the initial assessment that implementing such models at the sponsor company would significantly impact the current system.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

A. Present practice for the company

As discussed earlier, the company presently relies on the four criteria. Note that one of the key barriers in A&D is that the industry faces unique challenges related to regulatory compliance and strict security protocols. Therefore, too many criteria are still not crucial like in other sectors. Thus, the initial relationship matrix used in this study is presented in Table A1.

Table A.1
The relationship matrix derived from company interviews.

Criterion	Lead Time	Quality	Cost	Relationship
Lead Time	1	1/2	1/3	1/4
Quality	2	1	1/2	1/3
Cost	3	2	1	1
Relationship	4	3	1	1

B. Fuzzy integration in AHP and TOPSIS

In this section, we present the detail of the Fuzzy-TOPSIS method. Note that the method is based on the nine criteria instead of the four criteria. As shown in Table 1, researchers proposed various criteria to be used in the supplier selection process till we used those additional criteria, which appeared critical during our semi-structured interview. We use the following relationship matrix among criteria as shown Table B1 as our departure point.

Table B.1
The linguistic relationship matrix with additional criterion

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1		1/I	1/I	1/VI	1/AI	1/VI	1/AI	1/VI	1/MI
C_2	MI		EI	1/I	1/VI	1/I	1/VI	1/I	EI
C_3	I	EI		1/MI	1/I	1/MI	1/I	1/MI	MI
C_4	VI	I	MI		1/MI	EI	1/MI	EI	I
C_5	AI	VI	I	MI		MI	EI	MI	VI
C_6	VI	I	MI	EI	1/MI		1/MI	EI	I
C_7	AI	VI	MI	MI	EI	MI		MI	VI
C_8	VI	MI	MI	EI	1/MI	EI	1/MI		I
C_9	MI	1/MI	1/MI	1/I	1/VI	1/I	1/VI	1/I	

Similarly, we use the following triangular fuzzy number (Sun, 2010) for linguistic analysis among the performance of suppliers based on different criteria as shown in Tables B2 and B.3.

Table B.2
The triangular set and linguistic terminology for assessment

Fuzzy ratings for linguistic variables	
Fuzzy Number	Criteria Assessments
(1, 1, 3)	Very Poor (VP)
(1, 3, 5)	Poor (P)
(3, 5, 7)	Fair (F)
(5, 7, 9)	Good (G)
(7, 9, 9)	Very Good (VG)

Table B.3
Positive/negative linguistic scale for fuzzy number (Fu et al., 2020)

Statement	Positive Rating	Positive Fuzzy Set	Negative Rating	Negative Fuzzy set
Equally Important	$\tilde{1}$	(1, 1, 3)	$\frac{1}{\tilde{1}}$	$\left(\frac{1}{3},\frac{1}{1},\frac{1}{1}\right)$
Moderately Important	$\tilde{3}$	(1, 3, 5)	$\frac{1}{\tilde{3}}$	$\left(\frac{1}{5},\frac{1}{3},\frac{1}{1}\right)$
Important	$\tilde{5}$	(3, 5, 7)	$\frac{1}{\tilde{5}}$	$\left(\frac{1}{7},\frac{1}{5},\frac{1}{3}\right)$
Very Important	$\tilde{7}$	(5, 7, 9)	$\frac{1}{\tilde{7}}$	$\left(\frac{1}{9},\frac{1}{7},\frac{1}{5}\right)$
Absolutely Important	$\tilde{9}$	(7, 9, 9)	$\frac{1}{\tilde{9}}$	$\left(\frac{1}{9},\frac{1}{9},\frac{1}{7}\right)$

Next, we define the fuzzy relationship matrix to be used for weight computation. Using Table B1, we obtain the following relationship matrix as presented in Table B4.

Table B.4
The fuzzy triangular relationship matrix for AHP.

		C_1			C_2			C_3			C_4			C_5			C_6			C_7			C_8			C_9	
C_1	1.0	1.0	1.0	0.2	0.3	1.0	0.1	0.2	0.3	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.3	1.0
C_2	1.0	3.0	5.0	1.0	1.0	1.0	0.2	0.3	1.0	0.1	0.2	0.3	0.1	0.1	0.2	0.1	0.2	0.3	0.1	0.1	0.2	0.1	0.2	0.3	1.0	1.0	1.0
C_3	3.0	5.0	7.0	1.0	3.0	5.0	1.0	1.0	1.0	0.2	0.3	1.0	0.1	0.2	0.3	0.2	0.3	1.0	0.1	0.2	0.3	0.2	0.3	1.0	1.0	3.0	5.0
C_4	5.0	7.0	9.0	3.0	5.0	7.0	1.0	3.0	5.0	1.0	1.0	1.0	0.2	0.3	1.0	1.0	1.0	1.0	0.2	0.3	1.0	1.0	1.0	1.0	3.0	5.0	7.0
C_5	7.0	9.0	9.0	5.0	7.0	9.0	3.0	5.0	7.0	1.0	3.0	5.0	1.0	1.0	1.0	1.0	3.0	5.0	1.0	1.0	1.0	1.0	3.0	5.0	5.0	7.0	9.0
C_6	5.0	7.0	9.0	3.0	5.0	7.0	1.0	3.0	5.0	1.0	1.0	1.0	0.2	0.3	1.0	1.0	1.0	1.0	0.2	0.3	1.0	1.0	1.0	1.0	3.0	5.0	7.0
C_7	7.0	9.0	9.0	5.0	7.0	9.0	3.0	5.0	7.0	1.0	3.0	5.0	1.0	1.0	1.0	1.0	3.0	5.0	1.0	1.0	1.0	1.0	3.0	5.0	5.0	7.0	9.0
C_8	5.0	7.0	9.0	3.0	5.0	7.0	1.0	3.0	5.0	1.0	1.0	1.0	0.2	0.3	1.0	1.0	1.0	1.0	0.2	0.3	1.0	1.0	1.0	1.0	3.0	5.0	7.0
C_9	1.0	3.0	5.0	1.0	1.0	1.0	0.2	0.3	1.0	0.1	0.2	0.3	0.1	0.1	0.2	0.1	0.1	0.3	0.1	0.1	0.3	0.1	0.2	0.3	1.0	1.0	1.0

Once again, applying the similar procedure as presented in Section 3, we obtain the weights for each criterion through the AHP method, as shown in Table B5.

Table B.5
The resulting weights of the F-AHP

Criterion		w_i	
Flexibility	0.020	0.016	0.018
S & EA	0.031	0.029	0.031
Financial Stab.	0.051	0.056	0.074
Technology	0.128	0.119	0.125
Quality	0.241	0.257	0.235
Delivery	0.128	0.119	0.125
Cost	0.241	0.257	0.235
Relationship	0.128	0.119	0.125
Lead-Time	0.032	0.029	0.031

Next, we analyze the final ranking obtained through F-TOPSIS. We present linguistic ratings of each supplier based on the nine criteria in Table 3 and corresponding numerical representation in the following Table B6.

Table B.6
A translation of the linguistic decision matrix into triangular sets.

	C_1 C_2 C_3 C_4 C_5					C_6	C_7	C_8	C_9
S_1	5 7 9	1 3 5	5 7 9	5 7 9	3 5 7	3 5 7	5 7 9	5 7 9	5 7 9
S_2	3 5 7	5 7 9	5 7 9	3 5 7	5 7 9	7 9 9	7 9 9	5 7 9	3 5 7
S_3	5 7 9	5 7 9	5 7 9	7 9 9	5 7 9	5 7 9	3 5 7	7 9 9	1 3 5
S_4	5 7 9	1 1 3	1 3 5	1 3 5	7 9 9	3 5 7	3 5 7	5 7 9	5 7 9

(*continued on next page*)

Table B.6 (*continued*)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
S_5	5 7 9	1 3 5	3 5 7	5 7 9	7 9 9	3 5 7	1 3 5	5 7 9	3 5 7
S_6	7 9 9	1 1 3	1 3 5	3 5 7	1 3 5	7 9 9	5 7 9	3 5 7	5 7 9
S_7	5 7 9	5 7 9	3 5 7	7 9 9	7 9 9	1 1 3	7 9 9	3 5 7	3 5 7
S_8	1 1 3	7 9 9	7 9 9	5 7 9	5 7 9	3 5 7	1 3 5	5 7 9	7 9 9
S_9	1 1 3	3 5 7	3 5 7	3 5 7	1 3 5	3 5 7	5 7 9	7 9 9	3 5 7
S_{10}	3 5 7	1 1 3	1 3 5	1 1 3	3 5 7	7 9 9	1 3 5	5 7 9	5 7 9

Therefore, the normalized decision matrix is obtained as follows.

Table B.7
The normalized decision matrix for supplier performance.

	C_1			C_2			C_3			C_4			C_5			C_6			C_7			C_8			C_9		
S_1	0.56	0.78	1.00	0.11	0.33	0.56	0.56	0.78	1.00	0.56	0.78	1.00	0.33	0.56	0.78	0.33	0.56	0.78	0.56	0.78	1.00	0.56	0.78	1.00	0.56	0.78	1.00
S_2	0.33	0.56	0.78	0.56	0.78	1.00	0.56	0.78	1.00	0.33	0.56	0.78	0.56	0.78	1.00	0.78	1.00	1.00	0.78	1.00	1.00	0.56	0.78	1.00	0.33	0.56	0.78
S_3	0.56	0.78	1.00	0.56	0.78	1.00	0.56	0.78	1.00	0.78	1.00	1.00	0.56	0.78	1.00	0.56	0.78	1.00	0.33	0.56	0.78	0.78	1.00	1.00	0.11	0.33	0.56
S_4	0.56	0.78	1.00	0.11	0.11	0.33	0.11	0.33	0.56	0.11	0.33	0.56	0.78	1.00	1.00	0.33	0.56	0.78	0.33	0.56	0.78	0.56	0.78	1.00	0.56	0.78	1.00
S_5	0.56	0.78	1.00	0.11	0.33	0.56	0.33	0.56	0.78	0.56	0.78	1.00	0.78	1.00	1.00	0.33	0.56	0.78	0.11	0.33	0.56	0.56	0.78	1.00	0.33	0.56	0.78
S_6	0.78	1.00	1.00	0.11	0.11	0.33	0.11	0.33	0.56	0.33	0.56	0.78	0.11	0.33	0.56	0.78	1.00	1.00	0.56	0.78	1.00	0.33	0.56	0.78	0.56	0.78	1.00
S_7	0.56	0.78	1.00	0.56	0.78	1.00	0.33	0.56	0.78	0.78	1.00	1.00	0.78	1.00	1.00	0.11	0.11	0.33	0.78	1.00	1.00	0.33	0.56	0.78	0.33	0.56	0.78
S_8	0.11	0.11	0.33	0.78	1.00	1.00	0.78	1.00	1.00	0.56	0.78	1.00	0.56	0.78	1.00	0.33	0.56	0.78	0.11	0.33	0.56	0.56	0.78	1.00	0.78	1.00	1.00
S_9	0.11	0.11	0.33	0.33	0.56	0.78	0.33	0.56	0.78	0.33	0.56	0.78	0.11	0.33	0.56	0.33	0.56	0.78	0.56	0.78	1.00	0.78	1.00	1.00	0.33	0.56	0.78
S_{10}	0.33	0.56	0.78	0.11	0.11	0.33	0.11	0.33	0.56	0.11	0.11	0.33	0.33	0.56	0.78	0.78	1.00	1.00	0.11	0.33	0.56	0.56	0.78	1.00	0.56	0.78	1.00

Finally, using the methodology as presented in Subsection 3.3, we determine the Fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) as presented in Table B8 and B.9, respectively.

Table B.8
The FPIS scores for each alternative in relation to each criterion.

	Distance from FPIS									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	d_i^+
S_1	0.003	0.018	0.010	0.022	0.095	0.048	0.045	0.022	0.006	0.270
S_2	0.007	0.005	0.010	0.048	0.045	0.000	0.000	0.022	0.012	0.149
S_3	0.003	0.005	0.010	0.000	0.045	0.022	0.095	0.000	0.018	0.200
S_4	0.003	0.022	0.035	0.075	0.000	0.048	0.095	0.022	0.006	0.306
S_5	0.003	0.018	0.022	0.022	0.000	0.048	0.148	0.022	0.012	0.296
S_6	0.000	0.022	0.035	0.048	0.148	0.000	0.045	0.048	0.006	0.352
S_7	0.003	0.005	0.022	0.000	0.000	0.092	0.000	0.048	0.012	0.182
S_8	0.013	0.000	0.000	0.022	0.045	0.048	0.148	0.022	0.000	0.299
S_9	0.013	0.012	0.022	0.048	0.148	0.048	0.045	0.000	0.012	0.347
S_{10}	0.007	0.022	0.035	0.092	0.095	0.000	0.148	0.022	0.006	0.428

Table B.9
The FNIS scores for each alternative in relation to each criterion.

	Distance from FNIS									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	d_i^-
S_1	0.011	0.005	0.039	0.081	0.092	0.057	0.132	0.047	0.016	0.481
S_2	0.007	0.018	0.039	0.057	0.132	0.095	0.162	0.047	0.012	0.569
S_3	0.011	0.018	0.039	0.095	0.132	0.081	0.092	0.056	0.010	0.533
S_4	0.011	0.000	0.025	0.039	0.162	0.057	0.092	0.047	0.016	0.450
S_5	0.011	0.005	0.030	0.081	0.162	0.057	0.074	0.047	0.012	0.478
S_6	0.013	0.000	0.025	0.057	0.074	0.095	0.132	0.039	0.016	0.451
S_7	0.011	0.018	0.030	0.095	0.162	0.023	0.162	0.039	0.012	0.550
S_8	0.000	0.022	0.043	0.081	0.132	0.057	0.074	0.047	0.020	0.476
S_9	0.000	0.012	0.030	0.057	0.074	0.057	0.132	0.056	0.012	0.429
S_{10}	0.007	0.000	0.025	0.023	0.092	0.095	0.074	0.047	0.016	0.379

Finally, the CC_i for each alternative at any given criteria is determined, and the final ranking is presented in Table 2.

C. Step-wise computation for the SECA method

The following step-wise analysis is executed to obtain the final ranking by SECA. The first step is establishing a decision matrix, which is the same as Table B7 from the F-TOPSIS. To assign non-fuzzy weights, each fuzzy number is aggregated into a single crisp value, and the detail is presented in Table C1.

Table C.1
The aggregated decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
S_1	0.78	0.33	0.78	0.78	0.56	0.56	0.78	0.78	0.78
S_2	0.56	0.78	0.78	0.56	0.78	0.93	0.93	0.78	0.56
S_3	0.78	0.78	0.78	0.93	0.78	0.78	0.56	0.93	0.33
S_4	0.78	0.19	0.33	0.33	0.93	0.56	0.56	0.78	0.78
S_5	0.78	0.33	0.56	0.78	0.93	0.56	0.33	0.78	0.56
S_6	0.93	0.19	0.33	0.56	0.33	0.93	0.78	0.56	0.78
S_7	0.78	0.78	0.56	0.93	0.93	0.19	0.93	0.56	0.56
S_8	0.19	0.93	0.93	0.78	0.78	0.56	0.33	0.78	0.93
S_9	0.19	0.56	0.56	0.56	0.33	0.56	0.78	0.93	0.56
S_{10}	0.56	0.19	0.33	0.19	0.56	0.93	0.33	0.78	0.78

Next, we normalized the decision matrix by a similar approach as presented in Section 3.4, and the results are shown in Table C2.

Table C.2
The aggregated normalized decision matrix.

	C_1 C_2		C_3	C_4	C_5	C_6	C_7	C_8	C_9
S_1	0.84	0.36	0.84	0.84	0.60	0.60	0.84	0.84	0.84
S_2	0.60	0.84	0.84	0.60	0.84	1.00	1.00	0.84	0.60
S_3	0.84	0.84	0.84	1.00	0.84	0.84	0.60	1.00	0.36
S_4	0.84	0.20	0.36	0.36	1.00	0.60	0.60	0.84	0.84
S_5	0.84	0.36	0.60	0.84	1.00	0.60	0.36	0.84	0.60
S_6	1.00	0.20	0.36	0.60	0.36	1.00	0.84	0.60	0.84
S_7	0.84	0.84	0.60	1.00	1.00	0.20	1.00	0.60	0.60
S_8	0.20	1.00	1.00	0.84	0.84	0.60	0.36	0.84	1.00
S_9	0.20	0.60	0.60	0.60	0.36	0.60	0.84	1.00	0.60
S_{10}	0.60	0.20	0.36	0.20	0.60	1.00	0.36	0.84	0.84

Correlation coefficients are determined to capture the information from the between-criteria in the normalized decision matrix (Keshavarz-Ghorabaee et al., 2018), and the results are shown in Table C3.

Table C.3
Correlation matrix obtained from Table C2

	C_1 C_2 C_3			C_4	C_5	C_6	C_7	C_8	C_9
C_1	1	−0.471	−0.396	0.121	0.213	0.062	0.200	−0.491	−0.066
C_2	−0.471	1	0.795	0.630	0.315	−0.279	0.192	0.178	−0.436
C_3	−0.396	0.795	1	0.666	0.221	−0.157	0.048	0.361	−0.172
C_4	0.121	0.630	0.666	1	0.306	−0.514	0.210	−0.053	−0.277
C_5	0.213	0.315	0.221	0.306	1	−0.439	−0.220	−0.053	0.041
C_6	0.062	−0.279	−0.157	−0.514	−0.439	1	−0.139	0.175	−0.052
C_7	0.200	0.192	0.048	0.210	−0.220	−0.139	1	−0.320	−0.536
C_8	−0.491	0.178	0.361	−0.053	−0.053	0.175	−0.320	1	−0.297
C_9	−0.066	−0.436	−0.172	−0.277	0.041	−0.052	−0.536	−0.297	1

Next, the Standard Deviation (σ) is calculated to measure the spread of values for the ten alternative suppliers. This is shown in Table C4.

Table C.4
The Standard Deviation and their normalized values

C	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
σ	*0.28*	*0.31*	*0.23*	*0.26*	*0.25*	*0.25*	*0.26*	*0.13*	*0.20*
$N\sigma$	*0.13*	*0.14*	*0.11*	*0.12*	*0.11*	*0.12*	*0.12*	*0.06*	*0.09*

From Table C3, the Aggregated decision matrix is determined $\left(\pi_j = \sum_{l=1}^{m}(1 - r_{jl})\right)$

Table C.5
Transformed matrix obtained by following Step 3

	C_1 C_2 C_3			C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.000	1.471	1.396	0.879	0.787	0.938	0.800	1.491	1.066
C_2	1.471	0.000	0.205	0.370	0.685	1.279	0.808	0.822	1.436
C_3	1.396	0.205	0.000	0.334	0.779	1.157	0.952	0.639	1.172
C_4	0.879	0.370	0.334	0.000	0.694	1.514	0.790	1.053	1.277
C_5	0.787	0.685	0.779	0.694	0.000	1.439	1.220	1.053	0.959
C_6	0.938	1.279	1.157	1.514	1.439	0.000	1.139	0.825	1.052
C_7	0.800	0.808	0.952	0.790	1.220	1.139	0.000	1.320	1.536
C_8	1.491	0.822	0.639	1.053	1.053	0.825	1.320	0.000	1.297
C_9	1.066	1.436	1.172	1.277	0.959	1.052	1.536	1.297	0.000

The π values are then summarized from the transformed model and normalized as $N\pi$ illustrated in C.6.

Table C.6
The standard deviation for conflict between each criterion against other criteria (π and Nπ) values

C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
8.83	*7.08*	*6.63*	*6.91*	*7.61*	*9.34*	*8.57*	*8.50*	*9.80*
0.12	*0.10*	*0.09*	*0.09*	*0.10*	*0.13*	*0.12*	*0.12*	*0.13*

The results presented in Table C2 are used to construct the optimization problem as presented in Step 5. we use *Wolfram Mathematica* to solve the optimization problem. The weights obtained for various β values are presented in Table C7. As reported by (Keshavarz-Ghorabaee et al., 2018), the weights should be convergent; our results are also consistent with the observation. Note that weights are used (β = 5) for the final ranking, as shown in Table 2.

Table C.7
Various β values and corresponding weights for each criterion

β	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
0.1 0.3	0.06	0.00	0.00	0.00	0.14	0.07	0.18	0.32	0.22
0.5	0.06	0.02	0.00	0.05	0.12	0.15	0.17	0.26	0.18
1	0.06	0.05	0.04	0.05	0.09	0.17	0.14	0.22	0.16
2	0.08	0.08	0.07	0.06	0.08	0.18	0.12	0.17	0.15
3	0.11	0.09	0.08	0.08	0.10	0.16	0.11	0.13	0.14
5	0.12	0.10	0.09	0.08	0.11	0.15	0.11	0.11	0.13
	0.13	0.10	0.09	0.09	0.11	0.14	0.11	0.11	0.13

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