Applied Soft Computing 128 (2022) 109546

Contents lists available at ScienceDirect

Applied Soft Computing

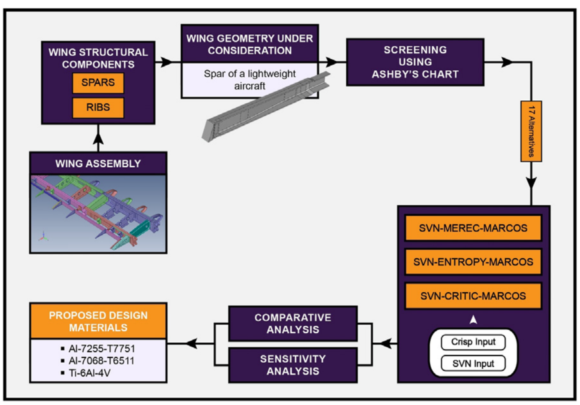
journal homepage: www.elsevier.com/locate/asoc

Sustainable material selection with crisp and ambiguous data using single-valued neutrosophic-MEREC-MARCOS framework

R. Sami Ul Haq [a], M. Saeed [a], N. Mateen [a], F. Siddiqui [a], M. Naqvi [a], J.B. Yi [b], S. Ahmed [a,*]

[a] Aerospace and Aviation Campus, Air University, Kamra, Pakistan
[b] Global Innovative Centre for Advanced Nanomaterials, School of Engineering, The University of Newcastle, Callaghan NSW 2308, Australia

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 11 October 2021
Received in revised form 10 August 2022
Accepted 16 August 2022
Available online 22 August 2022

Keywords:
Single-valued neutrosophic sets
Multi-criteria decision making
MEREC
MARCOS
Sustainable material selection
Structures
Lightweight aircraft
Wing spar

ABSTRACT

Many industries around the globe are opting for environment-friendly and intelligent solutions. In this regard, the materials and manufacturing sectors have also evolved beyond the fundamental requirements for industrial applications by incorporating sustainable practices into their operations. To promote carbon-neutral growth for sustainable production, green materials that can be reused and recycled have gained significant importance. Previous work on material selection has relied on parameters that either take crisp or ambiguous inputs. However, criteria based on the core concept of sustainability, such as environmental considerations, require uncertain or indeterminate expert assessments solved using single-valued neutrosophic sets (SVNSs). For this reason, sustainable material selection necessitates the development of a unique framework to evaluate both crisp and ambiguous data concurrently without losing any information. In this work, a novel integrated framework combining method based on the removal effects of criteria (MEREC) and measurement alternatives and ranking based on compromise solution (MARCOS) under the SVNSs environment is developed to assist designers in solving real-time engineering problems, taking inputs from three decision-makers. To demonstrate the applicability of the proposed framework, a case study for the material selection of a lightweight aircraft wing spar is considered. The criteria assessment factors used for the material selection are economic, structural, damage-tolerance, manufacturing, and environmental

Abbreviations: SVNSs, Single-Valued Neutrosophic Sets; MEREC, MEthod based on the Removal Effects of Criteria; MARCOS, Measurement Alternatives and Ranking according to COmpromise Solution; TODIM, Interactive and multiple attribute decision making; COPRAS, COmplex PRoportional ASsessment

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* Corresponding author.
E-mail addresses: ranasami@aerospace.pk (R.S. Ul Haq), maryam@aerospace.pk (M. Saeed), nomanmateen@aerospace.pk (N. Mateen), faisal@aerospace.pk (F. Siddiqui), messam@aerospace.pk (M. Naqvi), jiabao.yi@newcastle.edu.au (J.B. Yi), sohail.ahmed@aerospace.pk (S. Ahmed).

https://doi.org/10.1016/j.asoc.2022.109546
1568-4946/

impact. To underline the advantages of the proposed methodology, a comparative analysis is carried out with distinct integrated frameworks. Furthermore, the findings of sensitivity analysis indicate that the suggested technique is an effective, efficient, and practical decision-making tool. The excellent correlation of the Spearman coefficient of the proposed approach with interactive and multiple attribute decision making (TODIM) and complex proportional assessment (COPRAS) under SVNSs shows the legitimacy of the obtained ranking. The material selection tool is practical because it is developed using MATLAB and may be adapted to other applications with more criteria and alternatives.

Code metadata

Permanent link to reproducible Capsule: https://doi.org/10.24433/CO.9951885.v1.

1. Introduction

Amid rising global warming concerns, environmental pollution, and resource shortages, the world is striving towards a greener and more sustainable future by setting ambitious goals to reduce greenhouse gas emissions.[1] The aviation industry is the 17th largest contributor in terms of global GDP, which is more than some of the G20 member countries and is responsible for 2.1% of the global carbon dioxide production.[2] Therefore, in October 2021, the aerospace sector pledged to achieve net-zero CO_2 emissions as early as 2050 under the umbrella of the air transport action group (ATAG).[3] Sophisticated infrastructures, efficient manufacturing operations, environment-friendly technologies, sustainable aviation fuels (SAFs), and strong governmental support are groundbreaking measures in this domain [1,2]. For example, the new efficient Airbus A380 aircraft burns around 3 liters of fuel for every 100 passenger kilometers. To further improve the efficiency of flight operations through innovations in infrastructural design and materials, the use of composites is becoming increasingly common. However, we need to consider the environmental impacts of materials on the planet and opt for ethical material selection practices. In the post-COVID-19 time, the aviation industry aims for a green recovery and sustainable economic boom, which requires feasible pathways and methods in a multitude of sectors. For instance, for sustainable production supply chains, aircraft manufacturers approve materials that can be reused or recycled at the product end of life (EoL) [3]. At the same time, the manufacturing sector is condemning traditional practices and focusing on connectivity, the digital age, artificial intelligence, and sustainability during the product life cycle to make processes environment-friendly [4]. Owing to these developments, the governments and international organizations have also laid out policies regarding the circular economy, waste material recycling, and energy-saving opportunities, emphasizing the need for sustainable material selection in product design and development.

For product design, physical objects are mostly coherent in three critical areas: structural concepts, material selection, and manufacturability. Material selection is an intrinsic relationship between design specifications, including function, material, shape, and process [5]. The large set of materials, including metals and non-metals (estimated at around 80,000), poses a critical challenge for decision-makers in selecting the most appropriate material under the given constraints [6,7]. Typically, a number of critical factors are determined while choosing a suitable material for a specific application. For example, when designing and manufacturing a mechanical system, mechanical properties such as tensile strength, young's modulus, fatigue; physical properties such as density; thermal properties such as thermal expansion, service temperature, and impact/fracture properties are commonly considered [8]. However, when the goal is sustainability, additional parameters such as ease of manufacturing, recyclability, fatigue, corrosion, and CO_2 emissions are also taken into consideration.

Traditionally, decision-making methods based on the design of experiment (DoE) concept were used to find an optimum material. This methodology relied only on past user experience and overlooked a large subset of potential materials [9,10]. On the other hand, Researchers, including Ashby, provide standard procedural steps for effective and efficient material selection, with *screening* and *ranking* as the two most prominent steps [6,11]. Ashby's charts are often used to screen alternatives with superior properties, followed by multi-criteria decision making (MCDM) methods to systematically evaluate intricate and interdependent problems with multiple actors, criteria, and conflicting objectives [12]. Past researchers have extensively reviewed the significance and applicability of the MCDM methods in the context of material selection involving quantitative and qualitative criteria using simple, crisp inputs [13]. These include technique for order of preference by similarity to ideal solution (TOPSIS), multi-criteria optimization and compromise solution (VIKOR) [14], preference ranking organization method for enrichment evaluation (PROMETHEE-II) [15], complex proportional assessment (COPRAS), evaluation of mixed data (EVAMIX) [7] among others.

Designers or materials engineers experience problems where the inputs are not well defined and have to rely on the judgments of decision-makers. The decisions may generate imprecise or uncertain information based on the varying degrees of expertise levels, individual perceptions of the decision-makers, and the complexity of the problem. In such cases, theories such as fuzzy sets (FSs) [16], intuitionistic fuzzy sets (IFSs) [17], and neutrosophic sets (NSs) [18] address the uncertainties during the decision-making process. This study uses single-valued neutrosophic sets (SVNSs), a subset of NS developed by Wang et al. built on the fundamental concept of aggregating a number of inputs by multiple decision-makers into a single value [19]. SVNSs have acquired significant relevance for real-time problem solving since it also deals with indeterminacies or inconsistencies. Majumdar and Samanta presented similarity and entropy measures of SVNSs [20]. Similarly, Karaaslan studied SVN Refined (SVNR) sets based on Jaccard, Dice, and Cosine similarity measures [21]. Ye suggested a correlation coefficient of SVNSs followed by a decision-making method under an SVN environment [22]. Garg and Nancy gave new distance measures for SVNSs and investigated their relevance using extended TOPSIS [23]. Lu and Ye devised SVN hybrid operators to aggregate a decision matrix in an MCDM method [24]. Akram et al. applied the mathematical concept of Lie algebras to SVN sets [25]. SVNSs have been successfully used for real-time problem solving to achieve useful and practical solutions for a wide range of applications [26,27].

1 https://www.unido.org/our-focus-cross-cutting-services-green-industry/green-industry-initiative

2 https://www.atag.org/facts-figures.html

3 https://aci.aero/2021/10/05/aviation-industry-unites-to-adopt-2050-net-zero-carbon-goal

Nomenclature

Symbol	Description
L	Alternative
R	Crisp criteria
G	Ambiguous criteria
D	Decision-maker
B	Benefit criteria
C	Cost criteria
m	Number of alternatives
n	Number of criteria
r	Number of decision-makers
p	pth decision-maker
T	Crisp numerical value of alternative L_i over criteria R_j, where $T = (F_{ij})_{m\times n}$ and $(i, j) \in (m, n)$
U	Linguistic performance measure of alternative L_i over criteria G_j for pth decision-maker, where $U = ({F_{ij}}^{(p)})_{m\times n}$ and $(i, j, p) \in (m, n, r)$
A	Aggregated-SVN-Decision matrix, where $A = (¥_{ij})_{m\times n}$ and $¥_{ij} = (t_{ij}, i_{ij}, f_{ij})$
S	Score matrix, where $S = Ş((¥_{ij}))_{m\times n}$
$Ş$	Score function
ϖ_p	Weight of pth decision-maker, where $\varpi_p \geq 0$ and $\sum_{p=1}^{r} \varpi_p = 1$
W_p	Significance of pth decision-maker in SVNNs, where $W_p = (t_p, i_p, f_p)$
ω	Criteria weights for MEREC
Ψ	Criteria weights for entropy
Φ	Criteria weights for CRITIC
$\mathbb{W}_{inc}$	Variable incumbent weight ranging from 0 to 1
ω_{inc}	Incumbent weight of selected criterion
η	Normalized decision matrix for MEREC, where $\eta = (N_{ij})_{m\times n}$
$\check{n}$	Normalized extended decision matrix for MARCOS, where $\check{n} = (\mathbb{N}_{ij})_{m\times n}$
M_i	Overall performance of ith alternative
M^{*}_{ij}	Overall performance of ith alternative by removing jth criteria
E_j	Absolute deviation for jth criteria
L_{ID}	Ideal solution, where $L_{ID} = F_I$
L_{NI}	Non-ideal solution, where $L_{NI} = F_N$
V	Weighted matrix, where $V = (v_{ij})_{m\times n}$
$\acute{S}_i$	Weighted sum matrix
$\acute{S}_{ID}$	Weighted sum of an ideal solution
$\acute{S}_{NI}$	Weighted sum of non-ideal solution
K_i	Utility degree
$f(K_i)$	Utility function

Advancements in material technologies have allowed decision-makers to consider sustainability as an indispensable factor in the selection process [28]. In addition to material attributes, environmental considerations play an essential role in sustainable material selection [29]. Environmental factors require expert evaluations which are uncertain or indeterminate, whereas material properties like density, yield strength, and young's modulus have defined numerical values obtained from material databases, handbooks, and resource packs. Several studies exist in the literature that consider material selection problems while attending to the uncertainties and indeterminacies of the decision matrix through SVNSs. Zavadskas et al. attempted to explore the potential of converting crisp input parameters into single-valued neutrosophic numbers (SVNNs) to solve an MCDM problem [30]. Likewise, Farid and Riaz solved the selection problem of a cryogenic tank by gathering inputs on criteria from the decision-maker and subsequently applying the SVNS theory [31]. Although the prior studies demonstrate that SVNSs can be very useful for selecting optimal materials, they are solely intended to handle uncertain data obtained by qualitative judgments of criteria. It overlooks an essential aspect of real-time material selection, which involves employing crisp and defined quantitative measurements, resulting in information loss and unreliable results. Therefore, a more realistic approach is required that does not compromise the material selection process by losing critical information or the underlying structure of the data, either crisp or indeterminate.

In continuation of published work, this research offers a novel integrated framework combining method based on the removal effects of criteria (MEREC) and measurement alternatives and ranking based on compromise solution (MARCOS) under SVNSs environment. The underlying goals and the objectives of this study are:

(i) To propose a unique framework that concurrently analyzes crisp and imprecise or indeterminate input parameters, providing a more realistic approach to handling a multi-criteria problem.
(ii) To solve a material selection problem of a lightweight aircraft spar with conflicting objectives and mixed data types using a novel integrated SVN-MEREC-MARCOS approach.
(iii) To use a new criteria weighting method MEREC in SVNSs, which assesses the removal effects of criteria on performances of the alternatives.
(iv) To identify the advantages of the proposed integrated framework by comparing and validating the outcomes with prior work.

The scope of this work is given as follows: Section 2 examines the literature on fuzzy-based material selection, SVNSs, MEREC, MARCOS, and material selection of lightweight aircraft spar while highlighting the research gaps, motivation, and major contributions. Section 3 provides the preliminary definitions and the mathematical operations used to solve SVNSs, followed by the proposed methodology presented in Section 4. Section 5 details the application of the suggested technique to a real-time problem of a lightweight aircraft spar, including a comparative and sensitivity analysis. Finally, the research work is concluded in Section 6.

2. Literature review

2.1. Material selection in fuzzy environment

In the literature, material selection in a fuzzy environment is a profoundly researched topic. Researchers and scholars are continually focusing their efforts on utilizing fuzzy-based approaches for addressing problems characterized by uncertainty and ambiguity. For instance, Liao presented two fuzzy set theories to represent uncertainty, type 1 fuzzy [32] and two interval type 2 fuzzy [33], for solving the material selection problem of a jet fuel system nozzle. Similarly, Celik et al. introduced the fuzzy decision-making model based on trapezoidal numbers in response to ambiguous inputs encountered in a material selection problem of an automotive instrument panel [34]. Zoghi et al. developed an MCDM framework combining Kano model, fuzzy analytical hierarchy process (FAHP) and fuzzy TOPSIS to select suitable materials fulfilling design for deconstruction (DfD) requirements [35]. Zindani et al. proposed an integrated fuzzy approach using evaluation based on distance from average solution (EDAS) for selecting an appropriate material used in sand casting plate [36]. Vats and Vaish incorporated the VIKOR-based fuzzy method for identifying an optimal piezoelectric ceramic for transducer applications [37]. For aerospace cabin interior applications, Bhadra and Dhar applied fuzzy integrated AHP with three MCDM methods, i.e., TOPSIS, EDAS and COPRAS to select natural fibers for fabricating polymer-based composites [38]. Rathod and Kanzaria [39] and Loganathan and Mani [40] proposed fuzzy MCDM approaches to solve phase change material (PCM) selection problems in an uncertain environment.

2.2. Single-valued neutrosophic sets (SVNSs)

The designers often come across instances where the required data input is either incomplete, uncertain, imprecise, ambiguous, or indeterminate. To deal with incomplete and uncertain data, Zadeh pioneered the concept of FSs, where objects are defined by membership degree (validity) – a single value between the closed interval [0, 1] [16]. The inability of FSs to express a non-membership degree inspired Atanassov to introduce IFSs, which have a non-membership degree and hesitant degree in addition to a membership degree [17]. Thus, IFSs are more applicable and practical to use in real-time problem-solving. Conversely, in scenarios where it is difficult to define the elements of IFSs using a single value, Interval-Valued Intuitionistic Fuzzy Sets (IVIFSs) were introduced by Atanassov and Gargov as an extension of IFSs [41]. Some other theories of FSs include hesitant fuzzy sets (HFSs) [42], interval-valued hesitant fuzzy sets (IVHFSs) [43], and hesitant interval-valued intuitionistic fuzzy sets (HIVIFSs) [44], in which the individuals are apprehensive about expressing their preference regarding objects.

The existing theories of FSs have been widely explored to address fuzziness in real-time problems; however, the inflexibility of fuzzy sets to deal with indeterminate and inconsistent information facilitated the use of NSs presented by Smarandache [18]. The notion of NSs is defined by three membership functions: truthiness (T), falsity (F), and indeterminacy (I). Since there were no restrictions on the summation of membership functions, NSs could not be easily implemented in engineering or scientific applications. Therefore, Wang et al. developed SVNSs, restricting their sum so the elements must satisfy the condition $0 \leq T_{\breve{N}}(q_i) + I_{\breve{N}}(q_i) + F_{\breve{N}}(q_i) \leq 3$ [19]. Also, Ye introduced the simplified neutrosophic sets (SNSs), a subclass of NSs characterized using three real numbers in the unit interval [0, 1] and proposed aggregation operators of SNSs [45]. In addition, Wang et al. presented the theory of interval-valued neutrosophic sets (IVNSs), defined set-theoretic operators, and established the convexity of IVNSs [46].

Given the versatility of SVNS, the researchers paired it with various MCDM methodologies, which emerged as an effective and practical tool for handling complex engineering problems [47,48]. For example, for evaluating food waste treatment methods (FWTMs), Rani et al. employed the SVN framework in combination with criteria importance through intercriteria correlation (CRITIC) and multi-objective optimization by ratio analysis with the full multiplicative form (MULTIMOORA) [49]. Mishra et al. implemented the concept of SVNS on subjective and objective weight integrated approach (SOWIA) and weighted aggregated sum product assessment (WASPAS) for sustainable biomass crop selection [50]. Additionally, an integrated framework of CRITIC-CoCoSo in the SVNS setting has been applied for choosing a sustainable third-party reverse logistic provider (S3PRLP) in an electronic company [27]. Zavadskas et al. utilized SVNS with multi-attribute market value assessment (MAMVA) for a market evaluation of buildings [51] and WASPAS for incineration plant site selection [52]. Veysi Başhan estimated risks in ship navigation using the SVN-TOPSIS-based approach [53]. Despite the fact that SVNSs find their application in various distinct fields, research in real-time engineering problems concerning material selection is scarce. For instance, the work of Farid and Riaz focused on the use of the Einstein operator for material selection in the SVN context [31]. Similarly, Edmundas et al. applied the SVN framework with stepwise weight assessment ratio analysis (SWARA) and MULTIMOORA for selecting materials used in the construction of single-family houses [30]. Thus, this research work offers a novel integrated SVN framework applied to a real-time material selection problem of lightweight aircraft spar.

2.3. Group multi-criteria decision making (GMCDM)

GMCDM, an acronym for group multi-criteria decision making, refers to the opinion aggregation of experts to rank the alternatives in a real-time multi-criteria problem and provide the optimal solution. The GMCDM issue has attracted the attention of many academics, and several methods have been proposed in the literature concerning material selection under uncertainty. For example, Girubha and Vinodh [54] and Gul et al. [55] developed decision support systems using trapezoidal fuzzy linguistic VIKOR and PROMETHEE. Chen et al. proposed GMCDM frameworks using basic uncertain linguistic information (BULI) embedded with quality function deployment (QFD) and elimination and choice translating reality (ELECTRE-III) [56], and improved basic uncertain linguistic information (IBULI) with TOPSIS for sustainable building material selection [57]. Kirişci et al. introduced the novel Fermatean fuzzy ELECTRE method and merged the experts' opinions in a group decision-making process using the Fermatean fuzzy aggregated averaging (FFAA) operator [58]. Ünver et al. applied a fuzzy-COPRAS method in GMCDM [59]. Xue et al. [60] and Roy et al. [61] proposed group interval-valued intuitionistic fuzzy (IVIF) frameworks based on multi-attribute border approximation area comparison (MABAC) and combinative distance assessment (CODAS). Also, Zavadskas et al. developed IVIF-MULTIMOORA for use in group decision-making in an uncertain environment [62]. Considering the generic nature of SVNSs, researchers have proposed various GMCDM frameworks and their applications in the SVNS context, summarized in Table 1. However, there is little to no research on material selection utilizing SVNSs in group decision problems. Thus, this work justifies the need to develop a mathematical approach to handling complicated and unstructured material selection problems of uncertainty in group decision-making.

2.4. Method based on the removal effects of criteria (MEREC)

For a given application, the relative importance of criteria is appraised either objectively, subjectively, or a combination of both [68]. Entropy and CRITIC are examples of objective weighting methods most widely used in real-time applications [69,70]. In contrast, MEREC is a new objective weighting method suggested by Keshavarz-Ghorabaee et al. which assesses the criteria weighting based on the exclusion perspective; thus, a criterion has more weight when its removal significantly impacts the aggregated performance [71]. Prashar et al. have applied MEREC to compute objective weights for selecting a technologically advanced delta robot [72]. Keshavarz-Ghorabaee used MEREC to analyze the feasibility of warehouse sites for a logistic enterprise producing hygiene products [73]. A combined MEREC-VIKOR approach by Sabaghian et al. finds its application

Table 1
Recent applications of SVN-based GMCDM frameworks.

GMCDM framework	Application	Reference
SVN-COPRAS	Sustainable transport investment project	[47]
SVN-CRITIC-CoCoSo	Sustainable third party reverse logistic provider	[27]
SVN-SOWIA-ARAS	Electric vehicle charging station	[63]
SVN-SWARA-CoCoSo	Renewable energy resource	[64]
SVN-MEREC-MULTIMOORA	Low carbon tourism strategy	[48]
SVN-CRITIC-MULTIMOORA	Food waste treatment method	[49]
SVN-CoCoSo	Waste recycling partner	[65]
SVN-SOWIA-WASPAS	Sustainable biomass crop	[50]
SVN-DEMATEL-TODIM with QFD	Market segment evaluation	[66]
SVN-DEMATAL	Building structural crack	[67]

in problems regarding big data replication [74]. Mishra et al. proposed a hybrid MEREC-MULTIMOORA framework with generalized Dombi operators in SVNS settings to assess low carbon tourism strategies (LCTSs) [48]. Goswami et al. used the integrated MEREC-PIV technique to select the most appropriate renewable energy source [75]. Rani et al. applied MEREC-ARAS within the Fermatean fuzzy sets (FFSs) context for the selection of food waste treatment technology [76]. Sapkota et al. used MEREC to assign criteria weights and optimize the ultrasonic machining (USM) process by selecting a quality hole [77]. Simić et al. introduced Fermatean fuzzy model, which hybridizes MEREC and combined compromise solution (CoCoSo), taking into account the COVID-19 Pandemic in Urban Transportation Planning [78]. Nicolalde et al. utilized MEREC with MCDM methods to evaluate phase change materials on the vehicle rooftop [79]. Since MEREC has been successfully employed in numerous real-time engineering applications [80–82], therefore for the first time, MEREC under the SVNS environment is integrated into a real-time material selection problem to obtain criteria weights.

2.5. Measurement alternatives and ranking based on compromise solution (MARCOS)

MARCOS is a newly proposed multi-criteria method by Stević et al. [83]. Based on the compromise solution, MARCOS measures the distance of alternatives from the ideal and non-ideal solutions. Stević et al. also recognized the advantages of the proposed method with the traditional MCDM techniques such as MABAC, simple additive weighting (SAW), additive ratio assessment (ARAS), EDAS, WASPAS, and TOPSIS through a case study on healthcare industries. The model has proved to be flexible in dealing with a large number of alternatives and criteria while maintaining process stability. Additionally, it describes both ideal and non-ideal solutions at the outset of generating the initial decision matrix and compares alternate reference values to both these solutions, allowing for a more accurate assessment of the utility degree. Recent research has shown MARCOS to be a viable decision-making tool for evaluating the performance of alternatives against specific criteria [84,85]. Two distinctive integrated frameworks, D-MARCOS and Grey-MARCOS, are proposed to assist decision-makers in selecting suppliers in the iron and steelmaking industries [86,87]. Torkayesh et al. applied the Grey-MARCOS with best–worst method (BWM) based on geographic information system (GIS) [88]. Ulutaş et al. suggested a framework with correlation coefficient and the standard deviation (CCSD), indifference threshold-based attribute ratio analysis (ITARA), and MARCOS [89]. Stević and Brković evaluated human resources in a transport company using the full consistency method (FUCOM) and MARCOS [90]. Pamucar et al. [91] and Ecer et al. [92] employed MARCOS under neutrosophic fuzzy and intuitionistic fuzzy environments. Some other hybrid methods utilizing MARCOS with their applications are enlisted in Table 2. However, the existing literature on the application of MARCOS for material selection is limited to a few studies. Mondal et al. used MARCOS with BWM to find the best material for a wind turbine blade [93]. Similarly, Kumar et al. compared the outcomes of an integrated BWM with fuzzy MARCOS to choose coating materials for heat-treated industrial tools [94]. Varghese et al. used a hybrid AHP-MARCOS model to select a sustainable gear material [95]. There is no study employing MARCOS under an SVN environment for material selection; thus, this study fills the research gap by applying the integrated framework to an aerostructure.

2.6. Material selection of lightweight aircraft spar

As a literature problem of mechanical design, many academics have used the case of the wing spar of a lightweight aircraft to select an optimal material using MCDM. Dehghan-Manshadi et al. were the first to establish the applicability of the non-linear normalization technique with the modified digital logic (MDL) method on the material selection problem of a human powered aircraft (HPA) spar [102]. Fayazbakhsh et al. demonstrated the superiority of Z-transformation (Z-trans) normalization through the MCDM wing spar problem [103]. The previous researchers worked with traditional methods that relied on quantitative measurements. However, considering qualitative criteria, Khabbaz et al. presented fuzzy logic approach for an HPA spar, comparing the results with the work of Manshadi [104]. Nevertheless, the technique requires a large number of fuzzy IF-THEN rules. Conversely, Jahan et al. dealt with ordinal data involving user interaction with the linear assignment tool [105]. Jiao et al. employed PROMETHEE to evaluate spar materials [106]. Fatchurrohman et al. offered a hybrid method integrating QFD and AHP with the concurrent network (CE-ANP) for spar material selection [107]. Kasaei et al. applied the concept of material indices, establishing their inter-relationship using the house of quality (HoQ) matrix to select optimum spar material [12]. Das et al. solved the material selection problem of a spar by implementing a probabilistic approach through the conditional logit (CLGT) technique [108]. Furthermore, Iman Shokr et al. developed an augmented common weight data envelopment analysis (ACWDEA) model based on mathematical programming to rank candidate materials for spar [109]. Thus, the literature review indicates a need to simultaneously evaluate mixed data types, i.e., quantitative, and qualitative criteria, while considering the inputs from multiple decision-makers without losing information.

2.7. Research gaps, limitations, motivations, and major contributions

Some of the research gaps and limitations of the previously established techniques in the SVNS environment are as follows:

- In the context of material selection, SVNS is a rarely explored concept. The existing studies on the SVN-based material selection deal with only one data type, i.e., ambiguous or uncertain. In these studies [30,31], the authors either focus on developing an assessment matrix with SVN information

Table 2
MARCOS-based hybrid MCDM methods.

Hybrid MCDM method	Application	Reference
IT2F-BWM and IT2F-MARCOS	Risk in dam construction	[84]
IRN-BWM-MARCOS	Offshore wind farms site	[85]
IT2F-AHP-DEMATEL-MARCOS	Failure analysis of CNC machines	[96]
Fuzzy FUCOM-PIPRECIA-MARCOS	Sustainable traffic management	[97]
Rough PIPRECIA and fuzzy MARCOS	Sustainable forestry firm	[98]
LBWA and MARCOS	ICT development in G7 countries	[99]
IMF SWARA and fuzzy MARCOS	Safety degree of road sections	[100]
IFWA and IF-MARCOS	Performance of insurance company	[92]
FUCOM-F and SVNF-MARCOS	Sustainable alternative fuel vehicle	[91]
SVNF-MARCOS	Hybrid electric vehicle	[101]

using the inputs of a particular decision-maker or construct the crisp decision matrix after evaluating all the criteria and converting it into SVNNs.

- Myriad studies exist on the SVN-based GMCDM frameworks [27,48,63,64]. However, the SVN-MCDM methods on material selection [31] primarily rely on the judgment of one decision-maker for assessing multiple alternatives and criteria, which may lead to unreliable results. As a result, complex real-time problems require developing a GMCDM framework that aggregates the perspectives of multiple decision-makers to produce accurate results.
- Although several approaches such as FSs [54,55,59] and IVIFSs [60–62] have been explored in the past for solving group decision problems in material selection; yet, no research exists for handling indeterminacy through neutrosophic sets in real-time situations.
- Past researchers have solved the wing spar case as a literature problem using MCDM methods involving quantitative and qualitative criteria with simple, crisp inputs [102,103,105–109]. However, these techniques cannot be applied to handle indeterminate, inconsistent, incomplete, and uncertain data.

To address the limitations above, a novel GMCDM framework with SVN information is proposed with the following motivations:

- In GMCDM problems, transforming linguistic variables (LVs) into SVNNs generates significant information loss. Motivated by it, this study proposes a unique framework that reduces information loss in two ways: (1). For quantitative criteria, it inculcates crisp values taken directly from comprehensive material databases (2). For qualitative criteria, it aggregates the opinions of multiple experts at a time while also catering to the indeterminacies and uncertainties in the obtained data.
- In group decision making, direct assumptions of decision makers' weights with diverse levels of knowledge or providing the same weights to all decision-makers [91,110] may lead to ambiguous conclusions. In light of this, it is crucial to develop a method to accurately assess the importance of decision-makers in a multi-criteria problem.
- MCDM approaches with crisp technical requirements were the main focus of previous studies [102,103]. On the contrary, this study also embeds criteria from the sustainability perspective requiring uncertain or indeterminate expert assessment, emphasizing the need to evaluate mixed data types.
- Previously, the traditional MARCOS method has been applied in various uncertain contexts [92,97–100], which motivates its extension under the SVNS environment.

Some of the significant contributions of this research work are as follow:

- To propose a novel integrated SVN-MEREC-MARCOS framework distinguished by its ability to simultaneously evaluate crisp and ambiguous data without information loss.
- To implement the proposed framework into the material selection of lightweight aircraft wing spar under SVNSs, incorporating the technical requirements and the three key pillars of sustainability (economic, environmental, and social factors) into the selection criteria.
- To employ MEREC as a criteria weighting method for the spar application and establish its merits with other objective weighting methods such as CRITIC and entropy.

3. Preliminaries

The current section includes the underlying theory of SVNS, which will be induced subsequently in the proposed methodology for its implementation in real-time engineering problems.

Definition 1 (*[18]*)**.** Let Q be a universal set consisting of elements q_i then a Neutrosophic Set (NS) denoted by $\check{N}$ in Q is represented as,

$$\check{N} = \{(T_{\check{N}}(q_i)), (I_{\check{N}}(q_i)), (F_{\check{N}}(q_i))|q_i \in Q\}$$

$\check{N}$ can be categorized using the truth $T_{\check{N}}(q_i)$, indeterminacy $I_{\check{N}}(q_i)$, and falsity $F_{\check{N}}(q_i)$ membership functions. Here, $T_{\check{N}}(q_i)$, $I_{\check{N}}(q_i)$, and $F_{\check{N}}(q_i)$ signifies the degree of confidence, uncertainty, and skepticism, respectively, while belonging to real standard or non-standard subsets given as $T, I, F : Q \to \left]0^-, 1^+\right[$. The membership functions are added without any restriction and are represented by $0^- \le T_{\check{N}}(q_i) + I_{\check{N}}(q_i) + F_{\check{N}}(q_i) \le 3^+$.

Definition 2 (*[18,19]*)**.** Single-Valued Neutrosophic Set (SVNS) is an extension to NS defined within a real subset of [0, 1] instead of $\left]0^-, 1^+\right[$. Let $\check{C} \subseteq Q$ denote an SVNS with truth $t_{\check{C}}(q_i)$, indeterminacy $i_{\check{C}}(q_i)$, and falsity $f_{\check{C}}(q_i)$ as its membership functions, is represented as,

$$\check{C} = \{(t_{\check{C}}(q_i)), (i_{\check{C}}(q_i)), (f_{\check{C}}(q_i))|q_i \in Q\}$$

The sum of the membership functions in SVNS is restricted between 0 and 3 and must satisfy the relation, $0 \le t_{\check{C}}(q_i) + i_{\check{C}}(q_i) + f_{\check{C}}(q_i) \le 3$. A Single-Valued Neutrosophic Number (SVNN) is thus represented as $(t_{\check{C}}, i_{\check{C}}, f_{\check{C}})$.

Definition 3 (*[18]*)**.** Let $\partial_1 = (t_{\partial 1}, i_{\partial 1}, f_{\partial 1})$ and $\partial_2 = (t_{\partial 2}, i_{\partial 2}, f_{\partial 2})$ be two SVNNs and $h > 0$, then the ∂_1 and ∂_2 satisfies the following basic mathematical operations,

- $\partial_1{}^c = f_{\partial 1}, 1 - i_{\partial 1}, t_{\partial 1}$;
- $\partial_1 \cup \partial_2 = (\max\{t_{\partial 1}, t_{\partial 2}\}, \min\{i_{\partial 1}, i_{\partial 2}\}, \min\{f_{\partial 1}, f_{\partial 2}\})$;
- $\partial_1 \cap \partial_2 = (\min\{t_{\partial 1}, t_{\partial 2}\}, \max\{i_{\partial 1}, i_{\partial 2}\}, \max\{f_{\partial 1}, f_{\partial 2}\})$;
- $\partial_1 + \partial_2 = (t_{\partial 1} + t_{\partial 2} - t_{\partial 1}t_{\partial 2}, i_{\partial 1}i_{\partial 2}, f_{\partial 1}f_{\partial 2})$;
- $\partial_1.\partial_2 = (t_{\partial 1}t_{\partial 2}, i_{\partial 1} + i_{\partial 2} - i_{\partial 1}i_{\partial 2}, f_{\partial 1} + f_{\partial 2} - f_{\partial 1}f_{\partial 2})$;
- $h\partial_1 = (1 - (1 - t_{\partial 1})^h, i_{\partial 1}{}^h, f_{\partial 1}{}^h)$;

- $\partial_1{}^h = (t_{\partial 1}{}^h, 1-(1-i_{\partial 1})^h, 1-(1-f_{\partial 1})^h)$;
- $\partial_1 \subseteq \partial_2$, if $t_{\partial 1} \le t_{\partial 2}$, $i_{\partial 1} \ge i_{\partial 2}$ and $f_{\partial 1} \ge f_{\partial 2}$;
- $\partial_1 = \partial_2$, provided if $\partial_1 \subseteq \partial_2$ and $\partial_2 \subseteq \partial_1$.

Example 1. Let $\partial_1 = (0.80, 0.15, 0.20)$ and $\partial_2 = (0.30, 0.75, 0.70)$ be two SVNNs and $h = 2$, then the following results are obtained.

- $\partial_1{}^c = (0.80, 0.15, 0.20)^c = (0.20, 1-0.15, 0.80) = (0.20, 0.85, 0.80)$;
- $\partial_1 \cup \partial_2 = (\max\{0.80, 0.30\}, \min\{0.15, 0.75\}, \min\{0.20, 0.70\}) = (0.80, 0.15, 0.20)$;
- $\partial_1 \cap \partial_2 = (\min\{0.80, 0.30\}, \max\{0.15, 0.75\}, \max\{0.20, 0.70\}) = (0.30, 0.75, 0.70)$;
- $\partial_1 + \partial_2 = (0.80, 0.15, 0.20) + (0.30, 0.75, 0.70) = (0.80 + 0.30 - 0.80 \times 0.30, 0.15 \times 0.75, 0.20 \times 0.70) = (0.86, 0.11, 0.14)$;
- $\partial_1.\partial_2 = (0.80 \times 0.30, 0.15 + 0.75 - 0.15 \times 0.75, 0.20 + 0.70 - 0.20 \times 0.70) = (0.24, 0.79, 0.76)$;
- $h\partial_1 = (1-(1-0.80)^2, 0.15^2, 0.20^2) = (0.96, 0.02, 0.04)$;
- $\partial_1{}^h = (0.80^2, 1-(1-0.15)^2, 1-(1-0.20)^2) = (0.64, 0.28, 0.36)$.

Definition 4 ([49]). Let $\partial = (t_\partial, i_\partial, f_\partial)$ be an SVNN, then the score function $\mathbb{R} = \check{S}(\partial) \in [0, 1]$ used to deneutrosophy SVNN into a single real number is given by,

$$\mathbb{R} = \check{S}(\partial) = \frac{3 + t_\partial - 2i_\partial - f_\partial}{4} \tag{1}$$

Example 2. Let $\partial_1 = (0.80, 0.15, 0.20)$ be an SVNN, then the score function is as follows:

$$\mathbb{R} = \check{S}(\partial) = \frac{3 + 0.80 - (2 \times 0.15) - 0.20}{4} = 0.82$$

Definition 5 ([111]). Let $\partial_j = (t_j, i_j, f_j)$ be an SVNN; and $w_j = (w_1, w_2, \ldots, w_n)$ are the relative weights of ∂_j such that $w_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$. In that case, the SVN-weighted average (SVN-WA) operator used to aggregate data obtained from multiple inputs is given as follow:

$$SVN-WA(\partial_1, \partial_2, \ldots, \partial_n) = \left(1 - \prod_{j=1}^{n}(1-t_j)^{w_j}, \prod_{j=1}^{n}(i_j)^{w_j}, \prod_{j=1}^{n}(f_j)^{w_j}\right) \tag{2}$$

4. Proposed method

A novel framework combining MEREC and MARCOS is proposed to aid engineers and designers in selecting sustainable materials against conflicting criteria under an SVN environment. The SVN-MEREC-MARCOS approach offers flexibility to the designers to simultaneously evaluate defined information in terms of crisp values and ambiguous data in the form of LVs. The step-wise procedure for the proposed SVN-MEREC-MARCOS approach is given as follows.

Step 1 – Construct the combined Crisp-Decision Matrix (C-DM) and SVN-Decision Matrix (SVN-DM)

At first, the decision matrix is constructed for $'m'$ number of alternatives $\{L_1, L_2, \ldots, L_m\}$ over $'n'$ number of criteria $\{R_1, R_2, \ldots; \ldots, G_{n-1}, G_n\}$ where R and G represent crisp and ambiguous criteria, respectively. Then, a finite set of decision-makers $\{D_1, D_2, \ldots, D_r\}$ with experience and knowledge in the relevant domains assigns LVs to each alternative L_i on considered criteria G_j where $(i, j, p) \in (m, n, r)$. Table 3 illustrates the combined decision matrix, where $T = (F_{ij})_{m\times n}$ and $U = (F_{ij}{}^{(p)})_{m\times n}$. T represents the crisp values of alternative L_i over criteria R_j, whereas U represents the linguistic performance measure of alternative L_i over criteria G_j for pth decision-maker.

Step 2 – Analyze the weights (ϖ_p) of Decision-Makers

The importance of decision-makers participating in the MCDM process, owing to their acumen level in the SVNNs form expressed as $W_p = (t_p, i_p, f_p)$, is analyzed by determining their respective weights. The weight (ϖ_p) for the pth decision-maker is computed using Definition 4,

$$\varpi_p = \frac{3 + t_p - 2i_p - f_p}{\sum_{p=1}^{r}\left[3 + t_p - 2i_p - f_p\right]} \tag{3}$$

Where, $\varpi_p \ge 0$ and $\sum_{p=1}^{r} \varpi_p = 1$.

Step 3 – Aggregate the individual SVN-Decision Matrix (A-SVN-DM)

A number of decision-makers are involved in the MCDM process. Therefore, an aggregated value for the criteria G_j is required to embody the opinions of all the decision-makers in SVNNs. Let $A = (¥_{ij})_{m\times n}$ represents the aggregated-SVN-decision matrix (A-SVN-DM), computed using the SVN-WA operator given in Definition 5.

$$\begin{aligned} ¥_{ij} &= (t_{ij}, i_{ij}, f_{ij}) = SVN - WA_{\varpi}(¥_{ij}{}^{(1)}, ¥_{ij}{}^{(2)}, \ldots, ¥_{ij}{}^{(r)}) \\ &= \left(1 - \prod_{p=1}^{r}(1-t_{ij})^{\varpi_p}, \prod_{p=1}^{r}(i_{ij})^{\varpi_p}, \prod_{p=1}^{r}(f_{ij})^{\varpi_p}\right) \end{aligned} \tag{4}$$

Step 4 – Formulate the Score matrix using A-SVN-DM

Using the score function, the score matrix (S) is created from A-SVN-DM. Let $S = Ş((¥_{ij}))_{m\times n}$ represents the score matrix computed using Definition 4, given as

$$Ş(¥_{ij}) = \frac{3 + t_{ij} - 2i_{ij} - f_{ij}}{4} \tag{5}$$

Step 5 – Assign Criteria weights through MEREC

a. *Construct the Decision Matrix with Crisp inputs*

The deneutrosophication of SVNNs generates crisp values; hence the combined decision matrix contains only definite performances of $'m'$ alternatives over $'n'$ criteria. The combined decision matrix for weight estimation through MEREC is given in Table 4.

b. *Normalize the Decision Matrix*

The decision matrix is normalized using simple linear functions for cost and benefit criteria as given below,

$$\eta = (N_{ij})_{m\times n} = \begin{cases} \dfrac{\min F_{ij}}{F_{ij}}, & if\ j \in B \\ \dfrac{F_{ij}}{\max F_{ij}}, & if\ j \in C \end{cases} \tag{6}$$

Where B and C represent the beneficial and cost criteria, respectively.

c. *Compute the Overall performance*

MEREC utilizes a non-linear function to compute the overall performance of each alternative M_i by,

$$M_i = \ln\left(1 + \left(\frac{1}{m}\sum_{j}\left|\ln(\eta_{ij})\right|\right)\right) \tag{7}$$

Smaller values in the normalized decision matrix (η) significantly impact the performance when computed using a logarithmic function.

d. *Evaluate performance based on removing criteria*

Table 3
Combined decision matrix.

	R_1	R_2	...	G_{n-1}	G_n
L_1	F_{11}	F_{12}	...	$F^{(1)}_{1(n-1)}, F^{(2)}_{1(n-1)}, \ldots, F^{(r)}_{1(n-1)}$	$F^{(1)}_{1n}, F^{(2)}_{1n}, \ldots, F^{(r)}_{1n}$
L_2	F_{21}	F_{22}	...	$F^{(1)}_{2(n-1)}, F^{(2)}_{2(n-1)}, \ldots, F^{(r)}_{2(n-1)}$	$F^{(1)}_{2n}, F^{(2)}_{2n}, \ldots, F^{(r)}_{2n}$
L_3	F_{31}	F_{32}	...	$F^{(1)}_{3(n-1)}, F^{(2)}_{3(n-1)}, \ldots, F^{(r)}_{3(n-1)}$	$F^{(1)}_{3n}, F^{(2)}_{3n}, \ldots, F^{(r)}_{3n}$
...	...	...	...	...	...
L_m	F_{m1}	F_{m2}	...	$F^{(1)}_{m(n-1)}, F^{(2)}_{m(n-1)}, \ldots, F^{(r)}_{m(n-1)}$	$F^{(1)}_{mn}, F^{(2)}_{mn}, \ldots, F^{(r)}_{mn}$

Table 4
Combined decision matrix with crisp inputs.

	R_1	R_2	...	G_{n-1}	G_n
L_1	F_{11}	F_{12}	...	$F_{1(n-1)}$	$F_{1(n)}$
L_2	F_{21}	F_{22}	...	$F_{2(n-1)}$	$F_{2(n)}$
L_3	F_{31}	F_{32}	...	$F_{3(n-1)}$	$F_{3(n)}$
...	...	...	...	...	...
L_m	F_{m1}	F_{m2}	...	$F_{m(n-1)}$	$F_{m(n)}$

Table 5
Extended decision matrix.

	R_1	R_2	...	G_{n-1}	G_n
L_{NI}	F_{N1}	F_{N2}	...	$F_{N(n-1)}$	$F_{N(n)}$
L_1	F_{11}	F_{12}	...	$F_{1(n-1)}$	$F_{1(n)}$
L_2	F_{21}	F_{22}	...	$F_{2(n-1)}$	$F_{2(n)}$
L_3	F_{31}	F_{32}	...	$F_{3(n-1)}$	$F_{3(n)}$
...	...	...	...	...	...
L_m	F_{m1}	F_{m2}	...	$F_{m(n-1)}$	$F_{m(n)}$
L_{ID}	F_{I1}	F_{I2}	...	$F_{I(n-1)}$	$F_{I(n)}$

The overall performance of an alternative by removing each criterion M^*_{ij} is governed by (Eq. (8)),

$$M^*_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j} |\ln(\eta_{ik})|\right)\right) \tag{8}$$

e. *Estimate absolute deviations for criteria*

The absolute deviations E_j are estimated and summed using the formula given in (Eq. (9)),

$$E_j = \sum_i \left|M^*_{ij} - M_i\right| \tag{9}$$

f. *Determine the final weights*

The final weights ω_j are determined as

$$\omega_j = \frac{E_j}{\sum_j E_j} \tag{10}$$

Step 6 – Calculate Performance indices using MARCOS

a. *Extend the Decision Matrix*

The decision matrix in Table 4 is extended by incorporating ideal (L_{ID}) and non-ideal (L_{NI}) solutions, given Table 5.

Where L_{ID} and L_{NI} are governed by,

$$L_{ID} = F_I = \begin{cases} \max F_{ij}, & if\ j \in B \\ \min F_{ij}, & if\ j \in C \end{cases} \tag{11}$$

$$L_{NI} = F_N = \begin{cases} \min F_{ij}, & if\ j \in B \\ \max F_{ij}, & if\ j \in C \end{cases} \tag{12}$$

b. *Normalize the Extended Decision Matrix*

The extended decision matrix is normalized using (Eq. (13)),

$$\check{n} = (\mathbb{N}_{ij})_{m\times n} = \begin{cases} \dfrac{F_{ij}}{F_I}, & if\ j \in B \\ \dfrac{F_I}{F_{ij}}, & if\ j \in C \end{cases} \tag{13}$$

c. *Obtain the Weighted Matrix*

By multiplying the normalized decision matrix $\check{n}$ with the final criteria weights ω_j, the weighted matrix V is obtained. Let $V = (v_{ij})_{m\times n}$, then

$$v_{ij} = \mathbb{N}_{ij} \times \omega_j \tag{14}$$

d. *Summation of Weighted Matrix*

The weighted sum of the matrix is obtained using Eq. (15),

$$\acute{S}_i = \sum_{i=1}^{m} v_{ij} \tag{15}$$

e. *Determine the Utility Degree*

The utility degree K_i of an alternative with respect to ideal and non-ideal solutions is determined using (Eq. (16)) and (Eq. (17)).

$$\mathrm{K}_i^+ = \frac{\acute{S}_i}{\acute{S}_{ID}} \tag{16}$$

$$\mathrm{K}_i^- = \frac{\acute{S}_i}{\acute{S}_{NI}} \tag{17}$$

Where $\acute{S}_{ID}$ and $\acute{S}_{NI}$ are the weighted sums of ideal and non-ideal solutions, respectively.

f. *Compute the Utility Function*

The utility function $f(\mathrm{K}_i)$ corresponding to the final performance index of an alternative is computed using,

$$f(\mathrm{K}_i) = \frac{\mathrm{K}_i^+ + \mathrm{K}_i^-}{1 + \frac{1-f(\mathrm{K}_i^+)}{f(\mathrm{K}_i^+)} + \frac{1-f(\mathrm{K}_i^-)}{f(\mathrm{K}_i^-)}} \tag{18}$$

Where,

$$f(\mathrm{K}_i^+) = \frac{\mathrm{K}_i^-}{\mathrm{K}_i^+ + \mathrm{K}_i^-} \tag{19}$$

and

$$f(\mathrm{K}_i^-) = \frac{\mathrm{K}_i^+}{\mathrm{K}_i^+ + \mathrm{K}_i^-} \tag{20}$$

5. Case study: Material selection of a lightweight aircraft spar

To demonstrate the applicability of the proposed SVN-MEREC-MARCOS framework (see Fig. 1), a real-time sustainable material selection problem of a lightweight aircraft wing spar is considered.

Using Ashby's charts and expert advice, 17 candidate materials are shortlisted for the wing spar application, then analyzed using the SVN-MEREC-MARCOS framework (see Table 6). The selected materials represent all classes, including Metal Matrix Composites (MMCs), Polymer Matrix Composites (PMCs), Ceramic Matrix Composites (CMCs), Al-alloys, Ti-alloys, and Beryllium.

The critical design requirements are translated into eleven criteria based on expert input and available literature (see Fig. 2), which are: price (R_1), density (R_2), Young's modulus (R_3), tensile

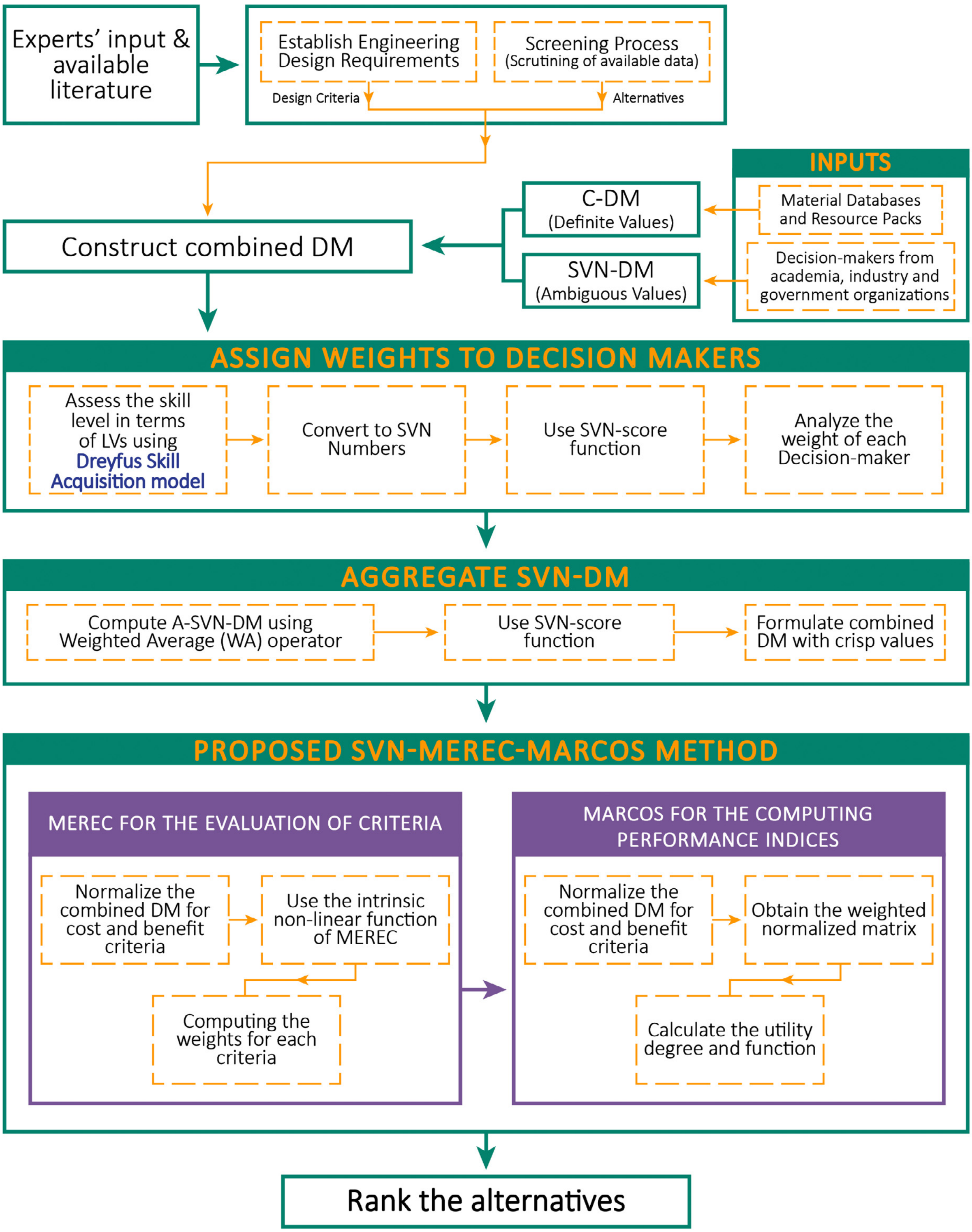


Fig. 1. Proposed novel SVN-MEREC-MARCOS framework for sustainable material selection of Lightweight aircraft spar.

strength (R_4), compressive strength (R_5), fracture toughness (R_6), creep resistance (G_1), fatigue resistance (G_2), machinability (G_3), recyclability (G_4), and carbon footprint during manufacture (G_5). All criteria except R_1, R_2, G_3, and G_5 are beneficial and hence maximized. Table 7 compares the criteria used in this research work with previous MCDM studies on the wing spar.

5.1. *Application of SVN-MEREC-MARCOS framework*

Steps 1 and 2

For the implementation of the proposed method, three different decision-makers (D_1, D_2, D_3) from academia (*Air University, Kamra*) and industry (*Pakistan Aeronautical Complex, Kamra*) are

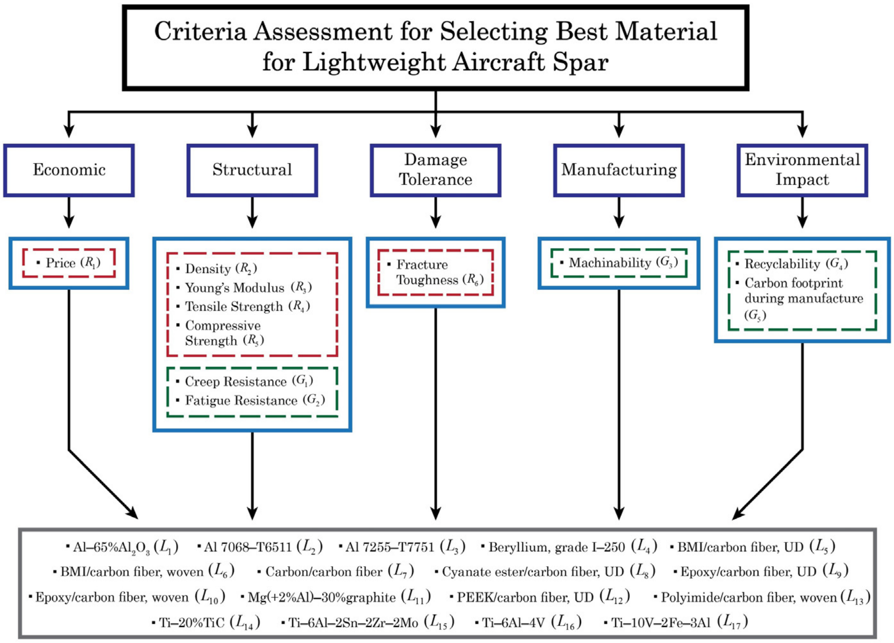


Fig. 2. Selection of criteria in the hierarchical framework.

asked to assess the material selection problem of a wing spar having 17 candidate materials and five criteria (G_1, G_2, G_3, G_4, G_5) under SVNSs environment (see Table 8). The significance of decision-makers in a given problem is determined using LVs converted into SVNNs describing their expertise level, a technique adapted from Rani et al. [49] in conjunction with Dreyfus et al. [112] skill acquisition model, as given in Table 9. The skill level of each decision-maker involved in the material selection process is shown in Table 10, with their respective weights calculated using Eq. (3).

Example calculation of the weight of D_1 using Eq. (3) is given as follows:

$$\varpi_{D_1} = \frac{3 + t_p - 2i_p - f_p}{\sum_{p=1}^{r}\left[3 + t_p - 2i_p - f_p\right]}$$
$$= \frac{3 + 0.80 - 2(0.25) - 0.20}{[3 + 0.80 - 2(0.25) - 0.20] + [3 + 0.60 - 2(0.35) - 0.40] + [3 + 0.40 - 2(0.55) - 0.55]}$$
$$= 0.4218$$

Similarly, for evaluating the alternatives over considered criteria, Zavadskas et al. [30] and Mishra and Rani [27] suggested a method for transforming LVs (or crisps terms) into SVNNs with the rules provided in Table 11. As a result, an SVN-DM is formulated by the decision-makers linguistically for alternative L_i over criteria G_j.

For each alternative ($L_1, L_2, \ldots, L_{17}$), the crisp values for criteria ($R_1, R_2, \ldots, R_6$) are obtained from the software package Cambridge Engineering Selector to construct C-DM. Table 12 displays the combined decision matrix with C-DM and SVN-DM.

Steps 3 and 4

The opinions of decision-makers involved in creating SVN-DM are aggregated to form A-SVN-DM using Eq. (4), as shown in Table 13. Subsequently, the combined decision matrix containing the crisp score values of A-SVN-DM (formulated using Eq. (5)) and C-DM is represented in Table 14.

Step 5

In this step, MEREC is used to assess the criteria weights for lightweight aircraft spar. At first, the combined decision matrix with crisp inputs in Table 14 is normalized using Eq. (6) while considering the cost and benefit criteria separately (see Appendix A, Table A.1). Then, the overall performance of the alternatives M_i is computed using Eq. (7). Next, the impact of the removal of each criterion on an alternative's performance M_{ij}^* is assessed using Eq. (8), as given in Table A.2 (Appendix A). Finally, using Eqs. (9)–(10), the absolute deviation E_j and final weights ω_j for criteria are calculated, as presented in Table 15.

Table 6
Lightweight aircraft spar candidate materials. (See Supplementary Information for a complete overview of screened-out materials).

Spar candidate materials	
Al-65%Al$_2$O$_3$ (L_1)	Epoxy/carbon fiber, woven (L_{10})
Al 7068-T6511 (L_2)	Mg(+2%Al)-30%graphite (L_{11})
Al 7255-T7751 (L_3)	PEEK/carbon fiber, UD (L_{12})
Beryllium, grade I-250 (L_4)	Polyimide/carbon fiber, woven (L_{13})
BMI/carbon fiber, UD (L_5)	Ti-20%TiC (L_{14})
BMI/carbon fiber, woven (L_6)	Ti-6Al-2Sn-2Zr-2Mo (L_{15})
Carbon/carbon fiber (L_7)	Ti-6Al-4V (L_{16})
Cyanate ester/carbon fiber, UD (L_8)	Ti-10V-2Fe-3Al (L_{17})
Epoxy/carbon fiber, UD (L_9)	

Step 6

The final step of the SVN-MEREC-MARCOS framework is to rank the alternatives based on their performance indices using MARCOS. Firstly, the combined decision matrix in Table 14 is extended by incorporating ideal and non-ideal solutions, normalized using Eq. (13), as given in Table A.3 (Appendix A). The normalized matrix $\check{n}$ is multiplied by MEREC criteria weights ω_j to get the weighted extended decision matrix V (see Appendix A, Table A.4). Using Eqs. (15)–(20), the values of $\acute{S}_i$, K_i^-, K_i^+, $f(K_i^-)$, and $f(K_i^+)$ are computed to obtain the performance index of an alternative $f(K_i)$, as shown in Table 16. The optimal choice is the one that has the highest performance index. Thus, it is inferred that Al 7255-T7751, Al 7068-T6511, and Ti-6Al-4V are the top-ranked alternatives for spar application using the SVN-MEREC-MARCOS framework.

Table 7
Criteria assessment for material selection in Lightweight aircraft spar.

MCDM methods			This work	Improved WPM	Z-trans	Fuzzy Logic	Ordinal data	CoNQA	QFD	CLGT
Year				(2007)	(2009)	(2009)	(2010)	(2012)	(2014)	(2019)
Reference				[102]	[103]	[104]	[105]	[106]	[107]	[108]
Class	*Environment*[a] *(This work)*	*Criteria*	*Criteria included in literature*							
Economic	Normal	Price (R_1)	✓	✓	✓	✓	✓	✓	✓	✓
Structural	Normal	Density (R_2)	✓	✓	✓	✓	✓	✓	✓	✓
		Young's modulus (R_3)	✓	✓	✓	✓	✓	✓	✓	✓
		Tensile strength (R_4)	✓	✓	✓	✓	✓	✓	✓	✓
		Compressive strength (R_5)	✓	✓	✓	✓	✓	✓	✓	✓
	SVN	Creep resistance (G_1)	✓	✓	✓	✓	✓	✓	✓	✓
		Fatigue resistance (G_2)	✓							
Damage tolerance	Normal	Fracture toughness (R_6)	✓							
Manufacturing	SVN	Machinability[b] (G_3)	✓							
Environmental impact (*Greenhouse and other emissions*)	SVN	Recyclability (G_4)	✓					✓		
		Carbon footprint during manufacture (G_5)	✓							

[a]The previous work on spar only considers criteria under normal or fuzzy environments.
[b]Machinability is defined here as a material property, not a measure of cutting speed or tool life.

Table 8
Credentials of decision-makers participating in the case study of the wing spar.

Decision-makers	Experience	Occupation
D_1	15 years of industrial experience	Chief Project Director at Aircraft Manufacturing Factory
D_2	More than 10 years of academic theoretical knowledge	Head of Department of Structures and Materials
D_3	5–7 years of industrial experience	Design Engineer at Aircraft Manufacturing Factory

Table 9
The LVs developed from the Dreyfus skill acquisition model to signify the importance of decision-makers.

LVs/ Crisp terms	SVNNs
Expert/ 0.9	(0.90, 0.10, 0.10)
Proficient/ 0.8	(0.80, 0.25, 0.20)
Competent/ 0.6	(0.60, 0.35, 0.40)
Advanced Beginner/ 0.4	(0.40, 0.55, 0.55)
Novice/ 0.2	(0.20, 0.75, 0.80)

Table 10
Decision-makers and their significance in the material selection process.

Decision-makers	LVs	SVNNs $W_p = (t_p, i_p, f_p)$	Weights ϖ_p
D_1	Proficient	(0.80, 0.25, 0.20)	0.4218
D_2	Competent	(0.60, 0.35, 0.40)	0.3401
D_3	Advanced beginner	(0.40, 0.55, 0.55)	0.2381

Table 11
The LVs transformed into SVNNs to evaluate alternatives over considered criteria.

LVs/ Crisp terms	SVNNs
Extremely High (EH)/ 1.0	(1.00, 0.00, 0.00)
Very Very High (VVH)/ 0.9	(0.90, 0.10, 0.10)
Very High (VH)/ 0.8	(0.80, 0.15, 0.20)
High (H)/ 0.7	(0.70, 0.25, 0.30)
Moderate High (MH)/ 0.6	(0.60, 0.35, 0.40)
Fair (F)/ 0.5	(0.50, 0.50, 0.50)
Moderate Low (ML)/ 0.4	(0.40, 0.65, 0.60)
Low (L)/ 0.3	(0.30, 0.75, 0.70)
Very Low (VL)/ 0.2	(0.20, 0.85, 0.80)
Very Very Low (VVL)/ 0.1	(0.10, 0.90, 0.90)
Extremely Low (EL)/ 0.0	(0.00, 1.00, 1.00)

5.2. Merits of MEREC

To thoroughly investigate the merits of the developed SVN-MEREC-MARCOS framework, the scope of this study is further enhanced by considering other integrated MCDM frameworks that use entropy and CRITIC as objective criteria weighting methods.

These techniques include SVN-entropy-MARCOS and SVN-CRITIC-MARCOS, which follow the same procedural steps 1–4 and 6 as given in the proposed method. In addition, step 5, which assesses the criteria weights using the entropy and CRITIC method, is given in the Supplementary Information.

Table 17 shows the criteria weights based on entropy and CRITIC. Subsequently, the ranks of the alternatives computed using the procedural steps of SVN-entropy-MARCOS and SVN-CRITIC-MARCOS frameworks are given in Fig. 3.

5.3. Comparative analysis

The proposed SVN-MEREC-MARCOS is compared with existing models like SVN-TOPSIS [27], SVN-MULTIMOORA [30], and other hybrid techniques such as COPRAS [7], TOPSIS [14], VIKOR [113], CLGT [108], Interactive and multiple attribute decision making (TODIM) [114], and PROMETHEE-II [15] for its validation (see Fig. 4). The aluminum alternatives L_2 and L_3 are the top-ranked alternatives by the proposed method and COPRAS. However, with the other considered methods like TOPSIS, VIKOR, and CLGT, the top-ranked alternatives even drop up to 13th position, which contradicts its broader applicability in the aerospace industry. All these methods ranked titanium alternatives L_{15}, L_{16}, and L_{17} as the best candidates for spar application.

Table 12
The combined decision matrix with C-DM and SVN-DM for Lightweight aircraft spar.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
L_1	8500	3400	251	1600	1700	10.5	(H,MH,H)	(VH,EH,H)	(VL,EL,EL)	(EL,VL,EL)	(VVL,VL,EL)
L_2	4.48	2850	73	648	655	17.8	(F,F,MH)	(VL,VL,ML)	(L,VVL,VVL)	(MH,H,H)	(VL,VL,VVL)
L_3	4.51	2860	72.8	627	607	26.4	(F,F,MH)	(F,L,F)	(L,VVL,VVL)	(MH,H,H)	(VL,VL,VVL)
L_4	660	1860	302	480	500	9	(VVH,VVH,VH)	(EH, MH, VVH)	(EH,EH,EH)	(F,MH,F)	(EH,EH,EH)
L_5	115	1610	59.8	430	420	5	(ML,ML,F)	(VVL,VVL,L)	(H,VH,ML)	(VVL,L,VVL)	(VH,H,VH)
L_6	172	1570	51.3	353	438	22	(ML,ML,F)	(VVH,L,VH)	(H,VH,ML)	(VVL,L,VVL)	(VH,H,VH)
L_7	228	1720	94.9	479	223	5.7	(EH, EH, EH)	(EL,EL,VVL)	(MH,MH,L)	(EL,VL,EL)	(H,MH,H)
L_8	235	1670	108	607	317	27.7	(VL,L,ML)	(VH,F,VH)	(H,VH,L)	(VVL,L,VVL)	(VH,H,VH)
L_9	41.6	1580	54.7	603	542	12.1	(VVL,L,L)	(VVL,VVL,L)	(H,VH,ML)	(VVL,L,VVL)	(VH,H,VH)
L_{10}	58.7	1610	46.2	450	470	32.4	(VLL,L,L)	(VH,ML,VH)	(H,H,L)	(VVL,L,VL)	(H,MH,H)
L_{11}	166	1860	89	650	650	10	(H,MH,H)	(ML,L,F)	(F,VL,VVL)	(ML,F,ML)	(ML,F,F)
L_{12}	120	1570	56.6	460	363	26.5	(VVL,ML,L)	(VH,ML,VH)	(VH,VVH,MH)	(VVL,L,VVL)	(VH,H,VH)
L_{13}	159	1630	43.9	465	400	32.6	(L,ML,F)	(VH,ML,VH)	(VH,VVH,MH)	(VVL,L,VVL)	(VH,H,VH)
L_{14}	145	4580	148	943	950	18.4	(VH,VH,VVH)	(ML,F,F)	(H,F,ML)	(H,VH,EH)	(MH,L,ML)
L_{15}	27.1	4550	117	933	933	64	(VVH,VVH,VVH)	(H,VH,MH)	(MH,VL,L)	(VVH,VH,VVH)	(ML,L,VL)
L_{16}	26.2	4430	115	1020	1100	82	(VH,VH,VVH)	(VH,VVH,H)	(H,L,ML)	(VVH,VH,VVH)	(MH,L,ML)
L_{17}	28.1	4670	113	1000	1060	54	(VH,H,VVH)	(VVH,VVH,VH)	(VVH,ML,H)	(VH,VH,VH)	(VH,ML,MH)

Table 13
The individual A-SVN-DM for material selection of Lightweight aircraft spar.

	G_1	G_2	G_3	G_4	G_5
L_1	(0.669, 0.280, 0.331)	(1.000, 0.000, 0.000)	(0.090, 0.934, 0.910)	(0.073, 0.946, 0.927)	(0.113, 0.905, 0.887)
L_2	(0.526, 0.459, 0.474)	(0.253, 0.797, 0.747)	(0.191, 0.833, 0.809)	(0.661, 0.288, 0.339)	(0.177, 0.862, 0.823)
L_3	(0.526, 0.459, 0.474)	(0.439, 0.574, 0.561)	(0.191, 0.833, 0.809)	(0.661, 0.288, 0.339)	(0.177, 0.862, 0.823)
L_4	(0.882, 0.110, 0.118)	(1.000, 0.000, 0.000)	(1.000, 0.000, 0.000)	(0.537, 0.443, 0.463)	(1.000, 0.000, 0.000)
L_5	(0.425, 0.611, 0.575)	(0.152, 0.862, 0.848)	(0.692, 0.264, 0.308)	(0.174, 0.846, 0.826)	(0.770, 0.178, 0.230)
L_6	(0.425, 0.611, 0.575)	(0.771, 0.219, 0.229)	(0.692, 0.264, 0.308)	(0.174, 0.846, 0.826)	(0.770, 0.178, 0.230)
L_7	(1.000, 0.000, 0.000)	(0.025, 0.975, 0.975)	(0.543, 0.420, 0.457)	(0.073, 0.946, 0.927)	(0.669, 0.280, 0.331)
L_8	(0.286, 0.764, 0.714)	(0.727, 0.226, 0.273)	(0.680, 0.273, 0.320)	(0.174, 0.846, 0.826)	(0.770, 0.178, 0.230)
L_9	(0.222, 0.810, 0.778)	(0.152, 0.862, 0.848)	(0.692, 0.264, 0.308)	(0.174, 0.846, 0.826)	(0.770, 0.178, 0.230)
L_{10}	(0.222, 0.810, 0.778)	(0.709, 0.247, 0.291)	(0.633, 0.325, 0.367)	(0.197, 0.834, 0.803)	(0.669, 0.280, 0.331)
L_{11}	(0.669, 0.280, 0.331)	(0.395, 0.641, 0.605)	(0.325, 0.689, 0.675)	(0.436, 0.595, 0.564)	(0.460, 0.559, 0.540)
L_{12}	(0.261, 0.771, 0.739)	(0.709, 0.247, 0.291)	(0.814, 0.160, 0.186)	(0.174, 0.846, 0.826)	(0.770, 0.178, 0.230)
L_{13}	(0.387, 0.649, 0.613)	(0.709, 0.247, 0.291)	(0.814, 0.160, 0.186)	(0.174, 0.846, 0.826)	(0.770, 0.178, 0.230)
L_{14}	(0.830, 0.136, 0.170)	(0.460, 0.559, 0.540)	(0.579, 0.397, 0.421)	(1.000, 0.000, 0.000)	(0.467, 0.526, 0.533)
L_{15}	(0.900, 0.100, 0.100)	(0.720, 0.228, 0.280)	(0.421, 0.567, 0.579)	(0.873, 0.115, 0.127)	(0.323, 0.727, 0.677)
L_{16}	(0.830, 0.136, 0.170)	(0.826, 0.148, 0.174)	(0.528, 0.456, 0.472)	(0.873, 0.115, 0.127)	(0.467, 0.526, 0.533)
L_{17}	(0.805, 0.162, 0.195)	(0.882, 0.110, 0.118)	(0.761, 0.235, 0.239)	(0.800, 0.150, 0.200)	(0.657, 0.302, 0.343)

Table 14
The crisp inputs of combined decision matrix with C-DM and A-SVN-DM for Lightweight aircraft spar.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
L_1	8500	3400	251	1600	1700	10.5	0.694	1.000	0.078	0.063	0.104
L_2	4.48	2850	73	648	655	17.8	0.533	0.228	0.179	0.687	0.158
L_3	4.51	2860	72.8	627	607	26.4	0.533	0.433	0.179	0.687	0.158
L_4	660	1860	302	480	500	9	0.886	1.000	1.000	0.547	1.000
L_5	115	1610	59.8	430	420	5	0.407	0.145	0.714	0.164	0.796
L_6	172	1570	51.3	353	438	22	0.407	0.776	0.714	0.164	0.796
L_7	228	1720	94.9	479	223	5.7	1.000	0.025	0.562	0.063	0.694
L_8	235	1670	108	607	317	27.7	0.261	0.750	0.704	0.164	0.796
L_9	41.6	1580	54.7	603	542	12.1	0.206	0.145	0.714	0.164	0.796
L_{10}	58.7	1610	46.2	450	470	32.4	0.206	0.731	0.654	0.181	0.694
L_{11}	166	1860	89	650	650	10	0.694	0.377	0.318	0.421	0.451
L_{12}	120	1570	56.6	460	363	26.5	0.245	0.731	0.827	0.164	0.796
L_{13}	159	1630	43.9	465	400	32.6	0.369	0.731	0.827	0.164	0.796
L_{14}	145	4580	148	943	950	18.4	0.847	0.451	0.591	1.000	0.471
L_{15}	27.1	4550	117	933	933	64	0.900	0.746	0.427	0.879	0.298
L_{16}	26.2	4430	115	1020	1100	82	0.847	0.839	0.536	0.879	0.471
L_{17}	28.1	4670	113	1000	1060	54	0.822	0.886	0.763	0.825	0.678

Table 15
The absolute deviation E_j and criteria weights ω_j using MEREC.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
E_j	4.558	0.707	0.637	0.498	0.822	1.209	0.817	2.735	0.613	1.314	0.580
ω_j	0.315	0.049	0.044	0.034	0.057	0.083	0.056	0.189	0.042	0.091	0.040

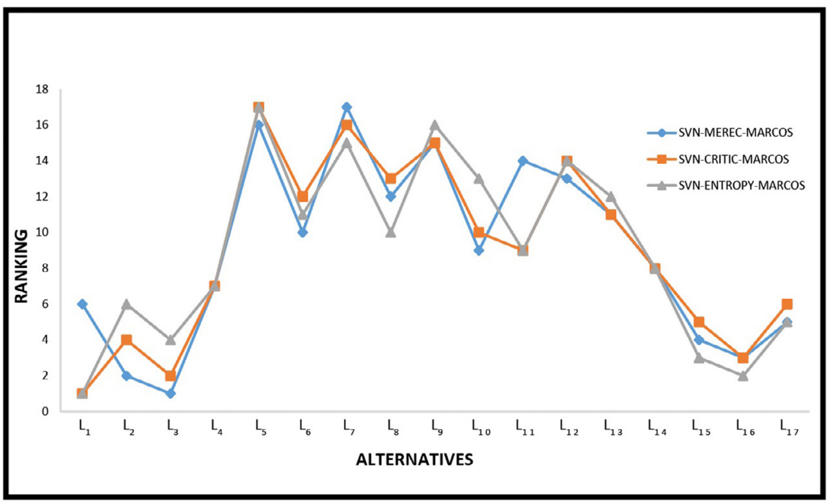
Spearman's Rank Correlation Coefficient (SRCC) shows that the proposed method strongly correlates with TODIM (0.92) and COPRAS (0.86). However, the correlation reduces to 0.77, 0.71, 0.71, and 0.70 in the case of PROMETHEE-II, SVN-TOPSIS, SVN-MULTIMOORA, and CLGT. Moreover, the proposed method has the lowest correlation with VIKOR (0.60) and TOPSIS (0.58), which

Table 16
Performance indices $f(K_i)$ and Ranking.

	$\acute{S}_i$	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Rank
L_{NI}	0.073	1.000	0.073	0.068	0.932	0.073	
L_1	0.477	6.572	0.477	0.068	0.932	0.475	6
L_2	0.586	8.077	0.586	0.068	0.932	0.583	2
L_3	0.629	8.671	0.629	0.068	0.932	0.626	1
L_4	0.419	5.776	0.419	0.068	0.932	0.417	7
L_5	0.172	2.370	0.172	0.068	0.932	0.171	16
L_6	0.303	4.179	0.303	0.068	0.932	0.302	10
L_7	0.167	2.298	0.167	0.068	0.932	0.166	17
L_8	0.301	4.141	0.301	0.068	0.932	0.299	12
L_9	0.197	2.720	0.197	0.068	0.932	0.197	15
L_{10}	0.314	4.322	0.314	0.068	0.932	0.312	9
L_{11}	0.276	3.810	0.277	0.068	0.932	0.275	14
L_{12}	0.294	4.046	0.294	0.068	0.932	0.292	13
L_{13}	0.302	4.157	0.302	0.068	0.932	0.300	11
L_{14}	0.357	4.914	0.357	0.068	0.932	0.355	8
L_{15}	0.495	6.823	0.495	0.068	0.932	0.493	4
L_{16}	0.531	7.313	0.531	0.068	0.932	0.528	3
L_{17}	0.494	6.802	0.494	0.068	0.932	0.491	5
L_{ID}	1.000	13.778	1.000	0.068	0.932	1.000	

Table 17
Entropy Ψ_j and CRITIC Φ_j weights.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
Ψ_j	0.079	0.103	0.086	0.105	0.096	0.070	0.101	0.091	0.101	0.066	0.100
Φ_j	0.153	0.112	0.039	0.045	0.116	0.119	0.078	0.096	0.089	0.063	0.089



MATERIALS	SVN-MEREC-MARCOS	SVN-CRITIC-MARCOS	SVN-ENTROPY-MARCOS
Al-65%Al_2O_3 (L_1)	6	1	1
Al 7068-T6511 (L_2)	2	4	6
Al 7255-T7751 (L_3)	1	2	4
Beryllium, grade I-250 (L_4)	7	7	7
BMI/carbon fiber, UD (L_5)	16	17	17
BMI/carbon fiber, woven (L_6)	10	12	11
Carbon/carbon fiber (L_7)	17	16	15
Cyanate ester/carbon fiber, UD (L_8)	12	13	10
Epoxy/carbon fiber, UD (L_9)	15	15	16
Epoxy/carbon fiber, woven (L_{10})	9	10	13
Mg(+2%Al)-30%graphite (L_{11})	14	9	9
PEEK/carbon fiber, UD (L_{12})	13	14	14
Polyimide/carbon fiber, woven (L_{13})	11	11	12
Ti-20%TiC (L_{14})	8	8	8
Ti-6Al-2Sn-2Zr-2Mo (L_{15})	4	5	3
Ti-6Al-4V (L_{16})	3	3	2
Ti-10V-2Fe-3Al (L_{17})	5	6	5

Fig. 3. Comparison of the proposed method with SVN-CRITIC and SVN-entropy.

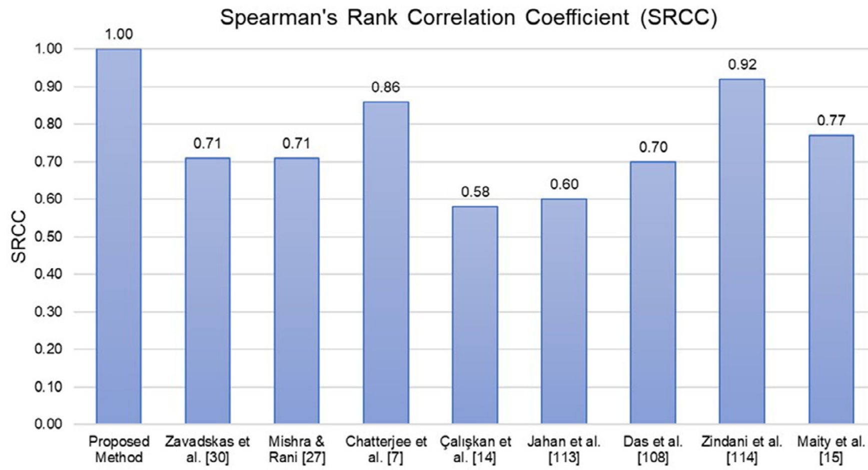


Fig. 4. SRCC of the proposed and extant methods.

Table 18
New criteria weights for 11 scenarios.

	Sc_1	Sc_2	Sc_3	Sc_4	Sc_5	Sc_6	Sc_7	Sc_8	Sc_9	Sc_{10}	Sc_{11}
R_1	0.388	0.349	0.310	0.271	0.233	0.194	0.155	0.116	0.078	0.039	0.001
R_2	0.061	0.055	0.049	0.043	0.037	0.031	0.025	0.018	0.012	0.006	0.000
R_3	0.054	0.049	0.043	0.038	0.032	0.027	0.022	0.016	0.011	0.005	0.000
R_4	0.042	0.038	0.034	0.030	0.025	0.021	0.017	0.013	0.008	0.004	0.000
R_5	0.070	0.063	0.056	0.049	0.042	0.035	0.028	0.021	0.014	0.007	0.000
R_6	0.103	0.093	0.082	0.072	0.062	0.051	0.041	0.031	0.021	0.010	0.000
G_1	0.070	0.063	0.056	0.049	0.042	0.035	0.028	0.021	0.014	0.007	0.000
G_2	0.000	0.100	0.200	0.300	0.400	0.500	0.600	0.700	0.800	0.900	0.998
G_3	0.052	0.047	0.042	0.036	0.031	0.026	0.021	0.016	0.010	0.005	0.000
G_4	0.112	0.101	0.089	0.078	0.067	0.056	0.045	0.034	0.022	0.011	0.000
G_5	0.049	0.044	0.039	0.035	0.030	0.025	0.020	0.015	0.010	0.005	0.000
$\sum \mathbb{W}_i$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

may be attributed to the mathematical differences [110] between these methods.

5.4. Sensitivity analysis

MCDM frameworks take hybrid inputs, which may be imprecise and subject to change; hence it is necessary to evaluate and analyze the potential changes in the model with respect to changing inputs. In this work, the sensitivity analysis is performed by altering the weight of a criterion while keeping all the other criteria weights proportionally constant. Based on Kirkwood's theory [115], the criterion chosen is the *incumbent weight* ($\mathbb{W}_{inc}$) and varies from 0 to 1. Attribute weights for the rest of the criteria are calculated using Eq. (21),

$$\mathbb{W}_i = (1 - \mathbb{W}_{inc}) \left(\frac{\omega_i}{1 - \omega_{inc}} \right) \tag{21}$$

In this study, the most significant criteria identified based on their weights are R_1 $(\omega_{R_1} = 0.3146)$ and G_2 $(\omega_{G_2} = 0.1887)$. However, G_2 is selected as the incumbent weight to analyze the model's sensitivity under the SVNS environment. So, the limit values of the G_2 criterion are $-0.1887 \leq \Delta x \leq 0.8113$, defined for 11 scenarios (Sc_i) that generate new criteria weights (see Table 18). The ranking obtained for all the scenarios is shown in Fig. 5.

5.5. Discussion

The results of the SVN-MEREC-MARCOS show that Al 7255-T7751 (L_3), Al 7068-T6511 (L_2), and Ti-6Al-4V (L_{16}) are the top-ranked sustainable materials for the spar application, as shown in Table 16. Because aluminum alloys L_2 (4.48\$/kg) and L_3 (4.51\$/kg) have the lowest R_1 values corresponding to the highest criteria weight $(\omega_{R_1} = 0.3146)$ with acceptable characteristics (see Tables 14 and 15), they outperform all the other alternatives. Notably, titanium alloys (L_{16}, L_{15}, L_{17}) possess better mechanical properties as compared to aluminum alternatives; however, they are five-fold more expensive (R_1), twice as dense (R_2), and have a relatively higher carbon footprint (G_5). Therefore, they are ranked consecutively next to aluminum alloys at 3rd, 4th, and 5th positions. Given that the criteria, R_1 and G_2, account for 50% of the overall weightage, L_{16}, with its low price (26.2\$/kg) and moderate fatigue resistance (0.8392) is deemed best choice among the titanium alloys.

The comparison of the proposed method with SVN-entropy and SVN-CRITIC shows similar trends in the ranking of the alternatives (see Fig. 3). However, L_3, the 1st ranked-choice by SVN-MEREC, descends to the 4th and 2nd position in SVN-entropy and SVN-CRITIC, respectively. In addition, Al-65%Al_2O_3 (L_1) is ranked as the best performing candidate material by both SVN-entropy and SVN-CRITIC methods due to its exceptional structural integrity, damage tolerance, manufacturability, and environmental compatibility. However, while considering the economic constraints, an anomaly is seen that L_1 has the highest price (8500\$/kg) among the alternatives, making it unfeasible for real-time engineering applications. This problem is accounted for in the proposed SVN-MEREC method, which ranks L_1 at the 6th position. Even the sustainability perspective supports ranking aluminum alternatives (L_2, L_3) at top positions, which are infinitely recyclable.

A glance at Fig. 4 demonstrates that the proposed method for wing spar material selection strongly correlates with TODIM

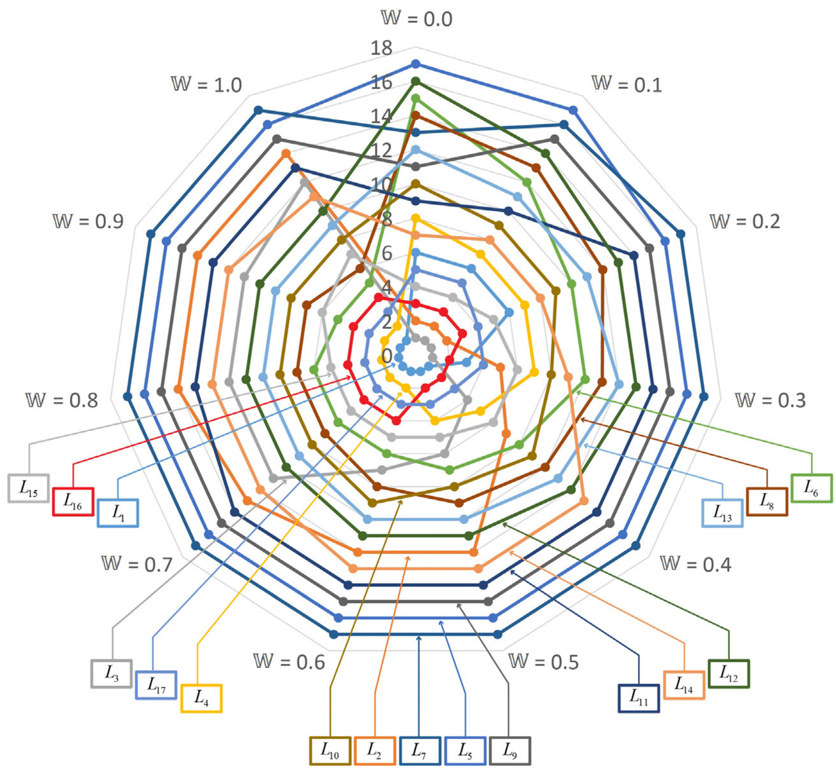


Fig. 5. Sensitivity analysis of 17 alternatives through 11 scenarios.

(0.92) and COPRAS (0.86). From the sensitivity analysis on SVN-MEREC, it can be construed that the present model is sensitive to changes in criteria weights (see Fig. 5). For example, the alternatives swap ranks as incumbent weight changes from 0 to 1. As a result, L_3 ranked as the most suitable material by SVN-MEREC falls to 12th position when the incumbent weight approaches 1. Additionally, it also ranks L_1 as the best choice when $\mathbb{W}_{inc} = 0.4$. The practicality of the work is that by reasonable control of critical property weights, a materials engineer can select better materials in terms of environmental impact, sustainability, and material attributes.

The salient features of the proposed SVN-MEREC-MARCOS framework are as follows:

1. SVN-MEREC-MARCOS is flexible enough to solve material selection problems while tackling crisp and ambiguous inputs simultaneously. Furthermore, the model deals with diverse opinions aggregated into meaningful data, easily computed for real-time engineering applications.
2. MEREC is a relatively new and simple objective weighting method that follows easy computational steps. Unlike entropy and CRITIC, it evaluates the significance of the weighting factors based on the removal effect of the criterion.
3. MARCOS, a compensatory method, follows a simple algorithm that does not complicate the engineering problem with the increasing number of alternatives or criteria. Moreover, it has the ability to process expert preferences regardless of the criteria type.

Although a comprehensive material selection tool is presented in this work, however, a few limitations of the research are outlined below:

- Eleven assessment criteria are included in this study, considering the technical, economic, environmental, and social aspects. In the future, the scope of the research problem can further be expanded to include additional parameters like corrosion and weldability.
- This research only integrates MEREC, CRITIC, and entropy with the proposed framework. Other criteria weighting methods such as AHP, BWM, FUCOM, SOWIA, and SWARA might be investigated for their potential.
- In this study, a limited number of decision-makers are involved in the material selection process. To achieve more reliable and accurate results, the number of decision-makers can be increased from 3 to 5, 7, or more.
- An offshoot of this study can be performed using other uncertainty theories, specifically IVNSs, as they deal with the indeterminacies and inconsistencies in intervals.

5.6. Practical implications

The current study presents a pragmatic approach to solving real-time material selection problems concerning sustainability. It is a recurrent tool for assisting the decision-making process and can be extended beyond the material selection problems of aircraft manufacturers. For the first time, a methodology embodies the opinions of experts along with crisp values to find an optimum alternative without losing information or compromising the solution. This research also shows that ethical material selection is no longer just based on technical operational requirements; environmental factors like carbon emissions and manufacturing energy have become more significant in recent years. This methodology incorporates internal operational requirements presented by the industry as well as external protocols imposed by governments or international organizations, such as environmental and health regulations.

6. Conclusion

Material selection for any structural application in the contemporary world is constrained by economic concerns, mechanical and chemical properties, environmental factors, and sustainable development goals. Hence sustainable material selection is an important tool for the manufacturing sector to meet its carbon-neutral goals. This research study aims to address the environmental challenges concerning the material selection of structures through a novel framework. MEREC under an SVN environment is used to determine objective criteria weights, followed by ranking the alternatives through MARCOS. SVNSs are employed to aggregate the opinions of three distinct experts, which are then deneutrosophied to attain crisp values to form the decision matrix. The applicability of the framework is demonstrated by implementing it to a real-time engineering problem of a lightweight aircraft wing spar. Comparative analysis and sensitivity analysis are performed to demonstrate the superiority of the framework over other MCDM methods. Moreover, the merits of MEREC are also established by comparing its results with other objective weighting methods. Another objective of this study is to help the aerospace industry decision-makers or material selectors make accurate and appropriate decisions. The results can help designers understand and evaluate materials with regard to their properties like sustainability, strength, and cost. The top-ranked materials serve as benchmarks, and the rest of the candidate materials are compared with them to identify their strengths and weaknesses. Additionally, this model allows group aggregation to combine the opinions of multiple decision-makers to produce the final results while also attending to the uncertainties and indeterminacies in the collected data. The results and ranking are elicited through an algorithm using MATLAB; in the future, this code can be extended to be used on other applications like green energy alternatives where two types of data sets are involved. The proposed framework can also be solved under different complex neutrosophic environments like interval-valued and rough sets. Finally, this framework provides the flexibility to the designer to opt for other weighting and ranking methods like AHP, SOWIA, TOPSIS, MULTIMOORA, or PROMETHEE for comparison. A limitation of the model is the restricted control of the decision-maker over assigning criteria weights. However, this may be tackled in future studies using integrated objective–subjective criteria weighting methods. Moreover, we plan to solve this framework using other uncertainty theories like IVNSs to perform a comparative analysis of the impact of using different approaches. Lastly, the application can be evaluated using other MCDM frameworks integrated with concepts of artificial intelligence, for instance, customer experience of high-speed rail system in China [116] and phase transformation prediction in complex material systems [117].

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

R. Sami Ul Haq: Methodology, Validation, Formal Analysis, Writing – original draft, Data curation, Visualization. **M. Saeed:** Methodology, Validation, Formal Analysis, Writing – original draft, Data curation, Visualization. **N. Mateen:** Writing – original draft, Data curation, Visualization. **F. Siddiqui:** Writing – review & editing, Resources. **M. Naqvi:** Writing – review & editing, Resources. **J.B. Yi:** Writing – review & editing, Resources. **S. Ahmed:** Conceptualization, Writing – review & editing, Supervision, Project administrator.

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

Data will be made available on request.

Acknowledgments

The authors would like to express their deep and sincere gratitude toward Ali Baig, Ali Mahmood and Muhammad Irshad Baig for their assistance and support.

Appendix A

See Tables A.1–A.4.

Appendix B

See Table B.1.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.asoc.2022.109546.

Table A.1
The normalized combined decision matrix η and overall performance of the alternatives M_i.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5	M_i
L_1	1.000	0.728	0.175	0.221	0.131	0.476	0.297	0.025	0.078	1.000	0.104	1.613
L_2	0.001	0.610	0.601	0.545	0.340	0.281	0.386	0.109	0.179	0.092	0.158	1.818
L_3	0.001	0.612	0.603	0.563	0.367	0.189	0.386	0.057	0.179	0.092	0.158	1.854
L_4	0.078	0.398	0.145	0.735	0.446	0.556	0.232	0.025	1.000	0.116	1.000	1.527
L_5	0.014	0.345	0.734	0.821	0.531	1.000	0.505	0.171	0.714	0.387	0.796	1.286
L_6	0.020	0.336	0.856	1.000	0.509	0.227	0.505	0.032	0.714	0.387	0.796	1.444
L_7	0.027	0.368	0.463	0.737	1.000	0.877	0.206	1.000	0.562	1.000	0.694	1.127
L_8	0.028	0.358	0.406	0.582	0.703	0.181	0.789	0.033	0.704	0.387	0.796	1.464
L_9	0.005	0.338	0.803	0.585	0.411	0.413	1.000	0.171	0.714	0.387	0.796	1.400
L_{10}	0.007	0.345	0.950	0.784	0.474	0.154	1.000	0.034	0.654	0.350	0.694	1.514
L_{11}	0.020	0.398	0.493	0.543	0.343	0.500	0.297	0.066	0.318	0.151	0.451	1.595
L_{12}	0.014	0.336	0.776	0.767	0.614	0.189	0.840	0.034	0.827	0.387	0.796	1.444
L_{13}	0.019	0.349	1.000	0.759	0.558	0.153	0.558	0.034	0.827	0.387	0.796	1.453
L_{14}	0.017	0.981	0.297	0.374	0.235	0.272	0.243	0.055	0.591	0.063	0.471	1.677
L_{15}	0.003	0.974	0.375	0.378	0.239	0.078	0.229	0.033	0.427	0.072	0.298	1.844
L_{16}	0.003	0.949	0.382	0.346	0.203	0.061	0.243	0.030	0.536	0.072	0.471	1.840
L_{17}	0.003	1.000	0.388	0.353	0.210	0.093	0.251	0.028	0.763	0.077	0.678	1.784

Table A.2
The overall performance matrix by removing criteria M^*_{ij}.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
L_1	1.613	1.597	1.522	1.535	1.506	1.575	1.551	1.409	1.477	1.613	1.493
L_2	1.451	1.797	1.797	1.793	1.773	1.765	1.778	1.723	1.745	1.716	1.740
L_3	1.504	1.835	1.834	1.831	1.814	1.787	1.816	1.735	1.784	1.756	1.779
L_4	1.378	1.476	1.416	1.510	1.482	1.495	1.444	1.303	1.527	1.403	1.527
L_5	0.933	1.210	1.264	1.272	1.241	1.286	1.238	1.156	1.262	1.218	1.270
L_6	1.182	1.377	1.434	1.444	1.403	1.352	1.403	1.216	1.424	1.386	1.430
L_7	0.780	1.043	1.063	1.102	1.127	1.116	0.990	1.127	1.079	1.127	1.097
L_8	1.232	1.403	1.411	1.433	1.444	1.360	1.451	1.245	1.444	1.408	1.451
L_9	1.002	1.330	1.386	1.366	1.343	1.343	1.400	1.284	1.379	1.339	1.385
L_{10}	1.194	1.453	1.511	1.500	1.472	1.405	1.514	1.307	1.490	1.454	1.493
L_{11}	1.372	1.547	1.558	1.563	1.539	1.559	1.531	1.446	1.535	1.494	1.553
L_{12}	1.154	1.377	1.429	1.428	1.415	1.340	1.434	1.221	1.433	1.386	1.430
L_{13}	1.188	1.389	1.453	1.437	1.418	1.337	1.418	1.232	1.442	1.396	1.439
L_{14}	1.466	1.676	1.618	1.630	1.607	1.614	1.608	1.531	1.652	1.539	1.641
L_{15}	1.586	1.843	1.804	1.804	1.785	1.737	1.784	1.699	1.809	1.734	1.795
L_{16}	1.580	1.838	1.801	1.797	1.775	1.723	1.783	1.690	1.815	1.730	1.810
L_{17}	1.510	1.784	1.744	1.740	1.717	1.679	1.724	1.622	1.773	1.670	1.768

Table A.3
The normalized extended decision matrix $\check{n}$.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
L_{NI}	0.0005	0.3362	0.1454	0.2206	0.1312	0.0610	0.2059	0.0248	0.0780	0.0634	0.1041
L_1	0.0005	0.4618	0.8311	1.0000	1.0000	0.1280	0.6944	1.0000	1.0000	0.0634	1.0000
L_2	1.0000	0.5509	0.2417	0.4050	0.3853	0.2171	0.5333	0.2278	0.4367	0.6866	0.6597
L_3	0.9933	0.5490	0.2411	0.3919	0.3571	0.3220	0.5333	0.4327	0.4367	0.6866	0.6597
L_4	0.0068	0.8441	1.0000	0.3000	0.2941	0.1098	0.8860	1.0000	0.0780	0.5468	0.1041
L_5	0.0390	0.9752	0.1980	0.2688	0.2471	0.0610	0.4074	0.1453	0.1092	0.1639	0.1308
L_6	0.0260	1.0000	0.1699	0.2206	0.2576	0.2683	0.4074	0.7764	0.1092	0.1639	0.1308
L_7	0.0196	0.9128	0.3142	0.2994	0.1312	0.0695	1.0000	0.0248	0.1389	0.0634	0.1499
L_8	0.0191	0.9401	0.3576	0.3794	0.1865	0.3378	0.2610	0.7505	0.1109	0.1639	0.1308
L_9	0.1077	0.9937	0.1811	0.3769	0.3188	0.1476	0.2059	0.1453	0.1092	0.1639	0.1308
L_{10}	0.0763	0.9752	0.1530	0.2813	0.2765	0.3951	0.2059	0.7312	0.1192	0.1811	0.1499
L_{11}	0.0270	0.8441	0.2947	0.4063	0.3824	0.1220	0.6944	0.3767	0.2451	0.4208	0.2309
L_{12}	0.0373	1.0000	0.1874	0.2875	0.2135	0.3232	0.2450	0.7312	0.0943	0.1639	0.1308
L_{13}	0.0282	0.9632	0.1454	0.2906	0.2353	0.3976	0.3691	0.7312	0.0943	0.1639	0.1308
L_{14}	0.0309	0.3428	0.4901	0.5894	0.5588	0.2244	0.8471	0.4508	0.1320	1.0000	0.2211
L_{15}	0.1653	0.3451	0.3874	0.5831	0.5488	0.7805	0.9000	0.7462	0.1827	0.8793	0.3497
L_{16}	0.1710	0.3544	0.3808	0.6375	0.6471	1.0000	0.8471	0.8392	0.1455	0.8793	0.2211
L_{17}	0.1594	0.3362	0.3742	0.6250	0.6235	0.6585	0.8217	0.8860	0.1022	0.8250	0.1537
L_{ID}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table A.4
The weighted extended decision matrix V.

	R_1	R_2	R_3	R_4	R_5	R_6	G_1	G_2	G_3	G_4	G_5
L_{NI}	0.000	0.016	0.006	0.008	0.007	0.005	0.012	0.005	0.003	0.006	0.004
L_1	0.000	0.023	0.037	0.034	0.057	0.011	0.039	0.189	0.042	0.006	0.040
L_2	0.315	0.027	0.011	0.014	0.022	0.018	0.030	0.043	0.018	0.062	0.026
L_3	0.312	0.027	0.011	0.013	0.020	0.027	0.030	0.082	0.018	0.062	0.026
L_4	0.002	0.041	0.044	0.010	0.017	0.009	0.050	0.189	0.003	0.050	0.004
L_5	0.012	0.048	0.009	0.009	0.014	0.005	0.023	0.027	0.005	0.015	0.005
L_6	0.008	0.049	0.007	0.008	0.015	0.022	0.023	0.147	0.005	0.015	0.005
L_7	0.006	0.045	0.014	0.010	0.007	0.006	0.056	0.005	0.006	0.006	0.006
L_8	0.006	0.046	0.016	0.013	0.011	0.028	0.015	0.142	0.005	0.015	0.005
L_9	0.034	0.048	0.008	0.013	0.018	0.012	0.012	0.027	0.005	0.015	0.005
L_{10}	0.024	0.048	0.007	0.010	0.016	0.033	0.012	0.138	0.005	0.016	0.006
L_{11}	0.008	0.041	0.013	0.014	0.022	0.010	0.039	0.071	0.010	0.038	0.009
L_{12}	0.012	0.049	0.008	0.010	0.012	0.027	0.014	0.138	0.004	0.015	0.005
L_{13}	0.009	0.047	0.006	0.010	0.013	0.033	0.021	0.138	0.004	0.015	0.005
L_{14}	0.010	0.017	0.022	0.020	0.032	0.019	0.048	0.085	0.006	0.091	0.009
L_{15}	0.052	0.017	0.017	0.020	0.031	0.065	0.051	0.141	0.008	0.080	0.014
L_{16}	0.054	0.017	0.017	0.022	0.037	0.083	0.048	0.158	0.006	0.080	0.009
L_{17}	0.050	0.016	0.016	0.021	0.035	0.055	0.046	0.167	0.004	0.075	0.006
L_{ID}	0.315	0.049	0.044	0.034	0.057	0.083	0.056	0.189	0.042	0.091	0.040

Table B.1
Abbreviations and their explanations.

Abbreviation	Explanation
ACWDEA	Augmented Common Weight Data Envelopment Analysis
AHP	Analytical Hierarchy Process
ARAS	Additive Ratio ASsessment
A-SVN-DM	Aggregated-SVN-Decision Matrix
ATAG	Air Transport Action Group
BWM	Best–Worst Method
BULI	Basic Uncertain Linguistic Information
CCSD	Correlation Coefficient and the Standard Deviation
C-DM	Crisp-Decision Matrix
CE-ANP	Concurrent Network
CLGT	Conditional logit
CoCoSo	Combined Compromise Solution
CODAS	COmbinative Distance ASsessment
COPRAS	COmplex PRoportional Assessment
CRITIC	Criteria Importance Through Intercriteria Correlation
DfD	Design for Deconstruction
DoE	Design of Experiment
EDAS	Evaluation based on Distance from Average Solution
ELECTRE	ELimination and Choice Translating REality
EoL	End of Life
EVAMIX	EVAluation of MIXed data
FFAA	Fermatean Fuzzy Aggregated Averaging
FFSs	Fermatean Fuzzy Sets
FWTMs	Food Waste Treatment Methods
FUCOM	Full Consistency Method
FSs	Fuzzy Sets
GIS	Geographic Information System
GMCDM	Group Multi-Criteria Decision Making
HoQ	House of Quality
HPA	Human Powered Aircraft
IFSs	Intuitionistic Fuzzy Sets
ITARA	Indifference Threshold-based Attribute Ratio Analysis
IVHFSs	Interval-Valued Hesitant Fuzzy Sets
IVIFSs	Interval-Valued Intuitionistic Fuzzy Sets
IVNSs	Interval-Valued Neutrosophic Sets
HFSs	Hesitant Fuzzy Sets
HIVIFSs	Hesitant Interval-Valued Intuitionistic Fuzzy Sets
LVs	Linguistic Variables
MABAC	Multi-Attribute Border Approximation area Comparison
MAMVA	Multi-Attribute Market Value Assessment
MARCOS	Measurement Alternatives and Ranking based on COmpromise Solution
MCDM	Multi-Criteria Decision Making
MDL	Modified Digital Logic
MEREC	MEthod based on the Removal Effects of Criteria
MULTIMOORA	Multi-objective optimization by ratio analysis with the full multiplicative form
NSs	Neutrosophic Sets
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
QFD	Quality Function Deployment
S3PRLP	Sustainable Third-Party Reverse Logistic Provider
SOWIA	Subjective and Objective Weight Integrated Approach
SRCC	Spearman's Rank Correlation Coefficient
SVN-DM	SVN-Decision Matrix
SVNNs	Single-Valued Neutrosophic Numbers
SVNSs	Single-Valued Neutrosophic Sets
SVN-WA	SVN-Weighted Average
SWARA	Stepwise Weight Assessment Ratio Analysis
TODIM	Interactive and multiple attribute decision making
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	Multi-criteria optimization and compromise solution
WASPAS	Weighted Aggregated Sum Product Assessment
Z-trans	Z-transformation

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