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Normalization Method Selection to Enhance Sustainable Manufacturing Decision-Making in Benefit and Cost-based Aspects of MCDM

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Abstract

In different qualitative and quantitative multi-criteria decision-making (MCDM) analysis under manufacturing sustainability involves evaluation of multiple, interrelated criteria that often differ significantly in magnitude, sign, units, and direction of preference. These wide variations create difficulty in data comparison and analysis, which leads to uncertainty and inconsistency in MCDM analysis. These challenges can be addressed by normalization process that converts diverse data values into a common and standardized range. However, the absence of consensus on the most suitable normalization method often compromises the reliability and accuracy of decision outcomes. This study aims to systematically evaluate, compare and prioritize to select the most effective normalization methods for handling wide variations of input values in MCDM processes applied to manufacturing sustainability assessment. A comprehensive comparison of widely used normalization methods were conducted under seven entry-value based scenarios/cases considering both benefit and cost optimization aspects. The result demonstrate that the Enhanced Accuracy normalization, and Max–Min Weitendorf's linear normalization methods were found as the first and second best normalization methods that consistently provides normalized values within the standard range [0-1], ensuring validity and stability across all cases. Consequently, these methods identified as the most robust, reliable and inclusive normalization methods for general-purpose benefit- and cost-based MCDM applications, capable of minimizing uncertainty and enhancing decision consistency. Their adoption supports more accurate and sustainable decision-making by improving data reliability and reducing risk during evaluation processes. In addition to these, other normalization methods have been prioritized as per their applicability. This research contributes a structured framework for normalization method selection in MCDM, offering practical guidance for decision-makers, engineers, policymakers engaged in sustainable manufacturing development and performance assessment.

Keywords: MCDM – normalization – comparison – selection scenarios – uncertainty - sustainable decision – manufacturing sustainability

1. Introduction

Sustainability fundamentally depends on the robustness, transparency, and factual soundness of the decision-making process. Decision-making constitutes a core component of socio-economic and industrial activities, as it directly influences system performance, resource utilization, and long-term viability. By its nature, decision-making is a multi-criteria process that involves the evaluation of competing and often conflicting factors, many of which incorporate subjective judgments. In sustainability-oriented decision frameworks, particularly within manufacturing systems, these subjective considerations are typically structured around key dimensions, namely social, environmental, economic, and technical criteria. Integrating these dimensions within a multi-criteria decision-making (MCDM) framework is therefore essential to improve decision accuracy and to support sustainable manufacturing outcomes. The effectiveness of the decision can be evaluated by the effect of the outcomes and impacts on the target dimensions [1]. Under these dimensions; factory, process, product and resource sustainability represent the core perspectives of manufacturing sustainability. Therefore, the more effective the decision outcome and the safer the consequences of the target activity, the higher the satisfaction of customers and the more sustainable the activity becomes. The effectiveness of the research analysis depends on the quality, reliability, and appropriateness of the data, as well as the precision of the analytical process. The need for continuous demand of a product with a continuous improvement of quality and minimum or optimized cost of manufacturing process as well as reduced negative impacts is referring to the term sustainability in manufacturing of a product. The concept of sustainability is a very vast and an important concept of modern market competitiveness [2]. Manufacturing as a core part of business operations require increased attention to sustainability, that's «manufacturing sustainability» or «sustainable manufacturing». Understanding and identifying the influencing factors for decision-making is the vital step in the decision-making process [3]. The ultimate goal of manufacturing sustainability is to produce products that continue to meet customer demands across all dimensions. According to the [4], manufacturing sustainability has been defined as the creation of manufactured products that minimize negative environmental impacts, conserve energy and natural resources, and are safe for employees, communities as well as consumers to be economically efficient. Manufacturing sustainability concerns may depend on the type and size of the industry, type of product and even location of the industry [5].

The new decisions-made to improve the manufacturing sustainability in its functionality and performance efficiency, may also encounter limitations and challenges. Any limitation or challenge arising from new or revised decisions within manufacturing industries that adversely affect operational or strategic performance is regarded as a risk. Such risks may result from erroneous decision-making or from unavoidable emerging challenges associated with data inaccuracy, uncertainty, or system complexity. The consequences of these risks can manifest in various forms, including loss of customers, increased national inflationary pressures, compromised product quality, erosion of public and

community trust, workforce instability, environmental pollution, restricted market access, adverse health impacts, and other related negative outcomes that undermine manufacturing sustainability. These adverse effects are collectively recognized as manufacturing risks [6]. In sustainability oriented decision-making, portion of decision risk originates not from the decision model itself, but from numerical distortions introduced during data normalization. When criteria with diverse characteristics: such as different value ranges and measurement units; are improperly normalized, uncertainty is significantly increased, preference structures are distorted, and final rankings become unstable. Therefore, normalization reliability represents a fundamental mechanism for controlling decision inaccuracy in MCDM systems.

Despite the critical role of normalization, existing studies primarily evaluate normalization methods using specific datasets or ranking comparisons, providing limited insight into their fundamental numerical behavior under extreme or limiting conditions. This research addresses this gap by establishing a scenario-based framework for systematically evaluating normalization reliability and stability as a core determinant of decision risk in sustainable manufacturing MCDM.

2. Literature Review

To ensure clarity and focus in the literature review, the research questions that delineate its scope are first explicitly defined. Establishing these questions helps to focus the investigation and ensures that the review systematically targets relevant prior studies aligned with the objectives of this research. Accordingly, a general research question is first articulated to provide an overarching direction for the review process. Subsequently, specific research questions are formulated to define the core aspects of the inquiry and clarify the issues examined. To enhance transparency and rigor in the review process, additional methodology-oriented, policy, and implementation-oriented research questions are also formulated, thereby ensuring a comprehensive and well-structured evaluation of the existing literature.

General research question:

How does the selection of normalization methods influence decision accuracy and consistency in MCDM analyses for manufacturing sustainability assessment?

Specific research questions:

- ☞ What challenges arise from wide variations in scales, units, and preference directions when applying MCDM methods in manufacturing sustainability evaluation?
- ☞ How do commonly used benefit-cost based normalization methods perform under different analytical scenarios involving in MCDM frameworks?
- ☞ Which normalization method demonstrates the highest level of stability, validity, and boundedness when processing heterogeneous data in MCDM process?
- ☞ To what extent does the choice of normalization method contribute to uncertainty reduction in MCDM-based sustainability decision-making?
- ☞ How does the robustness of normalization methods affect the reliability of sustainability rankings?

and final decision outcomes in manufacturing systems?

- ☞ Can a structured framework for normalization method selection improve decision consistency and reduce risk in sustainable manufacturing assessments?

Methodology-oriented research questions:

- ☞ How do different normalization methods behave across multiple analytical scenarios designed to reflect real-world manufacturing sustainability conditions?
- ☞ What criteria should be prioritized when selecting an appropriate normalization method for MCDM applications in sustainable manufacturing?

Policy- and implementation-oriented research question:

How can the adoption of a robust normalization method support: engineers, managers, decision-makers, and policymakers in achieving more sustainable manufacturing outcomes?

2.1 Manufacturing Sustainability and Multi-Criteria Decision-Making (MCDM)

Manufacturing sustainability has emerged as a central paradigm in contemporary industrial systems, driven by increasing regulatory pressures, resource constraints, market competitiveness, and societal expectations. Sustainable manufacturing extends beyond economic efficiency to encompass environmental stewardship, social responsibility, and technological robustness, thereby requiring decision-making frameworks capable of handling multidimensional and often conflicting objectives. Scholars consistently emphasize that sustainability-oriented manufacturing decisions must simultaneously balance cost efficiency, environmental impact reduction, worker safety, social equity, and long-term system resilience. Consequently, decision-making in sustainable manufacturing is inherently complex and cannot be adequately addressed using single-criterion or purely economic optimization approaches. Since manufacturing plays an important role in the world's economic development. The world's economic inflation is influenced by the manufacturing sector. On the other hand, it also affects the socio-environmental activities. The lack of manufacturing sustainability significantly affects the environment [7]. It is very important to improve and make the manufacturing factories and their products sustainable to handle the negative effects. The role of manufacturing in economic development and impact of its inefficiencies in the environment and social dimensions have been given great attention by researchers [8]. Given the complexity of mitigating these challenges, multi-criteria-based assessment approaches have been widely employed by researchers to identify and evaluate potential solutions [9]. It is therefore essential to conduct continuous assessments of all factors that may influence product demand. Such comprehensive evaluations facilitate the identification and characterization of sustainable performance indicators, thereby supporting proactive decision accuracy mitigation and enhancing overall product sustainability.

MCDM methods have therefore gained widespread acceptance as effective tools for structuring, analysing, and solving sustainability-related decision problems in manufacturing systems. MCDM frameworks enable decision-makers to integrate qualitative and quantitative criteria, reconcile

conflicting objectives, and incorporate expert judgment into a systematic evaluation process. Popular MCDM methods such as the Analytic Hierarchy Process (AHP) [10], Method for Order Preference by Similarity to Ideal Solution (TOPSIS) [11], VIKOR [12], ELECTRE [13], PROMETHEE [14], and their fuzzy as well as hybrid methods have been extensively applied in manufacturing sustainability assessments including supplier selection, process selection, technology evaluation, resource allocation, and performance benchmarking. However, despite their methodological sophistication, MCDM methods are highly sensitive to data pre-processing steps, particularly normalization. Since sustainability indicators are typically expressed in heterogeneous units, scales, and preference directions, normalization is a prerequisite for meaningful aggregation and comparison. The literature increasingly recognizes that inappropriate normalization can undermine the theoretical robustness of MCDM methods, distort preference structures, and lead to unreliable or inconsistent decision outcomes. As a result, normalization has shifted from being viewed as a purely technical pre-processing step to a critical determinant of decision accuracy and risk in sustainability-oriented MCDM applications.

2.2 Challenges of Data Heterogeneity in Manufacturing Sustainability Assessment

A defining characteristic of manufacturing sustainability assessment is the presence of wide variations in decision criteria. Regardless of their detail context, the environmental, economic and social dimensions of sustainability measurements are almost at a common level of consensus to be used as key sustainability dimensions by most researchers [7], [8], [15], [16]. Within the principal sustainability dimensions, sustainable manufacturing performance can be assessed through multiple levels or sub-categories of performance indicators. The environmental dimension, targeted in reducing or avoiding the gas emission, wastes, and resources inefficiency [17], [18], considered as the environmental performance indicators. Environmental indicators such as carbon emissions, energy consumption, and water usage may span several orders of magnitude, while social indicators such as occupational safety, job satisfaction, or community impact are often measured using ordinal or qualitative scales [19]. The factors affecting the economic performance of a product or/and a manufacturing industry are the economic performance indicators. According to [7]; quality, cost, delivery, and flexibility are considered as economic performance indicators in order to specifically evaluate the manufacturing performance. Thus the economic indicators may involve monetary units, ratios, or percentages, whereas technical indicators frequently rely on performance indices or efficiency metrics [20].

In addition, the factors affecting the social matters (such as labor conditions, occupational health and safety, community engagement, social equity, and stakeholder satisfaction) are the social performance indicators of sustainability [21]. To clearly understand the social performance indicators, it would be recommendable to refer the UN [22] and OECD [23] documents and articles specifically focusing and addressing the role of social indicators in overall sustainable development [24]. As stated, this review shows most of the researchers are focusing on the three sustainability dimensions. However, some arguments provided to claim the consideration of technical aspects as the fourth indispensable

sustainability dimension [25]. The argument focuses on the fact that the role of modern technology (innovative skills, technologies, etc.) has been neglected its influence on the decision accuracy during the MCDM analysis. **Table 1** presents to show how many of researchers consider the technical dimension in addition to the three common dimensions.

Table 1 Presents the literature review of general manufacturing sustainability dimensions.

Cited Article	Manufacturing Sustainability Dimensions				Remark
	Env	Eco	Soc	Tec	
[7]	*	*	*		<i>Excludes technical dimension</i>
[15]	*	*	*		<i>Excludes technical dimension</i>
[26]	*	*	*	*	<i>With some technical consideration</i>
[27]	*	*	*	*	<i>Technically intensive</i>
[28]	*	*	*		<i>Excludes technical dimension</i>
[29]	*	*	*		<i>Excludes technical dimension</i>
[30]	*	*	*	*	<i>Technically intensive</i>
[31]	*	*	*	*	<i>All equally considered</i>

Note: Env = Environmental, Eco = Economic, Soc = Social, Tec = Technical, and «» refers to considered.*

Prioritizing manufacturing sustainability performance indicators has a significant role to reach in to an agreed consensus on the most common indicators. A recent study has been investigated regarding this, using the Delphi method with an integrated MCDA approach to identify and prioritize the sustainability indicators [15]. According to [16], focused on proposing sound sustainability performance indicators in additive manufacturing and identified 29 for environment, 9 for economic, and 30 for social dimensions of indicators. As per this study nowadays, the main challenge is identification and utilization of comprehensive sustainable performance indicators and convenient manufacturing process because detailed descriptions and measuring strategies are neither available nor standardized. Based on the two recent researches [15], [16] which have reviewed above 180 different articles regarding manufacturing sustainability, it has been observed that there is no clear consensus in identifying, stating and context interpretation of the sustainable performance indicators under the most commonly agreed three key sustainability dimensions. These variations in magnitude, units, and measurement scales introduce significant challenges for data comparability and integration.

Several studies have highlighted that failing to address data heterogeneity effectively leads to biased weighting, dominance of high-magnitude criteria, and artificial amplification or suppression of certain indicators [32]. In manufacturing sustainability contexts, this problem is particularly critical because small numerical distortions can translate into substantial real-world consequences, such as suboptimal technology adoption, misallocation of resources, or increased environmental and social risks. Furthermore, sustainability data are often characterized by uncertainty, incompleteness, and subjectivity, further complicating the normalization process. Since the challenges associated with

decision risk ultimately stem from limitations in decision accuracy, this study focuses on investigating the impact and selection of normalization methods to improve decision accuracy within MCDM processes.

The literature also identifies the coexistence of benefit-type criteria (where higher values are preferred) and cost-type criteria (where lower values are preferred) as a major source of complexity in normalization. Improper handling of these preference directions can reverse rankings, violate monotonicity conditions, and reduce decision consistency. Consequently, scholars argue that normalization methods must not only rescale data but also preserve preference direction, boundedness, and proportionality across all criteria to ensure reliable sustainability evaluations.

2.3 Role of Normalization in MCDM Accuracy and Consistency

Normalization serves as the mathematical bridge between raw data and decision aggregation in MCDM. Its primary function is to transform heterogeneous input data into dimensionless, comparable values that can be meaningfully combined using weighting and aggregation operators [32]. While this transformation appears straightforward, its implications for decision accuracy and consistency are profound. Normalization determines the relative dispersion of criteria, affects the sensitivity of rankings to weight changes, and influences the stability of decision outcomes under varying scenarios [33]. A growing body of literature demonstrates that different normalization methods can produce significantly different rankings even when applied to the same dataset and MCDM method [34]. This phenomenon, often referred to as rank reversal or normalization-induced instability, has been documented across various sustainability assessment studies. Researchers have shown that normalization choices can outweigh the influence of weighting methods or even the selection of the MCDM method itself [35]. This insight challenges the conventional assumption that normalization is a neutral pre-processing step and underscores its central role in controlling decision risk. Moreover, normalization errors are closely linked to uncertainty propagation in MCDM models. When normalized values fall outside theoretical bounds, exhibit nonlinear distortions, or disproportionately compress or stretch data ranges, uncertainty is amplified rather than mitigated [36]. In manufacturing sustainability assessments, where decisions often involve high capital investment and long-term consequences, such amplification of uncertainty poses significant strategic and operational risks. As highlighted in your draft document, decision risk frequently originates not from the MCDM model structure but from numerical distortions introduced during normalization.

This study concentrates on making a sustainable decision by avoiding or reducing inaccuracy using an appropriate normalization method. Consistent with the stated research question, the present study systematically analyses the effects of normalization method and selection process to enhance decision accuracy within MCDM frameworks for manufacturing sustainability assessment. Accordingly, the study identifies suitable normalization methods for specific decision-making scenarios and systematically evaluates data variation, which are the main contributors to decision inaccuracy. So that,

this research study reviewed the decision-making process and uncertainty handling in line with possible encountering risk assessment approaches. The MCDM based AHP, TOPSIS, and their fuzzy or hybrid combination methods have been widely used in decision-making processes. AHP is the simplest user friendly method and is playing a significant role in making a decision in different areas of investment [37].

2.4 Common Normalization Methods and their Limitations

The literature identifies several commonly used normalization methods in MCDM, including vector normalization, linear sum normalization, max–min normalization, max normalization, logarithmic normalization, and various ratio-based approaches [38]. Including these classes and other types many more normalization methods have been investigated in general uses of MCDM processes [33]. According to this article, 11 normalization methods have investigated for the aspect of optimization orientation (benefit- & cost-aspect), and 10 non-benefit and –cost based normalization methods as well as two mixed methods in wider context. It assessed the overall possible normalization methods for general selection process. However, it did not show the detail suitability or specific validity of the benefit- and cost-based normalization methods in terms of entry values. That is why the benefit- and cost-based normalization methods have been becoming the target of this study.

Each class of normalization method has distinct mathematical equation, properties, advantages, and limitations in data value normalization [39]. Vector normalization, for example, preserves proportionality but may produce values that are difficult to interpret and can distort relative distances when criteria distributions are highly skewed [40]. Linear sum normalization is simple and intuitive but may fail to maintain boundedness under extreme values [41]. Max–Min normalization widely favored for its ability to map data into a fixed range, typically $[0,1]$, which enhances interpretability and comparability [42]. However, traditional min–max approaches are sensitive to outliers and may suffer from instability when applied to mixed benefit and cost criteria. Ratio-based methods, while effective in certain contexts, may generate normalized values exceeding unity or approaching zero, leading to aggregation bias and numerical instability [43]. Studies have shown that even with the same MCDM aggregation rule, normalized alternatives may produce distinct rankings depending on the normalization formula used, thereby introducing methodological uncertainty into decision-making processes [44].

In sustainability-assessment research, empirical evidence indicates that normalization choices such as sum, min-max, and vector normalization can yield divergent results in practice, affecting sensitivity and robustness outcomes. For example, in applications using the WSM or TOPSIS models, min-max normalization is often preferred because it bounds data within a fixed range $[0,1]$ and tends to balance sensitivity to variations while reducing the influence of outliers [44]. Several comparative studies have attempted to evaluate normalization methods based on ranking outcomes, correlation coefficients, or sensitivity analysis. While these studies provide valuable empirical insights, they often rely on specific datasets or case studies, limiting their generalizability. More importantly, many existing evaluations

overlook the fundamental numerical behaviour of normalization methods under extreme or boundary conditions, such as zero variance, identical alternatives, or highly asymmetric data distributions. This gap in the literature motivates the need for a scenario-based analytical framework, as proposed in your study, to assess normalization reliability and robustness across a wide range of conditions systematically. Selecting suitable normalization methods and specifying the limitations with respect to each possible method has investigated by different researchers like [45].

Table 2 The possible proposed normalization methods used in different single, hybrid and fuzzy MCDM processes.

Type of normalization method	Benefit criteria	Cost criteria	Reference
Sum-based Linear Normalization (N1)	$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$	$n_{ij} = \frac{1/x_{ij}}{\sum_{i=1}^m 1/x_{ij}}$	[33], [38]
Vector Normalization (N2)	$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij} ^2}}$	$n_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij} ^2}}$	[33], [38], [46]
Logarismic Normalization (N3)	$n_{ij} = \frac{\ln x_{ij}}{\ln \left(\prod_{i=1}^m x_{ij} \right)}$	$n_{ij} = \frac{1 - \frac{\ln x_{ij}}{\ln \left(\prod_{i=1}^m x_{ij} \right)}}{m-1}$	[33]
Maximum Linear Normalization (N4)	$n_{ij} = \frac{x_{ij}}{\max(x_{ij})}$	$n_{ij} = 1 - \frac{x_{ij}}{\max(x_{ij})}$	[33]–[35]
Minimum-Linear Normalization (N5)	$n_{ij} = 1 - \frac{\min(x_{ij})}{x_{ij}}$	$n_{ij} = \frac{\min(x_{ij})}{x_{ij}}$	[33], [34]
Max-Min Normalization (N6)	$n_{ij} = \frac{x_{ij}}{\max(x_{ij})}$	$n_{ij} = \frac{\min(x_{ij})}{x_{ij}}$	[33], [34]
/Max-Min/ (Juttler-Korth Normalization - N7)	$n_{ij} = 1 - \left \frac{\max(x_{ij}) - x_{ij}}{(\max(x_{ij}))} \right $	$n_{ij} = 1 - \left \frac{\min(x_{ij}) - x_{ij}}{(\max(x_{ij}))} \right $	[33]
Stopp Normalization (N8)	$n_{ij} = \frac{100x_{ij}}{\max(x_{ij})}$	$n_{ij} = \frac{100\min(x_{ij})}{x_{ij}}$	[33]
Nonlinear Normalization (Peldschus-N9)	$n_{ij} = \left(\frac{x_{ij}}{\max(x_{ij})} \right)^2$	$n_{ij} = \left(\frac{x_{ij}}{\max(x_{ij})} \right)^3$	[33]
Max-Min Normalization (Weitendorf's Linear = WL)	$n_{ij} = \frac{x_{ij} - \min(x_{ij})}{(\max(x_{ij}) - \min(x_{ij}))}$	$n_{ij} = \frac{\max(x_{ij}) - x_{ij}}{(\max(x_{ij}) - \min(x_{ij}))}$	[33], [35]
Z Score Normalization	$n_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$	$n_{ij} = -\frac{x_{ij} - \mu_j}{\sigma_j}$	[33], [34]
Nonlinear Normalization	$n_{ij} = \left(\frac{x_{ij}}{\max(x_{ij})} \right)^2$	$n_{ij} = \left(\frac{\min(x_{ij})}{x_{ij}} \right)^3$	[33], [34]
Enhanced Accuracy Normalization	$n_{ij} = 1 - \left(\frac{\max(x_{ij}) - x_{ij}}{\sum_{i=1}^m (\max(x_{ij}) - x_{ij})} \right)$	$n_{ij} = 1 - \left(\frac{x_{ij} - \min(x_{ij})}{\sum_{i=1}^m (x_{ij} - \min(x_{ij}))} \right)$	[33], [34]

Lai & Hwang Normalization	$n_{ij} = \frac{x_{ij}}{(\max(x_{ij}) - \min(x_{ij}))}$	$n_{ij} = \frac{x_{ij}}{(\min(x_{ij}) - \max(x_{ij}))}$	[34]
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Table 2, summarized the literature assessed regarding the common and possible normalization methods focused only benefit- and cost-based evaluations in MCDM processes. Which means the criteria, alternatives or/and items under assessment affected by optimization orientation (the process of maximizing or minimizing the values have direct impact on the decision). So that, we have considered only the benefit- and cost-based normalization methods in this study. Thus, the methodology has designed an approach to compare and select the most suitable method for a specific decision-making problem based on its entry values.

2.5 Normalization, Uncertainty Reduction, and Decision Risk

Normalization not merely a mathematical convenience but a critical factor in decision accuracy. When normalization poorly represents underlying data, it can propagate uncertainty through subsequent weighting and aggregation steps, leading to decisions that are inconsistent or sensitive to small changes in input values [44]. A study analyzing normalization effects on sustainability rankings found that the relative stability of ranks across methods is contingent on the normalization choice, with min-max normalization showing favorable stability characteristics in many engineering sustainability cases. Uncertainty, inherent feature of sustainability decision-making, arising from data variability, measurement error, subjective judgment, and future unpredictability [47]. In MCDM models, uncertainty is propagated through normalization, weighting, and aggregation stages. Among these, normalization plays a pivotal role because it directly transforms raw data into the decision space. If this transformation is unstable or inconsistent, subsequent analytical steps cannot compensate for the resulting distortions. Moreover, normalization contributes to how MCDM handles data uncertainty and risk [48]. In manufacturing sustainability assessment, where data may be incomplete, variable, or subject to measurement error, normalization must not only standardize units but also preserve the relative differences among alternatives. Poor normalization can exacerbate uncertainty and lead to mischaracterized risks, thereby undermining confidence in the decision model. Robust normalization methods should therefore support consistency both within and across analytical scenarios.

The literature increasingly frames normalization as a risk-control mechanism rather than a mere data transformation tool. Robust normalization methods expected to minimize uncertainty propagation, maintain boundedness, and ensure consistent preference representation across criteria [49], [50]. Studies in manufacturing risk management highlight that decision inaccuracies caused by poor normalization can lead to financial losses, environmental degradation, workforce instability, and reputational damage [51]. These consequences align with the concept of manufacturing risk described in your document, where decision-related errors undermine sustainability outcomes. Researchers have also emphasized the importance of normalization stability under scenario variation. Real-world manufacturing decisions are

rarely static; they evolve in response to market conditions, technological changes, and policy shifts. A normalization method that performs well under one dataset but fails under slightly altered conditions cannot be considered reliable. Therefore, scenario-based evaluation, incorporating both benefit and cost criteria under diverse analytical conditions, is increasingly advocated as a rigorous approach to normalization assessment. Under this concern, the limitations and invalidity ranges and possibilities of entry values have specified and investigated in *Table 3*. This helps to draw out the scenarios or cases of the entry values to make the selection approach clear.

2.6 Toward a Structured Framework for Normalization Method Selection

Despite the extensive application of normalization in MCDM, there is a notable lack of consensus regarding best practices for normalization method selection, particularly in manufacturing sustainability contexts [44]. Most studies select normalization methods based on convention, software defaults, or methodological convenience rather than systematic evaluation. This ad hoc approach contributes to inconsistent findings across studies and limits the comparability and reproducibility of sustainability assessments. Comparative analyses of normalization methods reveal a spectrum of approaches applied across sustainability and engineering decision problems [44]. In manufacturing research, studies demonstrate that sum-based (linear) and vector normalization methods frequently produce similar rankings in MCDM outcomes, while methods like min-max or z-score may diverge under certain data distributions, especially when outliers or non-linear relationships are present. Given the variability in outcomes associated with different normalization methods, recent research advocates for structured selection frameworks that consider data characteristics, decision criteria types, and the intended use of results [52]. Such frameworks move beyond ad-hoc normalization choices by evaluating how candidate methods perform across scenarios, with respect to boundedness, monotonicity, sensitivity, and preference preservation. This systematic evaluation aligns with efforts to address methodological uncertainty in MCDM by incorporating robustness analysis into normalization selection.

Recent literature calls for structured frameworks that guide normalization method selection based on decision context, data characteristics, and analytical objectives. Such frameworks should consider criteria type, data range, presence of outliers, preference direction, and desired properties such as boundedness, monotonicity, and stability. The scenario-based framework proposed in your study directly addresses this need by evaluating normalization methods across multiple analytical scenarios and identifying those that consistently satisfy theoretical and practical requirements. Prior work also points to the benefits of scenario-based testing, where normalization methods are assessed not only on theoretical properties but also on stability of outputs under simulated perturbations of input data. This approach is particularly crucial in manufacturing sustainability assessments, where variability and uncertainty are inherent to real-world data. In particular, the identification of the suitable normalization method as a robust and inclusive method for a specific problem contributes to the advancement of normalization theory in MCDM. By consistently producing normalized values within the standard and

most commonly expected range [0,1] and demonstrating stability across diverse scenarios, the proposed method helps to align with the core objectives of uncertainty reduction, decision accuracy, and sustainability-oriented risk mitigation. Its adoption offers practical benefits for engineers, managers, and policymakers seeking reliable decision-support tools for sustainable manufacturing development.

Concluding Synthesis of the Literature Review

In summary, the literature clearly establishes that normalization is a critical determinant of decision accuracy, consistency, and risk in MCDM-based manufacturing sustainability assessment. While MCDM methods provide powerful frameworks for integrating multidimensional sustainability criteria, their effectiveness is fundamentally constrained by the reliability of normalization processes due to variability of input data. Existing studies reveal substantial limitations in commonly used normalization methods and highlight the absence of systematic, scenario-based evaluation frameworks. By addressing these gaps, this research makes a timely and significant contribution to both the theoretical and practical advancement of sustainable manufacturing decision-making.

MCDM methods utilized for analyzing the risks associated with changes in decision for a given problem that requires further systematic investigation. The fuzzy AHP–TOPSIS method has been widely employed to prioritize risks based on their impact intensity and probability of occurrence [53]. Consequently, methodologies that are similar or conceptually aligned with this approach can contribute to more effective handling and mitigation of risks generated due to data variation during decision-making processes. [54], identified various hazard types within risk estimation methodologies and examined their probability, severity, and frequency, thereby highlighting the importance of incorporating these factors for more accurate and comprehensive risk assessment. Furthermore, probability and severity decision uncertainty are the most commonly emphasized dimensions. However, FAHP–TOPSIS based approaches have not been extensively extended to more diverse uncertainty assessment applications. Despite this limitation, the FAHP–TOPSIS framework remains a valuable tool for enhancing decision quality assessment through its structured and systematic data processing capabilities. This review highlights the critical need to identify effective approaches for reducing or avoiding decision risks and uncertainty arising from inappropriate normalization methods in MCDM processes [55]. Decision uncertainty introduced during data normalization can significantly compromise decision accuracy and consistency. To develop an effective decision-based risk assessment framework, several key factors must be carefully addressed, including the selection of an appropriate MCDM method, the establishment of a structured and reliable data collection strategy, the clear definition of underlying assumptions, the identification of relevant performance indicators, and the adoption of suitable data manipulation and standardization procedures. These elements collectively contribute to minimizing numerical distortions and narrowing uncertainty propagated through exaggerated data variations. Therefore, investigation of appropriate normalization method for a specific decision-making process [36].

The findings of this review emphasize the necessity of investigating an appropriate and reliable data normalization or standardization approach that can effectively reduce decision errors and associated risks while remaining practical and computationally efficient. Moreover, the effectiveness of any decision outcome is intrinsically linked to the performance of the decision-making process and the competence of the decision-maker. As discussed, the core challenge in MCDM lies in the simultaneous consideration of multiple criteria that often differ in assumptions, evaluation scales, measurement units, scopes, and contextual relevance. These disparities create ambiguity and complexity in the decision-making process, which manifest as uncertainty and may lead to both expected and unexpected decision risks. Decision-maker performance plays a significant role and reflects a combination of professional and technical expertise, availability and quality of data, access to analytical tools and technologies, clarity of assumptions, careful consideration of performance indicators, and proficiency in data manipulation and normalization method selection. Importantly, the review demonstrates that selecting a suitable MCDM method alone is insufficient to ensure optimal decision outcomes. Equally critical is the manner in which data are processed and standardized throughout the decision-making process. Given the substantial variation in criteria values, units, scales, and application contexts, systematic data normalization into a common and bounded range is essential for managing uncertainty and preserving the integrity of decision results. Within this framework of uncertainty management, the selection of an appropriate normalization method plays a pivotal role in harmonizing heterogeneous criteria and reducing decision inconsistencies. Accordingly, this research systematically compares and identifies a robust, generalizable normalization method suitable for a wide range of MCDM applications, based on comprehensive numerical validity and scenario-based evaluation.

Previous researches have explored the role of normalization methods in decision-making analyses. As stated in the earlier review section, normalization in MCDM processes referred to the value standardization among all the considered criteria or/and alternative during the decision-making process [33]. His normalization methods laid on the four general groups based on sum, maximum (max), minimum (min) and range categories. According to [34], 31 normalization methods have analysed, and [35], has studied and filtered four common normalization methods (max, max-min, sum-based and vector). However, most of the normalization methods found are common in these studies. The performance of normalization methods evaluated based on the normalized value range and scale specification to compare all possible methods for common use [34]. [56], has also examined the role of normalization in the integrated FAHP-TOPSIS model. In another study, [57], developed an integrated fuzzy AHP–fuzzy TOPSIS methodology for multi-criteria sustainable manufacturing process selection, demonstrating the practical advantages of combining fuzzy weighting and fuzzy ranking under complex sustainability conditions. While this framework achieved improved decision consistency, it also revealed the sensitivity of final rankings to data normalization procedures. This observation further emphasizes the necessity of systematically evaluating normalization methods. In addition, the Pearson

correlation coefficient has been used to measure similarities. The Ranking Consistency Index, has been proposed by [58] to compare normalization methods using a decision matrix case study. An improper ranking and selection of normalization method causes for rank reversal case. Hence, [50], have studied the cause and effect of rank reversal and have stated that rank reversal in AHP can be avoided when the output of the process is properly redefined as a weight-ratio matrix and multiplicative procedures used. [59], studied the rank reversal in TOPSIS and two causing factors have pointed out; the first is related to the norm utilized in the principal algorithm and the other to the definition of the positive and negative ideal solutions (PIS and NIS).

In concluding the review, the different possible MCDM methods that are used from simple to difficult decision-making problem cases have been reviewed and presented selectively in order to support the scientific background of this study. For example, using the combined or hybrid as well as fuzzy MCDM methods helps to make a better decision and uncertainty based risk handling but they are more complex in their analysis than the single method [60]. During utilization of MCDM methods for different decision-making analyses, systematic quantitative analysis used through each steps. Normalizing the numerical values or entry values either in weight determination or in alternatives preference ranking analysis, is one of the crucial procedures. Hence, the appropriate normalization method should be selected based on the entry value types. In order to carry out the selection process, selection consideration, method-validity evaluation cases and comparison procedures have been presented in the methodology section. As a result, this study focuses on how to standardize or normalize entry values into a standard range during the process in order to carefully manipulate the quantitative analysis. Because the data manipulation process determines the effectiveness of the decision-making process. Therefore, based on the review the possible proposed normalization methods applicable to both benefit- and cost-criteria have presented in **Table 2** for further filtering and investigation. The detail approaches and analysis for selecting the best normalization method provided in the methodology section.

3. Study Methodology

In conducting this research, the adoption of a targeted and systematic research methodology is essential to ensure that the findings provide meaningful and constructive contributions to the sustainable development of the manufacturing sector. The overarching methodological framework of this study grounded in the evaluation of harmonizing multiple criteria and analyzing them in a structured manner to derive optimal decisions for a defined problem. This approach formally recognized as MCDM. The study follows a review-assisted research design, incorporating insights from relevant literature to strengthen the methodological foundation and enhance the reliability of the research outcomes. Key elements of the research process include the identification of appropriate data sources and respondents, the use of computational tools and software for data analysis (primarily Microsoft Excel), the selection of suitable MCDM methods, the formulation of baseline assumptions, and the integration of supporting methodological components. MCDM methods and their associated hybrid methods are widely

acknowledged as effective tools for evaluating and standardizing performance indicators in manufacturing sustainability decision-making contexts [8]. Evidence from the literature further indicates that hybrid MCDM approaches often exhibit greater robustness and reliability than standalone or conventional methods, particularly when addressing complex decision environments characterized by uncertainty. Accordingly, this study adopts multi-criteria assessment frameworks based normalization methods comparison and selection approaches to achieve its research objectives. Within this context, the systematic identification, prioritization, and optimization of risk indicators are recognized as critical components in enhancing decision accuracy and reducing uncertainty in MCDM-based sustainability assessments.

This research work intended to clearly assess the normalization challenges and compare them to propose the suitable normalization method that can be used in different MCDM processes to handle the data values and units' variation gap that can cause for decision inaccuracy. The methodology of this study has planned and carried out well-organized research to compare and select the suitable normalization method that can be used for any MCDM problem or for any convenient problem in order to select the best alternative. In carrying out this research, some basic bottom-line assumptions have been considered to filter out the proposed normalization methods.

Stating the bottom-line assumptions:

- i. A criterion cannot be zero for all alternatives: i.e., no need decision-making analysis for a decision matrix with all elements zero value ($x_{ij}=0$ or zero matrix). In all cases of decision-making problem analyses all elements (x_{ij}) of a decision matrix should not be with zero values.
- ii. A criterion cannot be with equal value for all alternatives: i.e., no need decision-making analysis for a decision matrix with equal values of all elements ($x_{\max} - x_{\min} = 0$, or all elements of the decision matrix are with “a” value).
- iii. Considers only all rational numbers: The evaluation considers all rational numbers, reflecting the full numerical domain encountered in practical MCDM problems (did not consider complex numbers).
- iv. Benefit and cost criteria aspects of optimization are considered: only normalization methods that can be applicable for both benefit and cost criteria optimization orientations are chosen from the reviews.

Filtering and preparing the proposed normalization methods:

Based on the reviewed studies and the inconsistencies observed in their conclusions, benefit- and cost-criteria-based normalization methods were compiled for comparative analysis. This paper focuses exclusively on benefit- and cost-based normalization methods selected from the literature and restructured for further comparison. As a result, the proposed normalization methods have filtered and organized into about 14 most important types based on their similarities. The limitations and possible application specifications of each method have been seriously investigated in *Table 3*.

Table 3: Benefit-cost criteria based filtered normalization methods limitation and possible application specifications for comparison.

Normalization method	Type of optimization	Basic Equation	Limitation	Recommended case of application	Reference
Sum-Based Linear Normalization (N1)	Benefit criteria	$n_{ij} = \frac{x_{ij}}{\sum_{j=1}^m x_{ij}}$	$\sum x_{ij} \neq 0$	For all except for elements with zero sum (existence of negative element/s). [effect of -ve]	<i>Ahmet Aytekin et al. (2021)</i> <i>Nazanin Vafaei et al. (2016)</i>
	Cost criteria	$n_{ij} = \frac{1/x_{ij}}{\sum_{j=1}^m 1/x_{ij}}$	$x_{ij} \neq 0, \sum (1/x_{ij}) \neq 0$	For all except, for none of the elements and sum of their reciprocals are zero. [effect of -ve]	
Vector Normalization (N2)	Benefit criteria	$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^m x_{ij} ^2}}$	$\sum (x_{ij})^2 \neq 0$	For all cases with positive value elements. [effect of -ve]	<i>Alberto Vega et al. (2014)</i> <i>Ahmet Aytekin et al. (2021)</i> <i>Nazanin Vafaei et al. (2022)</i>
	Cost criteria	$n_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{j=1}^m x_{ij} ^2}}$	$\sum (x_{ij})^2 \neq 0$	For all cases with positive value elements. [effect of -ve]	
Logarithmic Normalization (N3)	Benefit criteria	$n_{ij} = \frac{\ln x_{ij}}{\ln \left(\prod_{j=1}^m x_{ij} \right)}$	$x_{ij} \neq 0, x_{ij} \neq -ve$ $\prod x_{ij} \neq 0, \prod x_{ij} \neq 1$	For cases at which the value of elements are none 0 and their product is different from 0 and 1. [effect of -ve]	<i>Ahmet Aytekin et al. (2021)</i>
	Cost criteria	$n_{ij} = \frac{1 - \ln x_{ij}}{\ln \left(\prod_{j=1}^m x_{ij} \right) - m + 1}$	$x_{ij} \neq 0, x_{ij} \neq -ve$ $\prod x_{ij} \neq 0, \prod x_{ij} \neq -ve$ $\prod x_{ij} \neq 1, m \neq 1$	For cases except the element values are out of 0, their product is different from 0, -ve, and 1. Also if the number of elements are more than 1 (m>1). [effect of -ve]	
Maximum - Linear Normalization (N4)	Benefit criteria	$n_{ij} = \frac{x_{ij}}{\max(x_{ij})}$	$\max(x_{ij}) \neq 0$	At least the values for the normalization calculations (x_{ij}) should be none 0. Better to be +ve. [effect of -ve]	<i>Ahmet Aytekin et al. (2021)</i> <i>Nazanin Vafaei et al. (2022)</i> <i>Jahan & Edwards et al. (2015)</i>
	Cost criteria	$n_{ij} = 1 - \frac{x_{ij}}{\max(x_{ij})}$	$\max(x_{ij}) \neq 0$	At least the values for the normalization calculations (x_{ij}) should be none 0. Better to be +ve. [effect of -ve]	
Minimum – Linear Normalization (N5)	Benefit criteria	$n_{ij} = 1 - \frac{\min(x_{ij})}{x_{ij}}$	$x_{ij} \neq 0$	When all elements are none 0. [effect of -ve]	<i>Ahmet Aytekin et al. (2021)</i> <i>Jahan & Edwards et al. (2015)</i>
	Cost criteria	$n_{ij} = \frac{\min(x_{ij})}{x_{ij}}$	$x_{ij} \neq 0$	When all elements are none 0. [effect of -ve]	
Max-Min Normalization (using 0-1 interval) N6	Benefit criteria	$n_{ij} = \frac{x_{ij}}{\max(x_{ij})}$	$\max(x_{ij}) \neq 0$	When its maximum element value is different from 0. [possibility of -ve]	<i>Ahmet Aytekin et al. (2021)</i> <i>Jahan & Edwards et al. (2015)</i>
	Cost criteria	$n_{ij} = \frac{\min(x_{ij})}{x_{ij}}$	$x_{ij} \neq 0$	When all elements are none 0. [possibility of -ve]	
/Max-Min/ (Jüttler-Körth Normalization N7)	Benefit criteria	$n_{ij} = 1 - \left \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij})} \right $	$\max(x_{ij}) \neq 0$	When the maximum value from the elements is none 0.	<i>Ahmet Aytekin et al. (2021)</i>
	Cost criteria	$n_{ij} = 1 - \left \frac{\min(x_{ij}) - x_{ij}}{\max(x_{ij})} \right $	$\max(x_{ij}) \neq 0$	When the maximum value from the elements is none 0.	
Stopp Normalization (N8)	Benefit criteria	$n_{ij} = \frac{100x_{ij}}{\max(x_{ij})}$	$\max(x_{ij}) \neq 0$	When the maximum value from the elements is none 0. [possibility of -ve, & range out of 1]	<i>Ahmet Aytekin et al. (2021)</i>
	Cost criteria	$n_{ij} = \frac{100\min(x_{ij})}{x_{ij}}$	$x_{ij} \neq 0$	When all elements are none 0. [possibility of -ve, & range out of 1]	
Nonlinear (Peldschus) Normalization (N9)	Benefit criteria	$n_{ij} = \left(\frac{x_{ij}}{\max(x_{ij})} \right)^2$	$\max(x_{ij}) \neq 0$	When the maximum value from the elements is none 0.	<i>Ahmet Aytekin et al. (2021)</i>
	Cost criteria	$n_{ij} = \left(\frac{x_{ij}}{\max(x_{ij})} \right)^3$	$\max(x_{ij}) \neq 0$	When the maximum value from the elements is none 0. [possibility of -ve]	

Max-Min (Weitendorf's Linear Normalization)	Benefit criteria	$n_{ij} = \frac{x_{ij} - \min(x_{ij})}{(\max(x_{ij}) - \min(x_{ij}))}$	$(\max(x_{ij}) - \min(x_{ij})) \neq 0$	For all except, when the difference b/n the maximum and minimum is 0. [possibility of -ve]	Ahmet Aytekin et al. (2021)
	Cost criteria	$n_{ij} = \frac{\max(x_{ij}) - x_{ij}}{(\max(x_{ij}) - \min(x_{ij}))}$	$(\max(x_{ij}) - \min(x_{ij})) \neq 0$	For all except, when the difference b/n the maximum and minimum is 0.	Nazanin Vafaei et al. (2022)
Z Score Normalization Depending Optimization Aspect	Benefit criteria	$n_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$	$\sigma_j \neq 0$	When the standard deviation is not 0. [possibility of -ve]	Ahmet Aytekin et al. (2021)
	Cost criteria	$n_{ij} = -\frac{x_{ij} - \mu_j}{\sigma_j}$	$\sigma_j \neq 0$	When the standard deviation is not 0. [possibility of -ve]	A. Jahan, K.L. Edwards et al (2015)
Nonlinear Normalization	Benefit criteria	$n_{ij} = (\frac{x_{ij}}{\max(x_{ij})})^2$	$\max(x_{ij}) \neq 0$	It can work for all cases except if the max of the element value is 0.	A. Jahan, K.L. Edwards et al (2015)
	Cost criteria	$n_{ij} = (\frac{\min(x_{ij})}{x_{ij}})^3$	$x_{ij} \neq 0$	It works for all none 0 element values.	Ahmet Aytekin et al. (2021)
Enhanced Accuracy Method	Benefit criteria	$n_{ij} = 1 - (\frac{\max(x_{ij}) - x_{ij}}{\sum_{i=1}^m (\max(x_{ij}) - x_{ij})})$	$\Sigma(\max(x_{ij}) - x_{ij}) \neq 0$	It's applicable except for sum is 0.	A. Jahan, K.L. Edwards et al (2015)
	Cost criteria	$n_{ij} = 1 - (\frac{x_{ij} - \min(x_{ij})}{\sum_{i=1}^m (x_{ij} - \min(x_{ij}))})$	$\Sigma(x_{ij} - \min(x_{ij})) \neq 0$	It's applicable except for sum is 0.	Ahmet Aytekin et al. (2021)
Lai & Hwang Method	Benefit criteria	$n_{ij} = \frac{x_{ij}}{(\max(x_{ij}) - \min(x_{ij}))}$	$\max(x_{ij}) - \min(x_{ij}) \neq 0$	It works if the max & min are not equal.	A. Jahan, K.L. Edwards et al (2015)
	Cost criteria	$n_{ij} = \frac{x_{ij}}{(\min(x_{ij}) - \max(x_{ij}))}$	$\min(x_{ij}) - \max(x_{ij}) \neq 0$	It works if the max & min are not equal.	

Specify maximum possible comparison scenarios (Seven-cases):

Then by observing the formula of each collected normalization method, each limitation has been analysed and specified clearly. From the reorganized **Table 3**, it obliged us to analyse the specified limitations and then investigated an approach to compare these normalization methods. Thus, based on the numeric values of the formulas seven basic cases or scenarios have identified for comparison by validity check-up. Four arbitrary alternatives considered in the decision matrix for this comparison. The seven-cases categorized for this comparison in the decision matrix are articulated as; Case 1: if $x_{ij} > 0$ - strictly positive, Case 2: if $x_{ij} \geq 0$ (if $x_{\min} = 0$) - positive including zero, Case 3: if $x_{ij} < 0$ - strictly negative, Case 4: if $x_{ij} \leq 0$ (if $x_{\max} = 0$) - non-positive, Case 5: if $x_{ij} \in Q$ - rational numbers, mixed, Case 6: if $\Sigma x_{ij} = 0$ - summation zero, and Case 7: if $\Sigma(1/x_{ij}) = 0$ - reciprocal summation zero.

4. Analysis

The analysis conducted in this study focuses on the systematic comparison and evaluation of benefit–cost criteria–based normalization methods to determine their suitability for improving decision accuracy and consistency in MCDM-based manufacturing sustainability assessments. Drawing on methods identified through an extensive literature review, the normalization methods were analytically examined under multiple predefined numerical scenarios representing heterogeneous data conditions, including wide variations in magnitude, mixed preference directions, and extreme boundary values. Each normalization method was assessed against key analytical criteria such as boundedness, numerical validity, stability, and consistency of normalized outputs across scenarios. Particular attention was given to the ability of each method to maintain normalized values within the standard range and to preserve

the relative preference structure of alternatives under both benefit and cost criteria. Through this scenario-based comparative analysis, all the proposed normalization methods in **Table 3** need to equally evaluate and compare them objectively. Consequently, the analysis supports the selection of the possible methods as a reliable normalization approach for reducing uncertainty and enhancing decision consistency in manufacturing sustainability-oriented MCDM applications. Therefore, the analysis follows some deceive steps to carry out.

Step-1: Define and specify possible data range to incorporate the seven-cases

The possible sample range of input data values for normalization in any decision analysis to clearly define and interpret the possible data values that can be collected or considered through consecutive analysis. That means these scenarios or cases are used to represent the possible numerical data value types (i.e., the numerical values using in the normalization process maybe a type of either one or more of the seven-case types of numerical classes). The data values maybe collected from alternatives' utility performance evaluation or criteria importance comparison. This data values normalization maybe carried out during weight determination or/and alternatives preference ranking analysis. But what matters is the identify the type of numerical values going to standardize within common and known range of values for the clarity of the analysis as well as narrowing variations. Accordingly, to be able to select the type of normalization method by testing on each of the seven cases. These cases accompany all possible input or any numerical values that ca be used during normalization of any decision-making application. In general, this study considers any rational number (excluding complex numbers). The seven-cases have defined, interpreted and classified as follows:

Case 1: Numerical values greater than zero. If the numerical values collected or considered for normalization are all positive.

Case 2: If the data value is greater than or equal to zero. That means, this case becomes "Case 1" + "zero".

Case 3: Represents numerical values with less than zero. If all values to normalize are negative.

Case 4: All negative numerical values including zero. Any less than or equals to zero numerical value are classified under this case.

Case 5: This case incorporates all rational numbers in one class. If numerical values to normalize include all type of rational numbers.

Case 6: If the sum of all the input numerical values (values to normalize) is zero.

Case 7: Represents if the sum of the reciprocals of the input numerical values is zero.

These cases appear to be numerical constraints or properties for columns in a mathematical or statistical exercise, possibly to illustrate different sign restrictions, summation invariants, or rational number sets.

Table 4: Sample possible range of input numerical values for normalization have considered based on the above stated cases.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Data number	$x_{ij} > 0$	$x_{ij} \geq 0$	$x_{ij} < 0$	$x_{ij} \leq 0$	$x_{ij} \in Q$	$\sum(x_{ij}) = 0$	$\sum(1/x_{ij}) = 0$
N1	0.001	0	-0.001	0	-1000	-10000	-500
N2	1	0.001	-10	-0.001	-30	-51	-24
N3	10	500	-5	-1	0	1	-8
N4	5	40	-50	-1000	100	30	9
N5	200	1000	-500	-5000	2000	20	18
N6	1000	20000	-1000	-10000	7000	10000	500

Step-2: Apply each normalization method in each of the seven-cases

The normalization carried out using the equation provided for each normalization in each of the demonstrated cases in **Table 3**. The numerical values provided in **Table 4** are arbitrarily assigned according to the defined cases for the purpose of methodological assessment. This sample data is not prescriptive; the values are interchangeable based on the stated cases (Case 1 to 7) to evaluate and test systematically the proposed normalization methods under the considered alternative scenarios/cases. Hence, changing the numeric entry values based on the scenarios could not affect the target evaluation of the methods. Therefore, that is possible to use different groups of numeric values, which can satisfy the cases considered. According to this governing concept and analysis approach, the evaluation of the normalization methods taken place for general functionality check-up. From the numerical calculation of each method by its respective benefit and cost criteria based general formula, the normalized range has determined. The numerical calculation carried out for the benefit and cost-criteria independently. The normalized range of values found different among the benefit and cost criteria optimization concepts within single method. Then it is possible to identify the functionality of the method for the specific cases from this calculated value. The «Range» column shown in **Table 5** presents the outcomes of the numerical analysis using each method. This validity decision has provided in the next section.

5. Result and Discussion

Based on the assessment described above, the target research findings of this study have been presented in this result section followed by brief discussion on the findings. It targeted to focus on normalized values shown under the «Range» column in **Table 5**. By observing the normalized range of the calculated values, it is possible to decide whether the normalization method could be applicable in each of the cases or not. The applicability of each method should be checked out in both the benefit and cost-criteria. If a method applicable/valid either for benefit or cost criteria and not applicable/invalid in either of them, then overall decision has to be invalid. A normalization method to be valid or accepted in its overall decision it should be valid or applicable in both the benefit and cost criteria. As a result, it has compared and selected a best normalization method for any MCDM problem in order to select the best alternative. Thus, the calculated range and validity check-up of the normalization method presented in

Table 5.

Table 5 Result summary for validity check-up of all the proposed normalization methods.

Normalization method	Optimization aspect	Range							Decision Selection	For general use
		Case 1 (C1)	Case 2 (C2)	Case 3 (C3)	Case 4 (C4)	Case 5 (C5)	Case 6 (C6)	Case 7 (C7)		
Sum-based Linear	Benefit	(0-0.83)	(0-1)	(0-0.64)	[0-0.63]	(-0.13-0.87)	undefined	(-100-100)	Possible except C6 with range limit.	Rejected
	Cost	(1-0)	undefined	(1-0)	undefined	undefined	(-E4-E4)	undefined	Possible for C1, & C3 with range limit.	
Vector	Benefit	(0-1)	[0-1]	(-1-0)	(-1-0]	(-0.14-1)	(-0.7-7)	(-0.7-0.7)	Possible for all cases with range limit.	Recommended
	Cost	(0.02-1)	(0-1)	(1-2)	[1-2]	(0.05-1.14)	(0.2-1.7)	(0.2-1.7)		
Max (N4)	Benefit	(0-1)	[0-1]	[1-E6]	undefined	(-0.15-1]	[-1-1]	[-1-1]	Maybe for all except C4	Rejected
	Cost	[0-1]	[0-1]	(-E6-0]	undefined	[0-1.15)	[0-2]	[0-2]		
Logarithmic	Benefit	(-0.8-0.8)	Impossible	Impossible	Impossible	Impossible	Partially impossible	Impossible	Impossible for all except C1.	Rejected
	Cost	(0.05-0.4)	Impossible	Impossible	Impossible	Impossible	Partially impossible	Impossible		
Minimum-Linear (N5)	Benefit	[0-1]	Partially undefined	(-E6-0]	Partially undefined	Partially undefined	(-195-335)	(-62-57)	It looks undefined & unpredicted for all except for C1.	Rejected
	Cost	[0-1]	Partially undefined	(E6-1]	Partially undefined	Partially undefined	(-334-196)	(-56-63)		
Max-Min (N6)	Benefit	(0-1)	[0-1]	[1-E6]	undefined	(-0.15-1]	[-1-1]	[-1-1]	Maybe for C1 only.	Rejected
	Cost	[1-0]	Partially undefined	(E6-1]	Partially undefined	Partially undefined	(-334-196)	(-56-21)		
/Max-Min/ (N7)	Benefit	(0-1)	[0-1]	(-E6-1]	undefined	(-0.15-1]	[-1-1]	[1-1]	Maybe for C1, C2, C5, C6 & C7.	Rejected
	Cost	[1-0]	[1-0]	(-E6-1]	undefined	(-0.15-1]	[-1-1]	[-1-1]		
Stopp (N8)	Benefit	(0-100)	[0-100]	(100-E8)	undefined	(-15-100)	(-100-100)	(100-100)	Cannot give normalized value.	Rejected
	Cost	(100-0)	Partially undefined	(E8-100)	Partially undefined	Partially undefined	(-E4-E4)	(-E4-2000)		
Nonlinear (Peldschus-N9)	Benefit	(0-1)	[0-1]	[1-E12]	undefined	(0-1)	[1-1]	[1-1]	Maybe for C1, C2, C6 & C7.	Rejected
	Cost	(0-1)	[0-1]	[1-E18]	undefined	(-8-2)	[-1-1]	[-1-1]		
Max-Min WL	Benefit	[0-1]	[0-1]	[0-1]	[0-1]	[0-1]	[0-1]	[0-1]	Suitable for all cases.	Highly recommended
	Cost	[0-1]	[0-1]	[0-1]	[0-1]	[0-1]	[0-1]	[0-1]		
Z Score	Benefit	(-0.23-0.9)	(-0.2-0.92)	(-0.8-0.3)	(-0.8-0.3)	(-0.4-0.9)	(-0.7-7)	(-0.7-0.7)	Gives values but irrelevant value.	Rejected
	Cost	(-0.9-0.3)	(-0.9-0.2)	(-0.28-0.8)	(-0.29-0.8)	(-0.9-0.4)	(-0.7-0.7)	(-0.7-0.7)		
Nonlinear	Benefit	(0-1)	[0-1]	[1-E12]	undefined	(0-1)	[1-1]	[1-1]	Maybe for C1, C6 & C7.	Rejected
	Cost	(0-1)	Partially undefined	[1-E18]	Partially undefined	Partially undefined	(-1-1]	(-1-1]		
Enhanced Accuracy	Benefit	(0.7-1]	[0.7-1]	[1-0.3]	[1-0.3]	(0.7-1]	(0.6-1]	(0.6-1]	Possible for all with range limit.	Highly Recommended
	Cost	(0.1-1]	[0-1]	(0.7-1]	(0.7-1]	(0.4-1]	(0.6-1]	(0.6-1]		
Lai & Hwang	Benefit	(0-1)	[0-1]	(-1-0)	[-1-0]	(-0.13-0.9)	[-0.5-0.5]	[-0.5-0.5]	Possible for all with range limit.	Recommended
	Cost	(-1-0)	[-1-0]	(0-1)	[0-1]	(-0.9-0.13)	[-0.5-0.5]	[-0.5-0.5]		

The normalization methods assessment carried out with seven entry value scenarios were tested for numerical stability of normalized values in terms of analysis reliability, recommended range limit, and consistency with varied entry values. A normalization method can work and give numerical value, or fail to work due to different limitations (the reason that the seven cases classified). However, obtaining a numerical value cannot make the normalization method valid; rather the numerical value should be within a recommended range of limit (the shorter or closer range becomes the better method). Therefore, the normalization method with shorter range and same to all cases considered consistently acceptable method to all cases. The different shorter range of values in all cases within recommended range also be recommended normalization methods. Some normalization methods also can acceptably work for one or more cases but may fail in one or more cases. The normalization methods produced; undefined values, values with exponentials, produced a value with very high gaps considered as the invalid or failed methods. In the next sections, each of the methods with respect to the assessment cases have discussed in detail.

Sum-based linear normalization:

From the results, the method shows severe instability when applied across heterogeneous cases. For benefit criteria, the method behaves acceptably only, when all values are strictly positive and the column sum is nonzero (Cases 1–2). However, when the sum of criterion values equals zero (Case 6) or contains negative values (Cases 3–5), the normalization collapses entirely, producing division by zero errors or sign-inverted outputs respectively. For cost criteria, the situation worsens: inversion magnifies small denominators and introduces extreme numerical mess. The method therefore lacks domain robustness and fails under several realistic decision cases. Therefore, is not reliable enough for general decision problems. It only functions correctly under narrow assumptions (strict positivity and nonzero sums). Outside these conditions, it either collapses mathematically or produces misleading decision signals.

Vector Normalization: maintains mathematical consistency across most cases and avoids division-by-zero errors in many cases. For benefit criteria, it preserves proportionality but strongly reflects the original data magnitude, leading to dominance of high-range alternatives (e.g., N6 in Cases 1, 2, and 5). For cost criteria, inversion produces normalized values clustered tightly around 1 for most alternatives, reducing discrimination power. Although the method handles negative values better, the results show that it systematically biases rankings toward extreme magnitudes rather than relative performance. Therefore, is analytically consistent but practically biased toward high-magnitude criteria. It is suitable when criteria scales are comparable, but less reliable in general-purpose decision problems.

Max (N4) Normalization: this method also performs poorly in different datasets. For benefit criteria, dividing by the maximum produces extremely inflated values when negative or near-zero values are present, especially in Case 3. For cost criteria, inversion generates negative infinities and large negative magnitudes, leading to numerical inconsistency. The appearance of division-by-zero error in Case 4 further confirms poor performance. Therefore, this method is not reliable and should not be used in

general decision-making contexts.

Logarithmic Normalization: it demonstrated a very limited applicability because logarithm is undefined for zero and negative values. The method failed in most cases across benefit and cost perspective. Even when valid, there are inversion of signs. This behavior makes the method unsuitable for datasets with mixed signs or zero entries, which are common in real-world decision problems. This method is mathematically restrictive and practically unusable for general-purpose normalization.

Minimum-Linear (N5) Normalization: exhibits extreme numerical instability. For benefit criteria, subtracting the minimum value leads to explosive scaling when the minimum is highly negative, producing values about millions or more. For cost criteria, inversion amplifies this effect further, generating sign reversals and meaningless magnitudes. Although theoretically correct under strict assumptions, those assumptions are violated in most realistic datasets. In conclusion, this method is numerically unsafe and unsuitable for decision matrices.

Max-Min (N6) Normalization: shows behavior similar to Max (N4), with severe instability in cases involving zero ranges or negative values. The results indicate that when case 4 is applied, the method collapses entirely. For benefit criteria, scaling inflates differences excessively, while for cost criteria, inversion leads to exaggerated values. Max-Min (N6) Normalization is unreliable without preprocessing of the data and cannot be recommended for general use.

/Max-Min/ Normalization: this method exhibits even poorer behavior than its parent method. The outputs show sign inversions, extreme negative magnitudes, total failure in case 4 and loss of interpretability in both benefit and cost criteria. The transformation does not preserve ordinal relationships consistently and introduces artificial dominance effects unrelated to actual performance. This normalization method is mathematically inconsistent and should be avoided.

Stopp (N8) Normalization: magnifies numerical values aggressively, especially for benefit criteria. The results demonstrate exponential growth across cases with large input values, leading to dominance of high-range alternatives. For cost criteria, inversion causes similarly exaggerated results. While the method clearly separates alternatives, it does so at the expense of numerical stability and interpretability. Complete failure in case 4 considering benefit perspective and in case of cost perspective under case 4 and case 5, there is failure when value is 0. Therefore, Stopp is overly aggressive and unsuitable for balanced multi-criteria evaluation.

Nonlinear (Peldschus-N9) Normalization: The results show that strongly emphasizes extreme values. For benefit criteria, high-performing alternatives dominate almost completely, while mid-range alternatives collapse toward zero. For cost criteria, poor alternatives are excessively penalized. This method is highly sensitive to small data changes and lacks smooth discrimination across the decision space. It fails completely under case 4 considering both benefit and cost perspective. This method is appropriate only for threshold-based decisions, not general-purpose evaluation.

Max-Min WL Normalization: demonstrates significantly improved behavior compared to classical

Max–Min. The results show bounded outputs, smoother transitions, and consistent handling of both benefit and cost criteria. The weighted linear adjustment prevents extreme inflation and preserves relative differences without collapse. This method remains stable across all seven cases. Max–Min WL Normalization is reliable and suitable for general decision-making applications.

Z Score Normalization: produces statistically centered results with symmetric behavior for benefit and cost criteria. The outputs show stable numerical values without overflow or undefined operations. However, normalized values have inverted signs complicating interpretation in ranking-based MCDM methods. The method also assumes approximately normal distributions, which may not hold in practice. It is statistically sound but less intuitive for decision-making.

Nonlinear Normalization: displays extreme numerical instability in the results. The method generates astronomically large values, frequent division errors, and sign inconsistencies. Both benefit and cost criteria suffer from uncontrolled scaling, rendering the normalized values unusable for aggregation or comparison. This method is mathematically unsafe and unsuitable for any general-purpose application.

Enhanced Accuracy Normalization: demonstrates the most balanced behavior across all cases. The results show bounded, smooth, and interpretable normalized values for both benefit and cost criteria. The method avoids division-by-zero, controls outliers, and preserves discrimination without dominance distortion. Even in complex cases, the normalization remains stable. This method provides the best compromise between robustness, reliability, and interpretability.

Lai & Hwang Normalization: exhibits symmetric behavior for benefit and cost criteria, maintaining sign consistency and relative ordering. However, the results show limited dynamic range and sensitivity, causing clustering of alternatives. This method is stable and recommended.

Table 6 Applicability of the normalization methods under each case.

Proposed normalization methods	Applicable in cases within recommended range		Applicable in cases without range limit		Invalid	
	Benefit	Cost	Benefit	Cost	Benefit	Cost
Sum-based Linear Normalization	Case 1		Case 7	Case 1	Case 6	Case 2
	Case 2			Case 3		Case 4
	Case 3			Case 6		Case 5
	Case 4					Case 7
	Case 5					
Vector Normalization	Case 1	Case 1				
	Case 2	Case 2				
	Case 3	Case 3				
	Case 4	Case 4				
	Case 5	Case 5				
	Case 6	Case 6				
	Case 7	Case 7				
Max (N4) Normalization	Case 1	Case 1	Case 3	Case 3	Case 4	Case 4
	Case 2	Case 2				
	Case 5	Case 5				
	Case 6	Case 6				
	Case 7	Case 7				
Logarithmic Normalization	Case 1	Case 1			Case 2	Case 2
					Case 3	Case 3

					Case 4 Case 5 Case 6 Case 7	Case 4 Case 5 Case 6 Case 7
Minimum-Linear (N5) Normalization	Case 1	Case 1	Case 3 Case 6 Case 7	Case 3 Case 6 Case 7	Case 2 Case 4 Case 5	Case 2 Case 4 Case 5
Max-Min (N6) Normalization	Case 1 Case 2 Case 5 Case 6 Case 7	Case 1 Case 5 Case 6 Case 7	Case 3	Case 3 Case 6 Case 7	Case 4	Case 2 Case 4 Case 5
/Max-Min/ (N7) Normalization	Case 1 Case 2 Case 5 Case 6 Case 7	Case 1 Case 2 Case 5 Case 6 Case 7	Case 3	Case 3	Case 4	Case 4
Stopp (N8) Normalization			Case 1 Case 2 Case 3 Case 5 Case 6 Case 7	Case 3 Case 6 Case 7	Case 4	Case 2 Case 4 Case 5
Nonlinear (Peldschus-N9) Normalization	Case 1 Case 2 Case 5 Case 6 Case 7	Case 1 Case 2 Case 5 Case 6 Case 7	Case 3	Case 3	Case 4	Case 4
Max-Min WL Normalization	Case 1 Case 2 Case 3 Case 4 Case 5 Case 6 Case 7	Case 1 Case 2 Case 3 Case 4 Case 5 Case 6 Case 7				
Z Score Normalization	Case 1 Case 2 Case 3 Case 4 Case 5 Case 6 Case 7	Case 1 Case 2 Case 3 Case 4 Case 5 Case 6 Case 7				
Nonlinear Normalization	Case 1 Case 2 Case 5 Case 6 Case 7	Case 1	Case 3	Case 3 Case 6 Case 7	Case 4	Case 2 Case 4 Case 5
Enhanced Accuracy Normalization	Case 1 Case 2 Case 3 Case 4 Case 5 Case 6 Case 7	Case 1 Case 2 Case 3 Case 4 Case 5 Case 6 Case 7				
Lai & Hwang Normalization	Case 1 Case 2 Case 3 Case 4 Case 5	Case 1 Case 2 Case 3 Case 4 Case 5				

Case 6	Case 6
Case 7	Case 7

NB: *Applicable in cases without range limit = mathematically correct but its output range is irrelevant so it cannot be used as a normalization method under the listed cases.*

Across heterogeneous numerical ranges, mixed-sign data, and conflicting optimization aspects, normalization methods differ fundamentally in reliability and interpretability. According to [34], the normalization method with normalized value within or near the range 0 to 1 widely recommended as the best acceptable method. Hence, to compare and select best normalization method for specific decision problem comprehensively observe the analysis result provided in **Table 5**. Based on the comprehensive evaluation of all fourteen normalization methods across multiple numerical cases and under both benefit and cost criteria, **Enhanced Accuracy Normalization** is identified as the most suitable normalization method (with very short range of normalized values) for general-purpose MCDM applications. This selection is justified by its consistent numerical stability, bounded outputs, and balanced discrimination capability across all tested cases. Unlike other methods, **Enhanced Accuracy Normalization** does not suffer from division-by-zero errors, uncontrolled value inflation, or sign inconsistencies when dealing with heterogeneous, zero-inclusive, or mixed-sign datasets. Furthermore, it preserves the relative ordering of alternatives without allowing extreme values to dominate the decision space, ensuring both robustness, reliability and interpretability. In addition, the gap differences among the values are very low compared to Max-Min WL. These characteristics make it adaptable to a wide range of real-world decision problems without the need for extensive data preprocessing.

As a second-best alternative, **Max-Min WL** Normalization is recommended (with [0-1] range of normalized values in all cases). This method demonstrates improved performance over conventional max-min normalization by incorporating weighted linear adjustments that control numerical extremes. The results confirm that it remains stable under both benefit and cost criteria while maintaining meaningful discrimination among alternatives. However, its reliance on range-based scaling makes it slightly more sensitive to extreme values compared to Enhanced Accuracy Normalization.

The third-best option is **Vector Normalization**. This method offers strong mathematical stability and avoids undefined operations in most cases. It is particularly effective when criteria are measured on comparable scales. Nevertheless, the results indicate that it can introduce scale dominance, allowing high-magnitude alternatives to disproportionately influence the decision outcome, which limits its general applicability. The most recommended normalization methods are ranked sequentially from left to right as shown in **Fig. 1**.

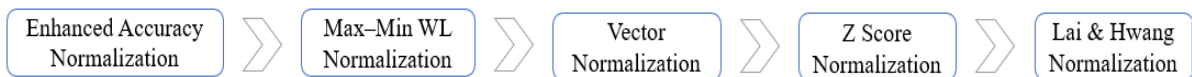


Fig. 1 Most recommended normalization methods highly applicable to all the evaluation cases ranked from left-to-right.

In conclusion, the range of normalized values, behavior of realistic analysis, and overall functional

validity have considered in selecting the normalization methods in **Table 5**. The Enhanced Accuracy Normalization and Max–Min WL Normalization become the most recommended methods as the primary and secondary normalization methods for general-purpose use respectively. Consecutively, the Vector, Z Score, and Lai & Hwang Normalization methods are the next most recommended options for general-purpose application respectively when problem-specific conditions justify their application. One or more normalization methods can be used during single decision-making analysis problem across either cases or optimization aspect wise. Generally, the other normalization methods can also apply based on the following priority from top-left to bottom-right direction **Fig. 2**. However, it is recommended to use the most suitable normalization method in order to make best decision.

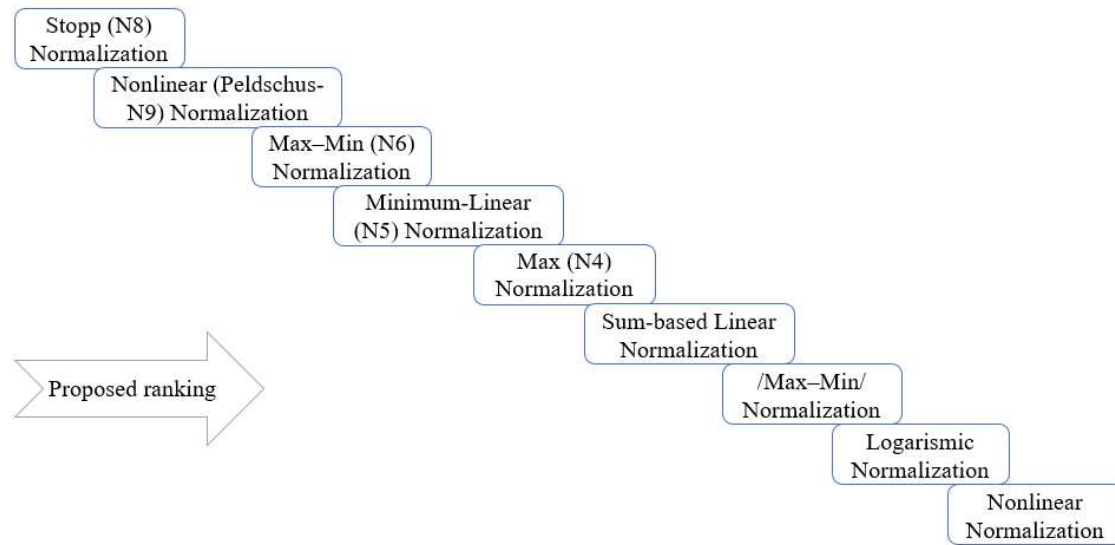


Fig. 2 Possible preference of the rest normalization methods priority from top-left to bottom-right direction.

6. Conclusion and Recommendation

The MCDM process performed by considering a number of factors that affect both the decision-making process and the final decision outcome. One of the key challenges in MCDM applications arises from the wide variation in input data, which may result from differences in measurement units, magnitudes, or evaluation scales. Such variations can negatively affect decision accuracy if they are not addressed appropriately. Consequently, the selection of an appropriate normalization method plays a significant role in ensuring reliable and accurate decision outcomes.

As discussed in the above sections, various normalization methods were examined and selected based on their capability to appropriately handle different cases under benefit and cost perspective. Those methods have been investigated whether they could be effectively applied across different MCDM analyses and scenarios/cases. To achieve the objective, seven cases or scenarios which reflect different numerical input conditions. In these cases, directly evaluated or exact values were used instead of relative importance-based ratios. The use of directly evaluated values significantly reduces uncertainty associated with subjective judgments and enhances the reliability of the decision-making process.

Following a comprehensive evaluation of the methods, several important observations were obtained. It

was observed that many normalization methods generated values outside the conventional [0-1] range, with unpredictable dispersion patterns, which limits their general applicability. However, eight normalization methods demonstrated comparatively acceptable behavior, producing normalized values predominantly within a bounded range of approximately [-2-2], as summarized in **Table 5**.

Among all the evaluated methods, Enhanced Accuracy normalization exhibited the most consistent and robust performance under both benefit and cost criteria. This method demonstrated balanced scaling behavior, reduced sensitivity to extreme values, and improved numerical stability across all tested cases. Importantly, it avoided excessive boundary saturation and maintained proportional discrimination among alternatives, making it well suited for general-purpose application. As a result, Enhanced Accuracy Normalization is identified as the most appropriate normalization method for achieving the objectives of this study and can be effectively applied in both simple and hybrid MCDM techniques to improve decision accuracy.

The Max–Min WL normalization method emerged as a strong secondary alternative. This method consistently normalized criterion values within the standard [0-1] range for both benefit and cost aspects demonstrated clear discrimination among alternatives. Its reliance on range-based scaling introduces a degree of sensitivity to extreme values and dataset composition, which slightly limits its robustness when compared to Enhanced Accuracy normalization. Nevertheless, Max–Min WL normalization remains a reliable and effective choice, particularly in applications where bounded normalization and strong interpretability are required. In addition, Vector, Z Score, Lai & Hwang, and so on normalization methods have been proposed respectively as suitable methods prioritized subsequently in **Fig. 1 & Fig. 2**.

In general, the comparative results indicate that while Max–Min WL normalization is capable of standardizing criterion values within a strict [0-1] range, Enhanced Accuracy normalization provides superior adaptability, numerical robustness, and balance across diverse decision scenarios. The primary objective of this research is to improve the accuracy of decision-making processes and support better decision outcomes. The findings contribute significantly to reducing risks associated with data variability and uncertainty in MCDM applications.

Furthermore, this study can provide meaningful contributions toward broader socio-economic development goals, including the United Nations Sustainable Development Goals (UN SDGs). Since decision-making methodology are widely applied across sectors such as engineering, sustainability, and policy planning, improving normalization reliability directly enhances the quality and sustainability of development-oriented decisions. Specifically, for benefit- and cost-based optimization aspects of decision-making processes.

Finally, as the accuracy of decision-making is progressive and heavily dependent on quality and reliability of input data, further research recommended to explore advanced methods for improving data quality and managing decision related risks. Future studies should focus on identifying more effective

approaches for obtaining high quality input data and suitable normalization methods. In this regard, machine learning based data and decision analysis processes maybe utilized to enhance data prediction and support more reliable decision-making processes.

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References

- [1] OECD, "Sustainable Manufacturing and Eco-innovation: towards a green economy. Organization for Economic Cooperation and Development, 2009.," in *Sustainable Manufacturing and Eco-innovation: towards a green economy*, OECD, Ed., OECD, 2009.
- [2] M. Shriberg, "Assessing sustainability: Criteria, tools, and implications," in *Higher education and the challenge of sustainability: Problematics, promise, and practice*, Springer, 2004, pp. 71–86.
- [3] P. Glavič and R. Lukman, "Review of sustainability terms and their definitions," *J. Clean. Prod.*, vol. 15, no. 18, pp. 1875–1885, 2007, doi: 10.1016/j.jclepro.2006.12.006.
- [4] US Department of Commerce, "Sustainable manufacturing initiative, in *Proceedings of the 2nd Annual Sustainable Manufacturing Summit 2009*." Chicago, USA., Chicago USA, 2009.
- [5] and A. K. S. Gupta, S., G. Dangayach, "Key determinants of sustainable product design and manufacturing," *Procedia CIRP*, vol. 26, pp. 99–102, 2015.
- [6] C. F. Oduoza, "Framework for sustainable risk management in the manufacturing sector," *Procedia Manuf.*, vol. 51, pp. 1290–1297, Jan. 2020, doi: 10.1016/j.promfg.2020.10.180.
- [7] E. Amrina and S. M. Yusof, "Key performance indicators for sustainable manufacturing evaluation in automotive companies," in *IEEE International Conference on Industrial Engineering and Engineering Management*, 2011, pp. 1093–1097. doi: 10.1109/IEEM.2011.6118084.
- [8] A. Jamwal, R. Agrawal, M. Sharma, and V. Kumar, "Review on multi-criteria decision analysis in sustainable manufacturing decision making," *Int. J. Sustain. Eng.*, vol. 14, no. 3, pp. 202–225, 2021, doi: 10.1080/19397038.2020.1866708.
- [9] A. Silvestri, F. De Felice, and A. Petrillo, "Multi-criteria risk analysis to improve safety in manufacturing systems," *Int. J. Prod. Res.*, vol. 50, no. 17, pp. 4806–4821, 2012, doi: 10.1080/00207543.2012.657968.
- [10] I. I. Karayalcin, "The analytic hierarchy process: Planning, priority setting, resource allocation," *Eur. J.*

- Oper. Res.*, vol. 9, no. 1, pp. 97–98, 1982, doi: 10.1016/0377-2217(82)90022-4.
- [11] C.-T. Chen, “Extensions of the TOPSIS for group decision-making under fuzzy environment,” *Fuzzy Sets Syst.*, vol. 114, no. 1, pp. 1–9, 2000, doi: [https://doi.org/10.1016/S0165-0114\(97\)00377-1](https://doi.org/10.1016/S0165-0114(97)00377-1).
 - [12] A. Alinezhad and J. Khalili, “VIKOR Method,” in *International Series in Operations Research and Management Science*, A. Alinezhad and J. Khalili, Eds., Cham: Springer International Publishing, 2019, pp. 23–27. doi: 10.1007/978-3-030-15009-9_4.
 - [13] B. Roy, “The outranking approach and the foundations of electre methods,” *Theory Decis.*, vol. 31, no. 1, pp. 49–73, 1991, doi: 10.1007/BF00134132.
 - [14] D. R. Tobergte and S. Curtis, “A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making),” *J. Chem. Inf. Model.*, vol. 53, no. 9, pp. 1689–1699, 2013.
 - [15] V. Swarnakar et al., “Prioritizing Indicators for Sustainability Assessment in Manufacturing Process: An Integrated Approach,” *Sustain.*, vol. 14, no. 6, 2022, doi: 10.3390/su14063264.
 - [16] G. Taddese, S. Durieux, and E. Duc, “Sustainability performance indicators for additive manufacturing: a literature review based on product life cycle studies,” *Int. J. Adv. Manuf. Technol.*, vol. 107, no. 7–8, pp. 3109–3134, 2020, doi: 10.1007/s00170-020-05249-2.
 - [17] and A. D. Bhatt, Y., K. Ghuman, “Sustainable manufacturing. Bibliometrics and content analysis,” *J. Clean. Prod.*, vol. 260, p. 120 988, 2020, doi: 10.1016/j.jclepro.2020.120988.
 - [18] J. Malek and T. N. Desai, “A systematic literature review to map literature focus of sustainable manufacturing,” *J. Clean. Prod.*, vol. 256, p. 120345, 2020, doi: 10.1016/j.jclepro.2020.120345.
 - [19] S. D. Goal, F. Principles, O. Statistics, S. Framework, and D. R. Reduction, “Global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development,” *UNSDG*, vol. E/CN.3/202, pp. 1–23, 2023, doi: <https://unstats.un.org/sdgs/indicators/indicators-list/>.
 - [20] D. Brackfield, “OECD Main Economic Indicators,” *Encycl. Qual. Life Well-Being Res.*, pp. 4468–4471, 2014, doi: 10.1007/978-94-007-0753-5_2002.
 - [21] OECD, “Interpreting OECD Social Indicators, in Society at a Glance 2019: OECD Social Indicators,” *OECD Publ. Paris.*, 2019, doi: 10.1787/bab0fe93-en.
 - [22] UN, “United Nations Statistical Commission: 53rd Session,” *Dep. Econ. Soc. Aff. Stat.*, 2022, doi: <https://unstats.un.org/UNSDWebsite/statcom/53>.
 - [23] M. Marcussen, “Organization for Economic Cooperation and Development,” *Int. Encycl. Soc. Policy*, pp. 960–961, 2013, [Online]. Available: <https://www.oecd-ilibrary.org/statistics>
 - [24] R. Schneider, “Measuring Social Dimensions of Sustainable Production,” *OECD iLibrary*, pp. 39–47, 2008, doi: 10.1787/9789264044135-6-en.
 - [25] P. Bhambri and P. Bajdor, “Technological sustainability unveiled: a comprehensive examination of economic, social, and environmental dimensions,” in *Handbook of technological sustainability*, CRC Press, 2025, pp. 80–98.
 - [26] A. Jamwal, R. Agrawal, M. Sharma, and V. Kumar, “Review on multi-criteria decision analysis in sustainable manufacturing decision making,” *Int. J. Sustain. Eng.*, vol. 14, no. 3, pp. 202–225, 2021, doi: 10.1080/19397038.2020.1866708.
 - [27] T. Waas, J. Hugé, T. Block, T. Wright, F. Benitez-Capistros, and A. Verbruggen, “Sustainability assessment and indicators: Tools in a decision-making strategy for sustainable development,” *Sustain.*, vol. 6, no. 9, pp. 5512–5534, 2014, doi: 10.3390/su6095512.
 - [28] M. H. Saad, M. A. Nazzal, and B. M. Darras, “A general framework for sustainability assessment of manufacturing processes,” *Ecol. Indic.*, vol. 97, pp. 211–224, 2019, doi: 10.1016/j.ecolind.2018.09.062.
 - [29] B. M. Angela, M. Simona, and L. Francesco, “A framework to assess the sustainability of additive manufacturing for spare parts,” *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 1509–1514, 2022, doi: 10.1016/j.ifacol.2022.09.604.
 - [30] H. Jayawardane, I. J. Davies, J. R. Gamage, M. John, and W. K. Biswas, “Sustainability perspectives – a review of additive and subtractive manufacturing,” *Sustain. Manuf. Serv. Econ.*, vol. 2, p. 100015, 2023, doi: 10.1016/j.smse.2023.100015.
 - [31] F. Jovane et al., “The incoming global technological and industrial revolution towards competitive sustainable manufacturing,” *CIRP Ann. - Manuf. Technol.*, vol. 57, no. 2, pp. 641–659, 2008, doi: 10.1016/j.cirp.2008.09.010.
 - [32] G. Pal, K. Atkinson, and G. Li, “Managing heterogeneous data on a big data platform: A multi-criteria decision making model for data-intensive science,” in *Proceedings - 2020 IEEE International Conference on Big Data and Smart Computing, BigComp 2020, IEEE, 2020*, pp. 229–239. doi: 10.1109/BigComp48618.2020.00-69.
 - [33] A. Aytekin, “Comparative analysis of normalization techniques in the context of MCDM problems,” *Decis. Mak. Appl. Manag. Eng.*, vol. 4, no. 2, pp. 1–25, 2021, doi: 10.31181/dmame210402001a.
 - [34] A. Jahan and K. L. Edwards, “A state-of-the-art survey on the influence of normalization techniques in

- ranking: Improving the materials selection process in engineering design," *Mater. Des.*, vol. 65, pp. 335–342, 2015, doi: 10.1016/j.matdes.2014.09.022.
- [35] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Assessing Normalization Techniques for Simple Additive Weighting Method," *Procedia Comput. Sci.*, vol. 199, pp. 1229–1236, 2021, doi: 10.1016/j.procs.2022.01.156.
- [36] D. T. Do, V. D. Tran, V. D. Duong, and N.-T. Nguyen, "Investigation of the Appropriate Data Normalization Method for Combination with Preference Selection Index Method in MCDM," *Oper. Res. Eng. Sci. Theory Appl.*, vol. 6, no. 1, pp. 44–64, 2023, [Online]. Available: <https://oresta.org/menu-script/index.php/oresta/article/view/329>
- [37] J. Kozłowska, M. A. Benvença, and I. de A. Nääs, "Investment Risk and Energy Security Assessment of European Union Countries Using Multicriteria Analysis," *Energies*, vol. 16, no. 1, p. 330, 2023, doi: 10.3390/en16010330.
- [38] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Normalization techniques for multi-criteria decision making: Analytical hierarchy process case study," in *IFIP Advances in Information and Communication Technology*, Springer, 2016, pp. 261–268. doi: 10.1007/978-3-319-31165-4_26.
- [39] B. Urugun and R. Rajan, "Developing an appropriate data normalization method," in *Proceedings - 10th International Conference on Machine Learning and Applications, ICMLA 2011, IEEE, 2011*, pp. 195–199. doi: 10.1109/ICMLA.2011.53.
- [40] O. Viikki and K. Laurila, "Cepstral domain segmental feature vector normalization for noise robust speech recognition," *Speech Commun.*, vol. 25, no. 1–3, pp. 133–147, 1998, doi: 10.1016/S0167-6393(98)00033-8.
- [41] N. Salkind, "Normalizing Data," *Encycl. Res. Des.*, vol. 1, pp. 935–938, 2012, doi: 10.4135/9781412961288.n278.
- [42] M. Mazziotto and A. Pareto, "Normalization methods for spatio-temporal analysis of environmental performance: Revisiting the Min–Max method," *Environmetrics*, vol. 33, no. 5, p. e2730, 2022, doi: 10.1002/env.2730.
- [43] Z. Wen, H. Liao, and E. K. Zavadskas, "MACONT: Mixed Aggregation by Comprehensive Normalization Technique for Multi-Criteria Analysis," *Inform.*, vol. 31, no. 4, pp. 857–880, 2020, doi: 10.15388/20-INFOR417.
- [44] S. Malefaki, D. Markatos, A. Filippatos, and S. Pantelakis, "A Comparative Analysis of Multi-Criteria Decision-Making Methods and Normalization Techniques in Holistic Sustainability Assessment for Engineering Applications," *Aerospace*, vol. 12, no. 2, p. 100, 2025. doi: 10.3390/aerospace12020100.
- [45] A. R. Krishnan, "Past efforts in determining suitable normalization methods for multi-criteria decision-making: A short survey," *Front. Big Data*, vol. 5, p. 990699, 2022, doi: 10.3389/fdata.2022.990699.
- [46] A. Vega, J. Aguarón, J. García-Alcaraz, and J. M. Moreno-Jiménez, "Notes on dependent attributes in TOPSIS," *Procedia Comput. Sci.*, vol. 31, pp. 308–317, 2014, doi: 10.1016/j.procs.2014.05.273.
- [47] D. Tuckett et al., "Uncertainty, Decision Science, and Policy Making: A Manifesto for a Research Agenda," *Crit. Rev.*, vol. 27, no. 2, pp. 213–242, 2015, doi: 10.1080/08913811.2015.1037078.
- [48] M. Yazdi, S. Kabir, and M. Walker, "Uncertainty handling in fault tree based risk assessment: state of the art and future perspectives," *Process Saf. Environ. Prot.*, vol. 131, pp. 89–104, 2019.
- [49] D. Singh and B. Singh, "Feature wise normalization: An effective way of normalizing data," *Pattern Recognit.*, vol. 122, p. 108307, 2022.
- [50] J. Barzilai and B. Golany, "Ahp Rank Reversal, Normalization And Aggregation Rules," *INFOR Inf. Syst. Oper. Res.*, vol. 32, no. 2, pp. 57–64, May 1994, doi: 10.1080/03155986.1994.11732238.
- [51] L. Wang and P. Rani, "Sustainable supply chains under risk in the manufacturing firms: an extended double normalization-based multiple aggregation approach under an intuitionistic fuzzy environment," *J. Enterp. Inf. Manag.*, vol. 35, no. 4/5, pp. 1067–1099, 2022.
- [52] J. B. Cabral and A. R. Schachner, "Addressing Methodological Uncertainty in MCDM with a Systematic Pipeline Approach to Data Transformation Sensitivity Analysis," *arXiv Prepr. arXiv2509.24996*, 2025, [Online]. Available: <http://arxiv.org/abs/2509.24996>
- [53] M. Gul and A. F. Guneri, "A fuzzy multi criteria risk assessment based on decision matrix technique: A case study for aluminum industry," *J. Loss Prev. Process Ind.*, vol. 40, pp. 89–100, 2016, doi: 10.1016/j.jlp.2015.11.023.
- [54] P. K. Marhavilas and D. E. Koulouriotis, "A risk-estimation methodological framework using quantitative assessment techniques and real accidents' data: Application in an aluminum extrusion industry," *J. Loss Prev. Process Ind.*, vol. 21, no. 6, pp. 596–603, 2008, doi: 10.1016/j.jlp.2008.04.009.
- [55] M. Baydaş, T. Eren, and M. Iyibildiren, "Normalization Technique Selection for MCDM Methods: A Flexible and Conjunctural Solution that can Adapt to Changes in Financial Data Types," *J. Fac. Polit. Sci.*, vol. 5, no. December, pp. 148–164, 2023.

- [56] A. Çelen, "Comparative analysis of normalization procedures in TOPSIS method: with an application to Turkish deposit banking market," *Informatica*, vol. 25, no. 2, pp. 185–208, 2014.
- [57] L. G. Kitila, E. Duc, S. Durieux, and G. A. Taddese, "An integrated fuzzy AHP-fuzzy TOPSIS approach for multi-criteria decision-making framework in sustainable manufacturing process selection," *Int. J. Adv. Manuf. Technol.*, vol. 142, no. 1–2, pp. 559–583, Dec. 2026, doi: 10.1007/s00170-025-16881-1.
- [58] S. Chakraborty and C.-H. Yeh, "A simulation based comparative study of normalization procedures in multiattribute decision making," in *Proceedings of the 6th Conference on 6th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering and Data Bases*, 2007, pp. 102–109.
- [59] M. S. García-Cascales and M. T. Lamata, "On rank reversal and TOPSIS method," *Math. Comput. Model.*, vol. 56, no. 5–6, pp. 123–132, 2012, doi: 10.1016/j.mcm.2011.12.022.
- [60] M. Chandra, F. Shahab, V. KEK, and S. Rajak, "Selection for additive manufacturing using hybrid MCDM technique considering sustainable concepts," *Rapid Prototyp. J.*, vol. 28, no. 7, pp. 1297–1311, 2022, doi: 10.1108/RPJ-06-2021-0155.