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Decision Analysis for Non-value-added Activities using Z-numbers in the Mass-Customized Machinery Industry

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Abstract
To meet the demands of esteemed consumers, the mass customization industry must achieve an optimal lead time. To achieve the optimal lead time, identifying the production output metric with the most significant impact is imperative. A group of industrial experts uses subjective assessments based on qualitative criteria to make informed decisions. The resilience of Z-number-based fuzzy set theory is effectively employed to ascertain a viable solution for uncertain data with a significant level of reliability. This paper presents a novel hybrid model for Group Multi-Criteria Decision-Making (GMCDM) that combines Z-number-based Consistent Fuzzy Analytic Hierarchy Process (Z-CFAHP) and Z-number-based Fuzzy VIekriterijumsko KOmpromisno Rangiranje (Z-FVIKOR). The distinctive methodology comprises four discrete stages. The first step is to examine the consistency of the opinions provided by the group of industry experts. In the second stage, decision-makers' perspectives are employed to determine the global weight for each sub-criterion with respect to the criteria, which is calculated using the Z-CFAHP approach. The production output metrics are compared and ranked in the third step using the Z-FVIKOR approach. A total of 63 sensitivity analysis experiments were performed in the final stage to evaluate the robustness of the proposed model. The sensitivity analysis conducted on the proposed model demonstrates that the outcomes exhibit a consistency rating of 90.47%.

Keywords
Mass Customization, Z-numbers, ZCFAHP, ZFVIKOR, Sensitivity Analysis

Introduction

The rapidly emerging paradigm of "Mass Customization" (MC) challenges the existing "Mass Production" (MP) paradigm in numerous Small and Medium-Sized (SME) industries. The idea of MC was initially introduced by Davis in 1989. Its primary objective is to fulfil customer demands by offering customized products at a cost equivalent to those produced on a large scale. The increasing emphasis on differentiating between MP and MC in the context of manufacturing strategy planning is evident. The efficient comprehension of the role of technology and manufacturing in constraining a firm's strategic options is imperative for comprehending the distinction between MP and MC (Davis, 1989; Kotha, 1995). The MC gains from economies of scope, resulting in a minimized price by developing a variety of products and achieving economies of scale that reduce the cost of each product. It is widely used in the manufacturing industry to meet the needs of certain clients and maximize productivity and effectiveness (Taps et al., 2017). MC is a primary concern for corporate management and is still comparatively fresh in the industry. Due to its many benefits, customized manufacturing is expected to gain more popularity. Customers want to be unique and stand out, so the manufacturers must embrace this trend to compete (Karaköse & Yetiş, 2017). Pinpointing the optimal batch size in mass-customized manufacturing is the most effective method to achieve the optimal lead time, with decreased NVA waste, lower production costs, and improved overall operational efficiency (Balamurugan & Ranjitharamasamy, 2023).

In the manufacturing industry, it is crucial to categorize the three distinct types of activities: essential non-value-added activities (ENVA), non-value-added activities (NVA), and value-added activities (VA). ENVA that are necessary for an industry to operate but provide no value from the client's viewpoint (Ng et al., 2014). For instance, properly sharpening a saw is essential for enabling effective wood cutting. Nevertheless, it does not inevitably indicate an increased value in the finished product. Other typical ENVA examples include scheduling, equipment setup time, and part inspection. NVA is the term used to refer to operations carried out by the manufacturing sector that are not intended to meet the needs of end customers. NVA includes billing an end-user, monitoring the duration spent on a specific task, and transferring work-in-progress. VA is that which turns raw resources into completed goods that customers are willing to pay for. Examples of VA include assembling a product, forging a part, painting, treatment, milling, and a variety of additional tasks essential for finishing a product (P. M. Swamidass, 2000; Sudhakara et al., 2020). In mass-customized industries, top executives are concerned that increased NVA activities in the value stream will negatively impact industrial financial performance. According to Sasikumar et al. (2023), Lean Six Sigma methodology could potentially reduce these NVA activities in the industries.

Throughout the early 1970s, Multi-Criteria Decision Making (MCDM) attained recognition as a significant domain of scientific study. Within operations research, this particular category of decision-making problems is widely acknowledged. The primary objective of a typical MCDM task is to evaluate a set of possibilities while considering several decision criteria(Stanujkic & Urošević, 2015). The Saaty developed Analytic Hierarchy Process (AHP) is one of the most well-known methodologies in MCDM methods in 1987 (Saaty, 1987). A group of decision-makers will determine the process of evaluating, ranking, and selecting among various alternatives based on multiple criteria (Gökler & Boran, 2023). Decision-making challenges often involve a degree of ambiguity, which could be observed as uncertainty, partiality, or inaccuracy (Hudymáčová et al., 2010). Quantifying uncertainties is a significant challenge when dealing with precise numerical values. To mitigate the challenge of ambiguity, Zadeh was the first to propose fuzzy set theory in 1965 (Zadeh, 1965). Following that, a novel Z-number methodology was introduced, which involves integrating probability distributions into unobserved variables to address the uncertainty inherent in decision-making data (Demir et al., 2023; Jiang et al., 2017; Salah et al., 2023; Zadeh, 2011). Expert opinions add to the uncertainties in the decision-making process, and the reliability of decisions is also a critical factor. The Z-number originated as an advanced information system to efficiently understand the uncertainty and reliability of expert judgments in the decision-making process. As mentioned earlier, Z-numbers are used to tackle the reliability of decision-making challenges (R. Cheng et al., 2021). Numerous MCDM approaches, including the Z-number-based Fuzzy AHP, Fuzzy TOPSIS, Fuzzy DEMATEL, Fuzzy VIKOR, Fuzzy COPRAS, and Fuzzy CODAS techniques, have received extensive study interest (R. Cheng et al., 2021; Liu et al., 2015; Yilmaz et al., 2023). Since it consists of a fuzzy constraint and a reliability or confidence component, the Z-number is highly consistent with the way humans frequently express information. In recent years, there has been a significant increase in research conducted across various fields following the development of the concept of Z-numbers (Banerjee et al., 2022; Kang et al., 2012a, 2012b). Table 1 presents recent works on Z-number-based MCDM techniques, with a focus on their contributions to decision problems.

Tab. 1. Previous literature on Z-number-based decision-making techniques

Author and Year	Z-number-based decision-making techniques	Use cases
Ku Khalif et al. (2017)	Z-CFPR-TOPSIS	Assessing the Staff recruiting problem
Das et al. (2020)	Z-VIKOR	Assessing the FMEA-based priority of occupational hazards
Zafaranlouei et al. (2023)	Z-CoCoSo	Assessing the sustainable waste includes industrial waste, hospital waste, electronic waste, and urban waste management
Saif et al. (2025)	CFZN-TOPSIS	Improving predictive maintenance techniques in production environments
Haktanır & Kahraman (2024)	Z-AHP-TOPSIS	The decision-making problem for hydrogen storage systems
Hosseini Dehshiri & Amiri (2024)	Z-SWARA-CoCoSo	Assessing supply chain deployment strategies for blockchain technology
Zhang et al. (2024)	Z-BWM-TOPSIS	Choosing a robust, environment-friendly supplier that supports inclusive development
Shyur (2025)	Z-FAHP-CRITIC	Choosing platforms for Big Data services
Ullah et al. (2025)	Multi-polar fuzzy *Z*-number and Hamacher operations	Choosing a site for a diesel-fuelled power plant and treating medical waste
Xia et al. (2025)	Disc Fermatean Fuzzy Z-Number	Choosing the best options for land development
Proposed	Z-CFAHP-VIKOR	Examining NVA to choose performance metrics with significant impacts

This study examines the significant impact of production output metrics on lead times in manufacturing, particularly in the context of mass customization. We plan to conduct further research on NVA activities to carry out those mentioned earlier. This investigation will utilize group multi-criteria decision-making (GMCDM) techniques and involve a group of industry experts. In this study, we propose a novel approach called Z-CFAHP-VIKOR, which combines a Z-number-based consistent fuzzy AHP with fuzzy VIKOR, based on previous research findings. This study focuses on a specific case study in the mass-customized PQR Machinery Industry. To accomplish this, we develop a Z-number-based GMCDM approach. The objective is to identify the significant impact of output metrics on the optimal lead time for mass-customized manufacturing. The optimal lead time is the aim at the top of the hierarchy. Seven essential criteria based on the NVA compose the second-level hierarchy. The twenty-one sub-criteria, based on a group of industrial specialists and previous literature, were utilized as the basis for the third-level hierarchy. As an alternative for this research, the fourth level of the hierarchy comprises four production output metrics. The proposed approach has been evaluated using the measure of consistency for levels 2 and 3, and a sensitivity analysis was a validity test for the ZFVIKOR ranking.

The subsequent sections of this article are organized as follows: Section 2 encompasses an exploration of the foundational principles and preliminaries that underpin the development of the suggested framework. Section 3 contains non-value-added operations in the manufacturing process, accompanied by a comprehensive explanation. Section 4 encompasses the recommended framework model-solving approach that has been suggested. Section 5 of this paper includes a case study on the PQR Machinery Industry. In Section 6, the paper's discussion, conclusion, and recommendations for the future are discussed.

Preliminaries

This section entails a review of the fundamental concepts, followed by a discussion of the definitions outlined below.

Fuzzy Numbers

Definition 1: Zadeh (1965) initially formulated the fuzzy number, which is defined as a fuzzy subset in the set of real numbers (support R) that possesses the properties of being "normal" and "convex." In this context, the support of the fuzzy number, denoted as support (S), is the set of real numbers (x) such that x belongs to the set of real numbers (R) and x is greater than zero. The fuzzy set Si is defined inside a specific universe of discourse. The set U is characterized by a membership function $\mu\tilde{s}(r)$ where $\mu\tilde{s}(r)$ assigns a value to each element x in U, with x being a real integer inside the interval [0,1] (C.-H. Cheng, 1998).

Definition 2: A quadruplet with $\tilde{s} = [s1, s2, s3, s4]$ as its membership function defines a trapezoidal fuzzy number (TrFN) (Ku Khalif et al., 2017).

$$\mu_{\tilde{s}} = [s1, s2, s3, s4] = \begin{cases} \dfrac{r - s1}{s2 - s1} & if\ s1 \leq r \leq s2 \\ 1, & s2 \leq r \leq s3 \\ \dfrac{s4 - r}{s4 - s3} & if\ s3 \leq r \leq s4 \\ 0 & otherwise \end{cases} \tag{1}$$

Definition 3: The defuzzification value for the TrFN $m(\tilde{s})$ will be calculated as follows if we use the TrFNs $\tilde{s} = [s1, s2, s3, s4]$ (Krohling et al., 2019).

$$m(\tilde{s}) = \frac{(s1 + s2 + s3 + s4)}{4} \tag{2}$$

Z-numbers

Definition 1: Zadeh (2011) initially proposed the z-number technique in his work to establish a fundamental basis for computations with numbers that include inherent uncertainty. It is essential to consider the reliability variable in the context of fuzzy numbers to determine the dependability of the information. A *Z*-number is an organized collection of two type-1 fuzzy sets, denoted as $Z = (\tilde{s}, \tilde{t})$. The first element, $\tilde{s}$ is a real-valued measure of uncertainty on variable X, also known as a limitation or constraint variable. The second factor, denoted as $\tilde{t}$, serves as a reliability indicator or constraint determining the confidence level for $\tilde{s}$. According to Zadeh, the *Z*-number is a unique concept within the context of fuzzy set theory that offers improved capabilities in describing ambiguous and sophisticated information (Banerjee et al., 2022).

Definition 2: The *Z*-number is often defined as a sequential arrangement of fuzzy sets $(\tilde{s}, \tilde{t})$, where $\tilde{s}$ is a fuzzy value that represents the potential range of values for the variable *X*, and $\tilde{t}$ represents a possibility associated with $\tilde{s}$. The primary objective of *Z*-numbers is to provide a computational framework that utilizes numbers purposefully constructed to represent human knowledge more effectively, while still accommodating ambiguous information (Kang et al., 2012a, 2012b).

These two components are commonly denoted using linguistic terms such as "Absolutely High Impact" and "Sure." The concept of component $\tilde{t}$ in r was modified by substituting the word "probability" with "possibility." Additionally, *Z*-numbers were transformed into fuzzy sets by combining two elements, a positive coefficient obtained by integrating component $\tilde{t}$ (R. Cheng et al., 2021). The ability of *Z*-numbers to facilitate the communication of meaning helps to explain the fundamental idea behind *Z*-numbers from a linguistic perspective. For instance, the *Z*-number illustrates the Process Efficiency: (Around 95%, Perhaps), Manpower productivity (High, Sure).

TrFNs are utilized in this study (Fig. 1). The figure below illustrates the depiction of the trapezoidal membership function based on *Z*-numbers. (Tab.) displays linguistic terms for reliability and their corresponding *Z*-numbers based on a trapezoidal membership function (TrMF). This study used a notation $Z = (\tilde{s}, \tilde{t})$, where the first element $\tilde{s}$ denotes the fuzzy impact, and the second element $\tilde{t}$ reflects the confidence level associated with the selected $\tilde{s}$ values. The method for converting from *Z*-number to a standard fuzzy number has been outlined as follows, based on the following steps (Ku Khalif et al., 2017). Fig. 1a,b below illustrates the *Z*-number $Z = (\tilde{s}, \tilde{t})$. Assuming that $\mu\tilde{s}(r)$ and $\mu\tilde{t}(r)$ are $\{\tilde{s} = (r, \mu\tilde{s}) \mid r \in [0,1]\}$ and $\{\tilde{t} = (r, \mu\tilde{t}) \mid r \in [0,1]\}$ respectively are TrMF.

Step 1: Transforming the r coordinates confidence element into a crisp numeric technique (Ku Khalif et al., 2017).

$$m(\tilde{t}) = \alpha = \frac{2(t1 + t4) + 7(t2 + t3)}{18} \tag{3}$$

Step 2: Add the weight of the confidence element to the impact part. The weighted *Z*-number is usually represented as $Z\alpha = \{(r, \mu\tilde{t}\,\alpha(r)) \mid \mu\tilde{t}\,\alpha\,(r) = \alpha\,\mu\tilde{t}\,\alpha\,(r), r \in [0,1]\}$; Consequently, Fig. 1c is used to demonstrate Kang et al. (2012a).

$$E_{\tilde{s}^{\alpha}} = \alpha\, E_{\tilde{s}^{\alpha}}(r),\ \ r \in R \tag{4}$$

$$\mu_{\tilde{s}^{\alpha}} = \alpha\, \mu_{\tilde{s}^{\alpha}}(r),\ \ r \in R \tag{5}$$

$$E_{\tilde{s}^{\alpha}}(r) = s1, s2, s3, s4; \frac{2(t1+t4)+7(t2+t3)}{18} = [t1, t2, t3, t4; \alpha] = \alpha\, E_{\tilde{s}^{\alpha}}(r)$$
(6)

Step 3: Convert an irregular fuzzy number representing a weighted impact into a standard fuzzy number that implies $Z' = \{(r, \mu\tilde{z}'(r)) \mid \mu\tilde{z}'(r) = \mu\tilde{s}(\sqrt{\alpha r}), r \in [0,1]\}$. This step represents the conclusion that can be obtained from Proposition 3 for Z' has identical fuzzy anticipation to $Z\alpha$ when a fuzzy anticipation exists and both outcomes are equal; Consequently, Fig. 1d is used to demonstrate Kang et al. (2012a).

$$E_{Z'} = \alpha\, E_{\tilde{s}^{\alpha}}(r), \;\; r \in \sqrt{\alpha}R \tag{7}$$

$$\mu_{Z'} = \mu_{\tilde{s}}(\sqrt{\alpha}r), \;\; r \in \sqrt{\alpha}R \tag{8}$$

$$E_{\tilde{Z}'}(r) = s1, s2, s3, s4; \sqrt{\frac{2(t1+t4)+7(t2+t3)}{18}} = \left[s1, s2, s3, s4; \sqrt{\alpha}\right] = \sqrt{\alpha}\, E_{\tilde{s}^{\alpha}}(r) \tag{9}$$

$$E_{\tilde{Z}'}(r) = E_{\tilde{s}^{\alpha}}(r) \tag{10}$$

$$E_{\tilde{s}^{\alpha}}(r) = \alpha\, E_{\tilde{s}}(r) \tag{11}$$

$$E_{\tilde{Z}'}(r) = \alpha\, E_{\tilde{s}}(r) \tag{12}$$

$$E_{\tilde{Z}'}(r) = E_{\tilde{s}^{\alpha}}(r) \tag{13}$$

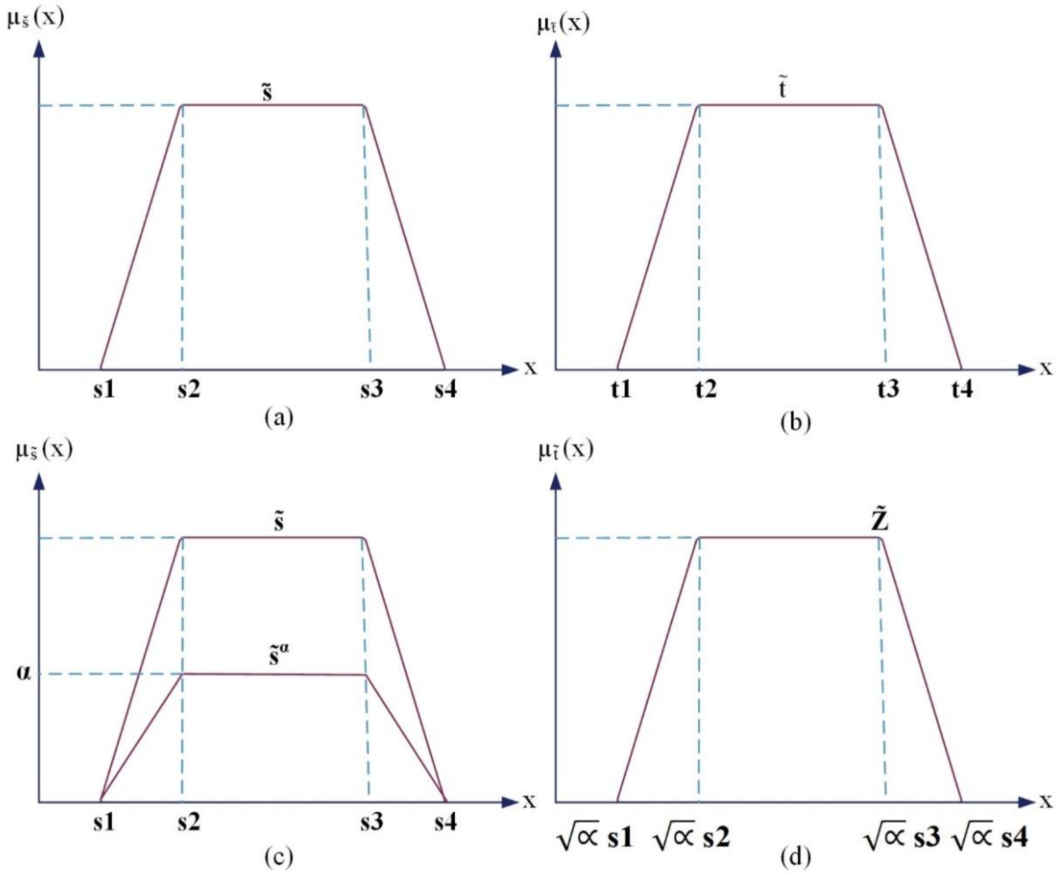

Fig. 1. (a) Impact element s̃ = [s1, s2, s3, s4], (b) Reliability element t̃ = [t1, t2, t3, t4], (c) Z-number following reliability multiplication, (d) Z-number transformed into standard fuzzy number

Tab. 2. Comprehensive TrFNs linguistic expression for reliability (Ku Khalif et al., 2017)

Crisp Numbers	Linguistic Expression	Comprehensive TrFNs
1	Absolutely Not Sure (ANS)	(0.00,0.00,0.00,0.25)
2	Not Sure (NS)	(0.00,0.25,0.25,0.50)
3	Perhaps (P)	(0.25,0.50,0.50,0.75)
4	Sure (S)	(0.50,0.75,0.75,1.00)
5	Very Sure (VS)	(0.75,1.00,1.00,1.00)

Conventional AHP

Definition 1: The Analytic Hierarchy Process (AHP), first proposed by Saaty (1987), is one of the MCDM techniques that includes organizing a complicated subject into a hierarchical framework. This phenomenon exhibits several types of irregularity and reflects how individuals make decisions (Abdul-Hamid et al., 1999; Saaty, 1987).

Definition 2: The AHP provides an extensive framework for successfully integrating intuitive, rational, and irrational components into the decision-making process. The strategy combines perception and intent to create a complete synthesis. It is not necessary for judgments to be transitive or consistent. The dependability of the decisions is measured as part of the AHP analysis. The following steps are included in the AHP methodology (Vaidya & Kumar, 2006).

Step 1: Understand the problem's primary objective or goal.

Step 2: Evaluate the criterion, sub-criteria, and output metric elements that impact the problem as stated in the objective.

Step 3: Consider the main objective, the primary criteria, the secondary sub-criteria, and the output metric components when constructing the problem into a hierarchy at various levels.

Step 4: Experts use Tab. to compare and calibrate the scale to obtain a crisp value for each component. The following evaluations are necessary since all diagonal elements have to equal 1; hence, it takes $n*(n-1)/2$ assessments, where n is the number of criteria. The remaining components are simply the reciprocal of the earlier comparisons. This process is equivalent to the pairwise comparison in Eq. (14). Using pairwise comparison, determine which criteria and sub-criteria are most important.

$$s=\begin{bmatrix} 1 & \tilde{s}_{12} & \cdots & \tilde{s}_{1n} \\ 1/\tilde{s}_{12} & 1 & \cdots & \tilde{s}_{2n} \\ \vdots & \vdots & 1 & \cdots \\ 1/\tilde{s}_{1n} & 1/\tilde{s}_{2n} & \cdots & 1 \end{bmatrix} \tag{14}$$

Step 5: For each criterion and sub-criterion, determine the Eigenvalue, normalized values, Consistency Index (CI), and Consistency Ratio (CR).

Step 6: Decisions depend on these normalized values, whether the absolute maximum Eigenvalue, CR, and CI are acceptable, if CI < 0.01, otherwise, the steps mentioned earlier are performed again until the results fall within the desired range.

Step 7: Before being added together to get the rank for every output metric, the outcomes were multiplied by the value associated with each preference. The value pertaining to the criterion weight element has been multiplied by every weighted value obtained from the sub-criteria field.

Z-number-based consistent Fuzzy AHP

An outline of Z-number-based consistent Fuzzy AHP steps is provided below (Azadeh et al., 2013).

Step 1: Designing assessment hierarchy frameworks that aim at the alternatives with the most significant impact while considering both the primary and secondary criteria into account.

Step 2: A pairwise comparison matrix (PCM) ought to be established for each expert. For the kth expert and above, the PCM is built using a Z-number-based evaluation of the assessment criteria. Each component from Tab. is compared and calibrated by experts to ensure its suitability level using a trapezoidal numerical scale.

Step 3: Using Eq. (3), every expert's *Z*-number to represent the reliability portion ought to be changed into a crisp number. The real number is used as a reliable weight.

Tab. 3. The fuzzy linguistic expressions for assessments in the Z-CFAHP (Ku Khalif et al., 2017)

Crisp numbers	Linguistic variables	TrFNs	Reciprocal TrFNs
1	Equally Impact (EI)	(1,1,1,1)	(1,1,1,1)
2	Intermediate Value (IV)	(1,3/2,5/2,3)	(1/3,2/5,2/3,1)
3	Slightly More Impact (MMI)	(2,5/2,7/2,4)	(1/4,2/7,2/5,1/2)
4	Intermediate (IV)	(3,7/2,9/2,5)	(1/5,2/9,2/7,1/3)
5	Impact (I)	(4,9/2,11/2,6)	(1/6,2/11,2/9,1/4)
6	Intermediate Value (IV)	(5,11/2,13/2,7)	(1/7,2/13,2/11,1/5)
7	Strongly Impact (SI)	(6,13/2,15/2,8)	(1/8,2/15,2/13,1/6)
8	Intermediate Value (IV)	(7,15/2,17/2,9)	(1/9,2/17,2/15,1/7)
9	Extremely Impact (EI)	(8,17/2,9,9)	(1/9,1/9,2/17,1/8)

Step 4: Expert preferences ought to be transformed between weighted *Z*-numbers and standard fuzzy numbers. The conversion process is calculated using the equation shown below.

$$\tilde{Z}' = \sqrt{\alpha} * s1, \sqrt{\alpha} * s2, \sqrt{\alpha} * s3, \sqrt{\alpha} * \ s4 \tag{15}$$

Step 5: Compile the overall preference of the experts by using the equation provided to compute the PCM of the experts' choices, where k is the number of experts. Let i be an integer ranging from 1 to m, and let j be an integer ranging from 1 to n.

$$\tilde{t}_{ij} = \left(\tilde{t}_{ij}^{1} * \tilde{t}_{ij}^{2} * \dots \dots * \tilde{t}_{ij}^{3}\right)^{1/k} \tag{16}$$

Step 6: Determine the fuzzy geometric mean (FGM) across all criteria and sub-criteria.

Step 7: Follows the total summation of all FGM, and finally, the total sum's inverse value in the opposite direction.

Step 8: Every inverted value was multiplied by FGM to determine each criterion and its sub-criterion local weights.

Step 9: To convert the estimated local fuzzy weights toward crisp weights by defuzzifying them using Eq. (2).

Step 10: In order to normalize the crisp weights, divide every crisp weight by the sum of all the local weights.

Step 11: Construct global weights from the criteria's and sub-criterion's local normalized weights. Finding the global weights by multiplying the local weights from the criteria and sub-criterion by the corresponding values.

Z-number-based VIKOR

S, *R*, and *Q* are vital to calculate for ranking using VIKOR. *S* is the utility measure, representing a weighted and normalized Manhattan distance, and *R* is the regret measure. It can be expressed as a weighted and normalized Chebyshev distance, and *Q* is an index value ranging from 0 to 1. The stages of computation are shown below (Das et al., 2020).

Tab. 4. The fuzzy linguistic expressions for assessments in the Z-FVIKOR (Das et al., 2020)

Crisp numbers	Linguistic terms	TrFNs
1	Equally Impact (EI)	(0.0,0.0,0.1,0.2;1.0)
2	Very Low Impact (VLI)	(0.1,0.2,0.2,0.3;1.0)
3	Low Impact (LI)	(0.2,0.3,0.4,0.5;1.0)
4	Fairly Impact (FI)	(0.4,0.5,0.5,0.6;1.0)
5	High Impact (HI)	(0.5,0.6,0.7,0.8;1.0)
6	Very High Impact (VHI)	(0.7,0.8,0.8,0.9;1.0)
7	Extremely High Impact (EHI)	(0.8,0.9,1.0,1.0;1.0)

Step 1: Construct the Z-number-based fuzzy decision matrix initially before evaluating the output metrics as alternatives in Z-number fuzzy VIKOR. Fuzzy decision matrices are developed using linguistic phrases to evaluate parameters from Tables 2 and 4.

Step 2: Use Eq. (3) and Eq. (15) to convert the *Z*-numbers constructed based on expert preferences into fuzzy numbers. Aggregate the importance of the individual experts. The Fuzzy Initial Decision Matrix (FIDM) reflecting experts' preferences is created using Eq. (16).

Step 3: To defuzzify the Fuzzy Initial Decision matrix using Eq. (2) to transform fuzzy numbers into crisp numbers.

Step 4: Determine the best (aj*) and worst (aj-) estimate for each of the following categories. Since we need to determine which output metric has the greatest impact on the study's goal, we will use this method's lowest value as the best and its highest value as the worst.

$$a_j^{HIIS} = \max_{i=m} b_{ij} \tag{17}$$

$$a_j^{LIIS} = \min_{i=m} b_{ij} \tag{18}$$

Step 5: Compute the normalized fuzzy distance fd_{ij}, i =1, 2….m, j = 1, 2……n

$$fd_{ij} = \frac{(a_j^{HIIS} - b_{ij})}{(a_j^{HIIS} - a_j^{LIIS})} \tag{19}$$

Step 6: Using the equation below to compute S_i, the maximum aggregate utility measure.

$$S_i = \sum_{j=1}^{m} w_j \, fd_{ij} \tag{20}$$

Step 7: Using the equation below to compute R_i, the minimum regret measure

$$R_i = \max_{i=m} w_j \, fd_{ij} \tag{21}$$

Step 8: Using the equation below to determine Q, the index value

$$S^* = min_i S_i \quad R^* = min_i R_i \tag{22}$$

$$S^- = max_i S_i \quad R^- = max_i R_i \tag{23}$$

$$Q = \vartheta \frac{S_i - S^*}{S^- - S^*} + (1 - \vartheta) \frac{R_i - R^*}{R^- - R^*} \tag{24}$$

Step 9: Sort the output metrics by the values S_i, R_i, and Q in ascending order to rank them. Three ranking lists are the outcome of the VIKOR to implement a compromise proposal or a range of compromise proposals.

Sensitivity Analysis

The primary focus of this analysis is to examine the impact of the global weight effect on the ranking of results, with the aim of validating the proposed methodology. Let us assume that the variable denoting the overall weights represents $W_j = (W_1, W_2, ..., W_K)$. When the normalized global weights sum equals 1, it can be considered an accurate representation (Alinezhad, 2011).

$$\sum_{j=1}^{k} w_j = 1 \tag{25}$$

Eq. (26) accounts for the variation in the overall weight of the criterion and sub-criteria of the MCDM approach as denoted by the variable c. The equations denoted as Eq. (27) decrease the residual global weight levels by a preset quantity, decreasing the overall count related to global weights to one.

$$W_c' = W_c + \Delta c \tag{26}$$

$$W_j' = \frac{1 - W_c - \Delta c}{1 - W_c} * W_j = \frac{1 - W_c'}{1 - W_c} * W_j \tag{27}$$

Manufacturing non-value-added Activities

Within the production industry, it is vital to identify the three primary categories of activities that are crucial for effective operations. Three distinct types of activities may be classified as value-added (VA), essential non-value-added (ENVA), and non-value-added (NVA) (Aughney & O'Donnell, 2015; Radwan et al., 2020; Saptari et al., 2019). This research examines non-value-added activities to reduce organizational inefficiencies and achieve the manufacturer's optimal lead time. From the literature and a group of industry experts' opinions, the seven major and twenty-one secondary criteria for the PQR Machinery Industry are presented in Tab. .

VA activities refer to those actions that, from the end consumer's perspective, enhance the perceived worth of a service or good (Karaköse & Yetiş, 2017). Assessing a VA activity is a relatively uncomplicated task, as industries may evaluate its worth by considering their willingness to pay for it (Gunaki et al., 2022).

ENVA activities refer to those operations that, from the end consumer's perspective, do not contribute to the overall value of a product or service. However, these activities become essential when the existing supply system undergoes significant alterations. Eliminating this wastage poses a greater challenge in the immediate future and should be the primary objective of long-term or transformative efforts (Saptari et al., 2019).

Tab. 5. Primary and secondary criteria for output metrics assessment (Aughney & O'Donnell, 2015; Cifone et al., 2021; Ng et al., 2014; Rawabdeh, 2005)

Criteria	Transport (T)	Inventory (I)	Motion (M)	Waiting (W)	Over Production(O)	Over Processing(P)	Defects (D)
Sub-criteria	Transport Batch (T1)	Raw Material (I1)	Machine Setup (M1)	Dispatching (W1)	Excess Material (O1)	Highly Polished (P1)	Excess Time (D1)
	Inefficient Schedule(T2)	Work-in-process (I2)	Employee Setup (M2)	Inspection (W2)	Excess labour (O2)	Material Waste (P2)	Labour Waste (D2)
	Movements (T3)	Finished Goods (I3)	Change in Fabrication (M3)	Maintenance Delay (W3)	Excess Storage (O3)	Power Consumption (P3)	Damaged Product (D3)

NVA activities refer to actions that, as determined by the end consumer, do not contribute to the overall value or cost of the product or service and are deemed redundant even under the existing circumstances. These behaviors can be seen as inefficient or unproductive, and it is recommended that they be discontinued or phased out within a specific timeframe. Fig. 2 depicts seven distinct criteria for NVAs. The NVA engages in activities commonly called the "TIMWOOD" acronym, which encompasses a collection of seven different types (Ahmad et al., 2019; Gunaki et al., 2022).

Transport - Transporting a product from one process to another via transportation does not increase its value. Excessive manipulation and agitation may harm the development, resulting in a decrease in its overall quality. Ensuring the delivery of goods to their designated purpose is crucial. Following the principles of continuous improvement, the material must be conveyed directly, originating from the supplier and reaching the specific location within the manufacturing process where it is intended to be employed (Cifone et al., 2021).

Inventory - Removing or reducing any form of inventory, such as raw materials, finished items, work-in-progress, or scrap, is recommended as it does not add value to the ultimate result. Surplus inventory results in the utilization of valuable floor space and obscures underlying process-related capabilities concerns. Excessive inventory is the root cause of several adverse outcomes, including extended lead times, product degradation, faulty items, escalated shipping and storage costs, and operational delays (Arya & Choudhary, 2015).

Motion - Any industrial operation completed by a worker that doesn't add value to the final product implies an unnecessary motion. Unsuitable process flows, floor layouts, cleaning practices, and irregular or poorly documented work procedures contribute to redundant actions (Brunet & New, 2003).

Waiting - Redundant waiting occurs when there is a lack of processing or movement of objects. In traditional mass production, it is common for a significant portion, frequently exceeding 99%, of the lifespan of a product to be characterized by periods of inactivity, which entails waiting to procure supplies, labor, data, equipment, and other necessary resources. The lean methodology emphasizes integrating processes to facilitate a smooth flow and reduce waiting time. It advocates for allocating resources in a just-in-time (JIT) manner, ensuring they are neither provided too early nor too late (Cifone et al., 2021).

Overproduction - There are two distinct types of overproduction. Producing a surplus of products beyond what is required can be considered a quantitative phenomenon, and manufacturing things before the designated timeframe can be referred to as early production. The overproduction process has always surpassed the expectations of clients. Overproduction in a manufacturing plant incurs significant costs due to its adverse effects on resource allocation, productivity, and quality (Arya & Choudhary, 2015).

Overprocessing - The overprocessing of components occurs without the inclusion of essential phases. Instances of this phenomenon that are more commonly observed encompass the acts of modifying, examining, and verifying, among others. Insufficient tool design, layout, and design for the product contribute to excessive motion and errors (Arya & Jain, 2014).

Defects - Both service and manufacturing errors are classified as defects. Engaging in a flawed consumption pattern resulted in significant financial losses for the firm. Defects incur a substantial proportion of manufacturing expenses in most organizations. The processes of reworking, replacing manufacturing components, and conducting inspection repairs result in the utilization of excessive processing time and resources (Krishna Priya et al., 2020).

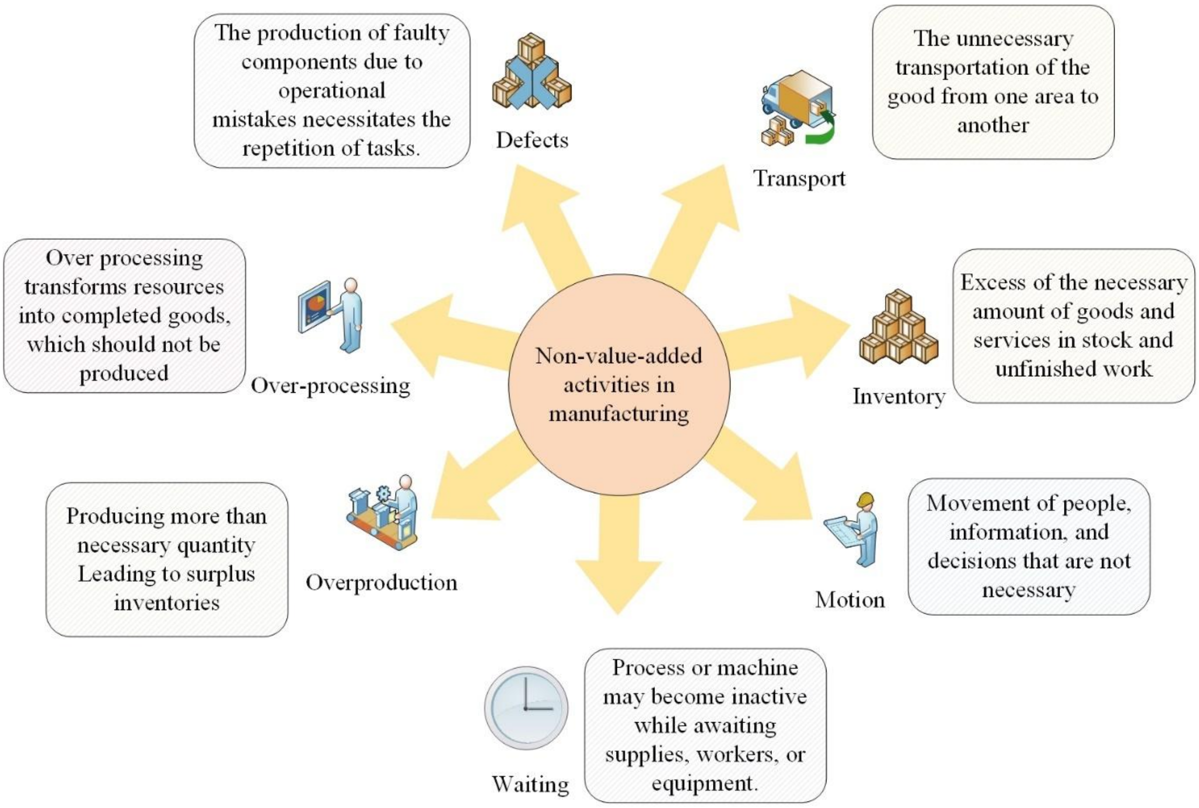

Fig. 2. Classification of manufacturing non-value-added activities (Arya & Choudhary, 2015; Arya & Jain, 2014; Rawabdeh, 2005)

Proposed Methodology

This work addresses the decision-making problems in the real-time industry. To handle uncertainty and reliability in decision-making problems, this study employed fuzzy numbers and Z-numbers, as introduced by Zadeh (1965, 2011), and then integrated these two decision-making methodologies. Saaty (1987) originally formulated the AHP, whereas Opricovic and Tzeng (2004) developed the VIKOR. This Z-number-based GMCDM technique is referred to as Z-CFAHP-VIKOR. The sensitivity analysis from Alinezhad's (2011) study was used to evaluate the robustness of Z-CFAHP-VIKOR. This section provides a comprehensive explanation of the study design, the number of experts involved, the data collection techniques, data analysis, and the data validation process. The explanations are presented straightforwardly and concisely. This research strategy utilizes a cross-sectional study to identify the factors (Makespan, Flow Time, Idle Time, and Efficiency) that need to be minimized to achieve optimal lead time. This study design incorporates qualitative research methodologies that involve empirical validation studies. In this context, data is collected from the PQR Machinery Industry with a group of three industry experts. This qualitative study design investigates the impact of various factors on the link between the criteria and sub-criteria. This study employs a cohort of industry experts to gather the necessary data for constructing the model. The experts' preferences regarding criteria, sub-criteria, and output metrics were collected through a formal questionnaire and a direct approach, in which the purpose of the study was disclosed to the experts. The flowchart depicting Z-number-based GMCDM methodologies, together with sensitivity analysis, is illustrated in

Fig. 3 below.

This study proposes an integrated approach called Z-CFAHP-VIKOR, which combines *Z*-number, relying on consistent fuzzy AHP with VIKOR. The objective is to enhance the efficacy of Z-number-based MCDM techniques by addressing the challenges related to accuracy, subjectivity, and uncertainty in evaluating research design concepts. The introduction of the Z-number into Multiple Criteria Decision Making (MCDM) effectively delineates the aspects of reliability, uncertainty, and subjectivity in impact evaluations. Initially, a group of three industry specialists from the PQR Machinery sector is selected as the panel experts. The individuals involved in the study decide on selecting assessment components, including evaluation criteria, sub-criteria, and output metrics. Each expert must independently assess the PCM in the output metric rankings' AHP and Z-number-based Fuzzy AHP evaluations, as well as the Z-number-based Fuzzy VIKOR judgment values. A Z-number-based GMCDM approach is developed to incorporate expert impact estimations and cumulative group assessments. The Z-number-based GMCDM procedure consists of four distinct phases, as seen in

Fig. 3. The first stage involves employing the AHP to assess the consistency of the preference values. Subsequently, the second stage entails utilizing the z-number-based fuzzy AHP to establish the global weights for the criteria and sub-criteria. Next, the third phase involves employing the Z-number-based fuzzy VIKOR method to rank the impact of the output metrics. Lastly, the fourth phase consists of validating the proposed approach.

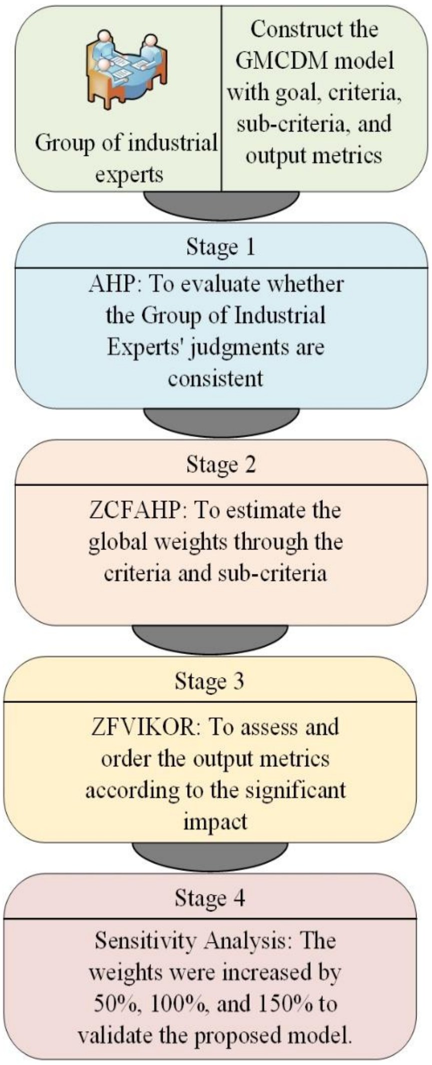

Fig. 3. Proposed Methodology Flow Chart

An Illustrated Case Study

This research aims to investigate a firm referred to as PQR Machinery Industry located in India. According to Sharma (2020), the recently revised Indian SME regulation classifies the machinery industry as a medium-sized enterprise if its investment in plant, machinery, or equipment does not surpass 500 million Indian rupees and its annual revenue remains below 2.5 billion rupees (A.K. Sharma, 2020). The mass-customized industry encompasses the production of more than twenty distinct kinds of vehicle components, serving prominent firms such as Maruti Suzuki, Suzuki, Tata Motors, Honda, Nissan, Volvo, Mahindra, and others. This particular industry fails to enhance the overall contentment of its consumer base effectively and often exceeds the expected lead time with certain customers. In investigating NVA to determine their underlying causes, the proposed GMCDM model, Z-CFAHP-VIKOR, is recommended. These techniques are utilized to identify the specific output metric among the several factors that significantly influence the lead time within this firm.

PQR Machinery Industry in India faces challenges in meeting client satisfaction due to exceeding lead times. To ascertain the significant impact of output metrics, our study examines NVA activities using four key output metrics. To evaluate the operations of the NVA, a group of experienced experts was chosen, along with four output metrics: Makespan, Flow Time, Idle Time, and Efficiency. The present study included seven criteria, with the selection of twenty-one sub-criteria being determined by a rigorous examination of relevant literature and insightful interviews conducted with industry professionals. Tab. displays the criteria and corresponding sub-criteria. The concept of attributes is represented briefly in this study by the notation $\mu_{\tilde{S}} \in [0,1]$ to denote fuzzified occurrences. Z-numbers correspond to the numerical representations of certain attributes. According to the depiction in Fig. 4, the hierarchical structure of this study is shown. A comprehensive survey was developed to assess the interconnected elements that influence the selection of output metrics. This survey aimed to evaluate the criteria and sub-criteria using linguistic evaluation factors, as shown in Tables 2 and 3. The parameters were reviewed by experts for the Z-number-based initial choice matrix, considering the linguistic evaluation component from Tables 2 and 4. The process flow approach used in mass-customized manufacturing is shown in Fig. 5.

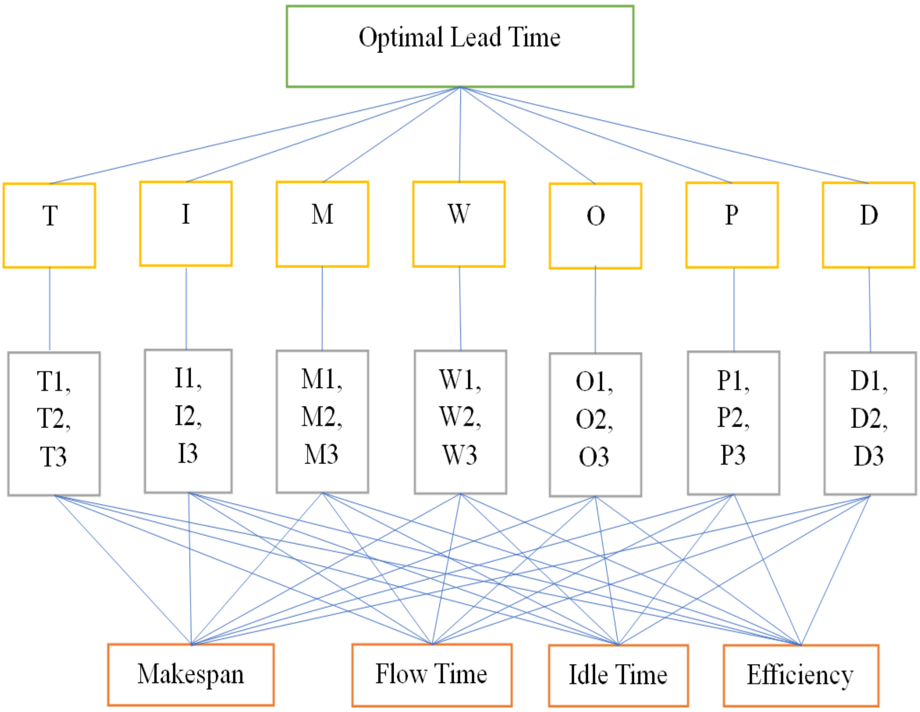

Fig. 4. The proposed model hierarchical structure

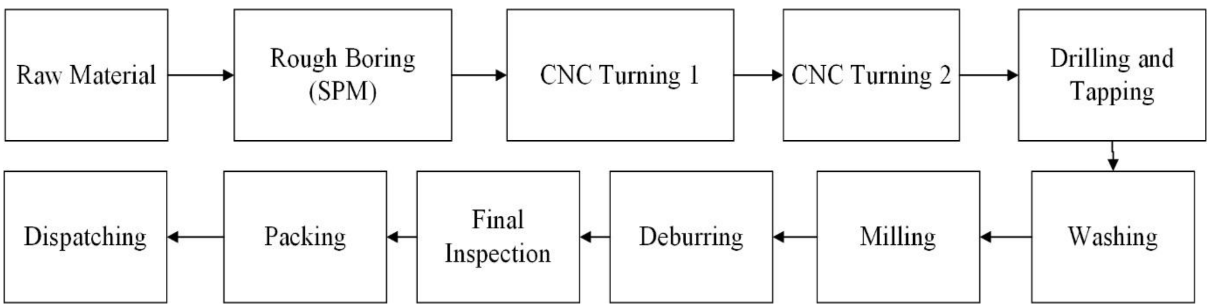

Fig. 5. Manufacturing process workflow

Stage 1: Consistency test by AHP

This section corresponds to the first stage of the proposed model, which involves implementing an AHP to evaluate the consistency of preferences expressed by the group of industrial experts. The primary objective of this stage is to relieve concerns related to the dependability of information and the subjective nature of design concept evaluation. After constructing the PCMs, it is necessary to conduct consistency tests to ascertain the suitability of these matrices before proceeding to the subsequent step. In order to meet the requirements of the consistency tests, the consistency ratio must be below 0.1. Utilize the conventional AHP methodology delineated in Section 2.3 to execute the present examination. Steps 1 to 4 involve the construction of the PCM using the input provided by the three experts, as shown in Tables 2 and 3. Following the structure of the PCMs, steps 5 to 7 were undertaken to ensure the comprehensive incorporation of experts' preferences and the consistency of the PCM construction process. (Tab. below shows the calculated criteria and sub-criteria consistency test results. All of the consistency ratio values presented in Tab. are below 0.1. The acceptability of the preferences used by the group of industrial specialists in constructing the PCMs is deemed satisfactory. The consensus among the experts about the preference values was consistent, indicating that the suggested model proceeded to the subsequent stages.

Tab. 6. Consistency outcomes for criteria and sub-criteria

Criteria	Consistency	Sub-criteria	Consistency
T	0.09995	T1, T2, T3	0.06890
I		I1, I2, I3	0.08259
M		M1, M2, M3	0.08206
W		W1, W2, W3	0.09463
O		O1, O2, O3	0.09463
P		P1, P2, P3	0.07534
D		D1, D2, D3	0.04668

Stage 2: Estimate the global weights by ZCFAHP

This section of the suggested technique involves using Z-CFAHP, as elucidated in Section 2.4. To determine the local weights among the criteria and sub-criteria, it is necessary to follow steps 1 through 11. Subsequently, the locally obtained weights will be converted into global weights. The consistent pairwise matrices obtained in Stage 1 are used to generate dependable consistency PCMs for all criteria and sub-criteria within the hierarchical systems. These matrices are based on the experts' preferences and confidence levels, as indicated in Tab. or the impact aspect and Tab. for the confidence aspect. Specifically, the PCM is constructed using the models presented in Tab. , which utilize crisp numbers instead of trapezoidal fuzzy numbers for the effect aspect to enhance comprehension. Similarly, proceed to compile the remaining PCMs for the criteria and sub-criteria as assessed by the group of industrial experts.

The subsequent step involves transforming reliability-based Z-numbers, which encode expert preferences, into conventional fuzzy numbers. One example is the use of fuzzy PCM by expert 1 to collect preferences, specifically in Transport * Defects. The corresponding values for $\tilde{s}$ and $\tilde{t}$ are given as follows: $\tilde{s} = (8,17/2,9,9)$ and $\tilde{t} = (0.75,1,1,1)$. These values are obtained from Table 3 and Table 2, respectively. The Z-number is a mathematical representation that can be used to quantify expertise. It is expressed as $Z = (\tilde{s},\tilde{t})$: $Z = (8,17/2,9,9)\ (0.75,1,1,1)]$. The reliability weight element was initially transformed into a crisp number using Eq. (3). The crisp number for the weight component, represented as α, has been calculated to be 0.9722. Once the reliability component has been determined and quantified as a precise value, the Z-number representing the c   Afterward, it is necessary to transform weighted Z numbers into standard fuzzy numbers. Equation (15) was used to modify the weighting of the confidence component in the impact section, resulting in the derivation of a typical fuzzy number denoted as $Z' = (7.88, 8.38, 8.87, 8.87)$. The calculation of the residual weighted confidence component for the criteria and sub-criteria, based on the input from the three experts, may be performed in a manner consistent with the previously stated methodology. It includes converting the data into a typical fuzzy number. The final PCM is generated by integrating the expert views using Eq. (16). Next, use steps 5 to 11 to compute the comprehensive weights for both the criteria and sub-criterion. Subsequently, the stage 3 Z-number-based fuzzy VIKOR methodology will be employed to evaluate the impact of each output parameter on the optimal time, taking into account the criteria and sub-criteria global weights presented in Table 8.

Tab. 7. Expert 1 PCM of criteria with reliability part w.r.t goal

Goal	Transport	Inventory	Motion	Waiting	Overproduction	Over processing	Defects

Transport	1 (VS)	3 (VS)	4 (VS)	2 (VS)	9 (VS)	7 (VS)	9 (VS)
Inventory	1/3 (VS)	1 (VS)	2 (VS)	2 (VS)	5 (VS)	3 (VS)	6 (VS)
Motion	1/4 (VS)	1/2 (VS)	1 (VS)	2 (VS)	3 (S)	2 (S)	7 (VS)
Waiting	1/2 (VS)	1/2 (VS)	1/2 (VS)	1 (VS)	9 (VS)	8 (VS)	9 (VS)
Overproduction	1/9 (VS)	1/5 (VS)	1/3 (S)	1/9 (VS)	1 (VS)	1 (S)	3 (VS)
Overprocessing	1/7 (VS)	1/3 (VS)	1/2 (S)	1/8 (VS)	1 (S)	1 (VS)	7 (VS)
Defects	1/9 (VS)	1/6 (VS)	1/7 (VS)	1/9 (VS)	1/3 (VS)	1/7 (VS)	1 (VS)

Tab. 8. Global weights computed from criteria and sub-criteria

Criteria	Local weight	Sub-criteria	Local weight	Global weight	Rank
Transport	0.3672	Transport Batch	0.5477	0.2011	1
		Inefficient Schedules	0.3792	0.1392	2
		Movement	0.0731	0.0269	11
Inventory	0.1904	Raw Material	0.6952	0.1323	3
		Work-in-process	0.0831	0.0158	12
		Scrap	0.2217	0.0422	7
Motion	0.1359	Machine Setup	0.6267	0.0852	5
		Employee Setup	0.2827	0.0384	9
		Change in fabrication process	0.0906	0.0123	15
Waiting	0.1913	Dispatching	0.0796	0.0152	13
		Inspection	0.2320	0.0444	6
		Maintenance Delay	0.6884	0.1317	4
Over Production	0.0401	Excess Material	0.0842	0.0034	20
		Excess Labour	0.2284	0.0092	16
		Excess Storage	0.6874	0.0276	10
Over Processing	0.0553	Highly Polished	0.1619	0.0089	17
		Material Waste	0.1155	0.0064	18
		Power Consumption	0.7226	0.0399	8
Defects	0.0198	Excess Time	0.6424	0.0127	14
		Labour Waste	0.2114	0.0042	19
		Damaged Product	0.1462	0.0029	21

Stage 3: Ranking output metrics by ZFVIKOR

The Z-number-based fuzzy VIKOR, as discussed in section 2.5, is used in the third stage of the proposed technique. To assess and prioritize the output metrics, it is necessary to follow a sequential process, comprising steps 1 to 9. This procedure facilitates the evaluation and ranking of the metrics, ultimately enabling the identification of the metric that substantially influences the optimal lead time. The Z-Fuzzy Initial Decision Matrix (ZFIDM) is constructed to assess the parameters according to the criteria and sub-criteria, using the linguistic expressions provided in Tables 2 and 4. Specifically, the ZFIDM method was developed using the Experts (E1, E2, E3) models presented in Table 9, which concern the Transport criteria, utilizing linguistic expressions instead of generalized TrFNs. The purpose of this approach was to enhance comprehension and facilitate understanding. To transform weighted z numbers into standard fuzzy numbers and z numbers into crisp numbers, it is recommended to follow the procedures outlined in Section 4.2. To develop the Zero Forcing Interference Decoding Matrix (ZFIDM), it is essential to incorporate the expert's viewpoint using Eq. (16). Subsequently, proceed to assess and prioritize the output metrics by following steps 3 to 9. Consequently, the S_i, R_i, and Q_i values for each parameter are calculated. The results are shown in Table 10. The Makespan output metric substantially influences the optimal lead time in the mass-customized machinery industry. Makespan, Flow time, Idle Time, and Efficiency have been evaluated based on their influence.

Tab. 9. The experts ZIFDM w.r.t Transport criteria

Sub Criteria	Parameters	Experts

		E1	E2	E3
Transport Batch	Makespan	EHI (VS)	EHI (VS)	EHI (VS)
	Flow Time	VHI (VS)	EHI (S)	VHI (VS)
	Idle Time	VHI (S)	VHI (S)	HI (VS)
	Efficiency	FI (VS)	FI (S)	FI (VS)
Inefficient Schedules	Makespan	VHI (VS)	EHI (S)	VHI (VS)
	Flow Time	EHI (VS)	EHI (VS)	EHI (VS)
	Idle Time	VHI (S)	HI (S)	VHI (S)
	Efficiency	HI (VS)	FI (S)	HI (VS)
Movements	Makespan	VHI (S)	VHI (S)	VHI (VS)
	Flow Time	VHI (S)	VHI (S)	HI (VS)
	Idle Time	VHI (VS)	HI (S)	FI (VS)
	Efficiency	EHI (VS)	EHI (VS)	EHI (VS)

Tab. 10. ZFVIKOR ranking outcomes

Parameters	S_i	Rank S_i	R_i	Rank R_i	Q_i	Rank Q_i
Makespan	0.1924	1	0.0475	1	0.0000	1
Flow Time	0.3634	2	0.0792	2	0.2292	2
Idle Time	0.5315	3	0.1086	3	0.4488	3
Efficiency	0.8712	4	0.2011	4	1.0000	4

Stage 4: Sensitivity analysis

Finally, the fourth stage involves conducting a sensitivity analysis to assess the stability of the proposed Z-CFAHP-VIKOR model. The recommended MCDM technique incorporates sensitivity analysis through weight exchange, especially at 50%, 100%, and 150%. The primary purpose of performing a sensitivity analysis is to examine the extent to which the sub-criteria influence the ranking of outcomes concerning the overall weights assigned to the criterion. The subsequent tests are conducted by incrementing the first sub-criteria weight by 50%, 100%, and 150% relative to the criterion's weight. Eqs. (26) and (27) are used to calculate the values of the sub-criteria related to the criteria, which are subsequently reduced by a specific value.

On the contrary, when any sub-criteria value is enhanced, the remaining sub-criteria are subjected to normalization, ultimately requiring that the total of all sub-criteria equals 1. In a sequence of evaluation iterations, the relative significance of each criterion is adjusted by 50%, 100%, and 150%, respectively. The third stage is subsequently employed to establish the ranking criteria. The suggested model, Z-CFAHP-CoCoSo, encompasses a scenario with 63 assessment runs. If the weight assigned to the sub-criteria were to be increased by 50%, a revised set of weights corresponding to the sub-criteria concerning the criterion would be formulated. As seen in the preceding instance, the Maintenance Delay (W3) concept concerning Waiting using Eq. (26) is 0.1974. Eq. (27) is subsequently employed to equalize the overall weight of other sub-criteria concerning the criterion. For instance, the weight of Inspection (W2) concerning Waiting is normalized to 0.0410. In a similar manner, calculate the adjusted set of global weights by increasing them by 50% for each sub-criterion concerning the criteria. Subsequently, include the modified sets of global weights onto the ZFIDM from stage 3, and proceed with the same process to ascertain the ranking of parameters. The Q_i index value for each measure is generated using an updated set of global weights, as seen in Fig. 6.

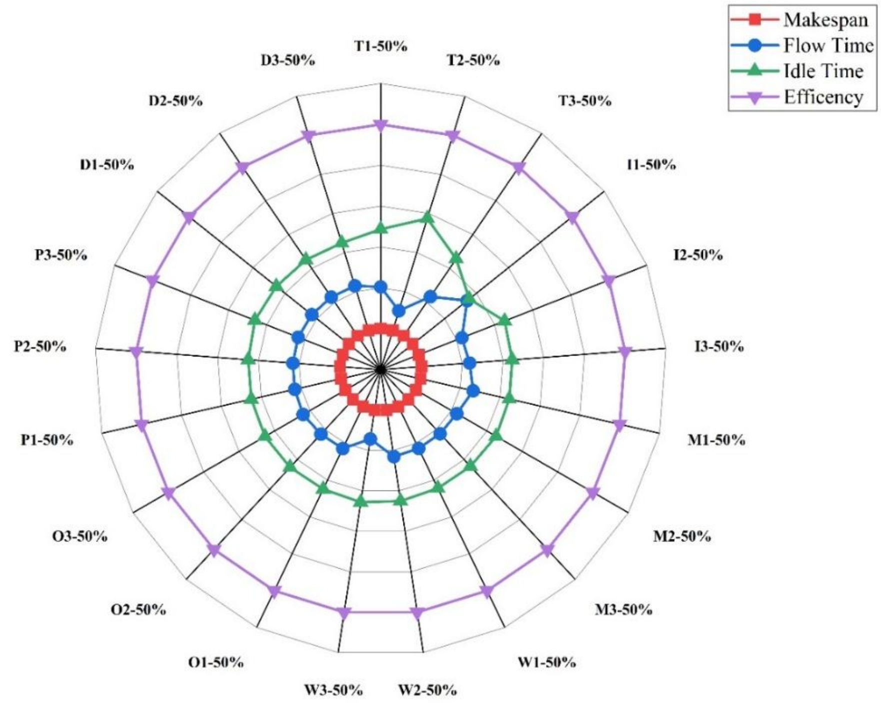

Fig. 6. Global weights increased by 50%

Similarly, calculate the adjusted set of global weights by increasing them by 100% for each sub-criterion concerning the criteria. Subsequently, include the modified sets of global weights onto the ZFIDM from stage 3, and proceed with the same process to ascertain the ranking of parameters. The Q_i index value for each measure is generated using an updated set of global weights, as seen in Fig. 7.

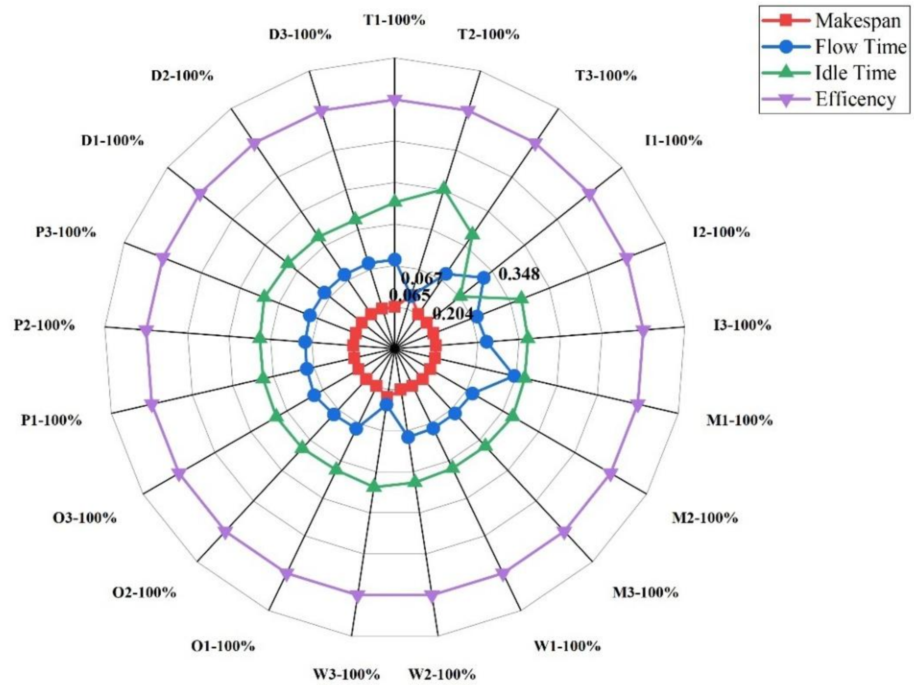

Fig. 7 Global weights increased by 100%

Similarly, calculate the adjusted set of global weights by increasing them by 100% for each sub-criterion concerning the criteria. Subsequently, include the modified sets of global weights onto the ZFIDM from stage 3, and proceed with the same process to ascertain the ranking of parameters. The Q_i index value for each measure is generated using an updated set of global weights, as seen in Fig. 8.

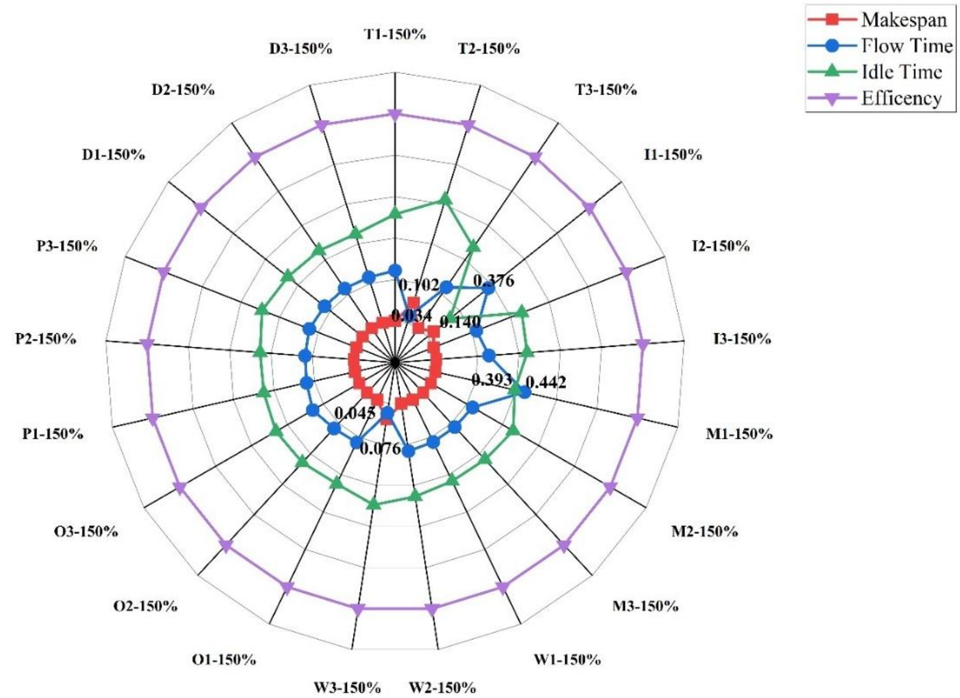

Fig. 8 Global weights increased by 150%

Discussion and Managerial Implications

Non-value-added tasks substantially influence production output metrics, such as makespan, flow time, idle time, and efficiency, in the mass-customized machinery industry. Managers must be aware of the effects of these actions and take preventive action to rectify them. These activities use resources without directly adding value to the finished product. As a result, higher expenses, extended lead times, and decreased customer satisfaction. Managers should thoroughly evaluate their processes, identify areas of waste, and apply lean concepts to simplify operations, thereby combating these difficulties. Managers can unleash operational excellence, better allocate resources, and position their manufacturing businesses for long-term development and competitive advantage by carefully identifying and removing non-value-added operations. The proposed Znumbers-based GMCDM offers manufacturers a systematic method for initially prioritizing and selecting which non-value-added tasks to focus on. The present study employed the Z-CFAHP-VIKOR approach to examine the interrelationships among production metrics within the mass-customized machinery industry. The determination was made regarding the production measure that had the greatest impact on the ideal lead time. The initial step was convening a meeting with the expert group within the organization to establish the NVA criteria and sub-criteria for assessing the aspect. The application of AHP to ensure consistent testing of feedback by industry experts, along with the utilization of Z-CFAHP to calculate the global weights of sub-criteria, reveals that the criteria order of Transport (T), Waiting (W), Inventory (I), Motion (M), Over Processing (P), Over Production (O), and Defects (D) retain the most significance. The sub-criteria were determined in the following order: T1 > T2 > I1 > W3 > M1 > W2 > I3 > P3 > M2 > O3 > T3 > I2 > W1 > D1 > M3 > O2 > P1 > P2 > D2 > O1 > D3. Following the procedure mentioned earlier, Z-FVIKOR was employed to yield production output metrics with substantial significance. The framework the GMCDM advocates incorporates several production output metrics, including Makespan, Flow Time, Idle Time, and efficiency. Makespan has the most significant influence among these production metrics, followed by Flow Time, Idle Time, and efficiency in that specific sequence, as indicated by Z-FVIKOR.

To evaluate the robustness of the suggested approach, sensitivity analyses are conducted in conjunction with the case study. The global weights increased by 50%, 100%, and 150% during the sensitivity study. Based on the above conditions, Fig. 6 illustrates that a 50% Q_i index value has increased global weights. According to the outcomes derived from our Z-CFAHP-VIKOR model, the rankings remain consistent with the original order, which is as follows: Makespan > Flow Time > Idle Time > Efficiency. The sub-criteria of inefficient schedule (T2), raw materials (I1), machine setup (M1), and maintenance delay (W3) have been assigned priority weights of 100% and 150% for the transport, inventory, motion, and waiting criteria, respectively. The priority ordering for these sub-criteria, as depicted in Fig. 7 and Fig. 8, is as follows: Flow Time > Makespan > Idle Time > Efficiency for T2-100%, T2-150%, W3-150%, and Makespan > Idle Time > Flow Time > Efficiency for I2-100%, I2-150%, M1-150%, respectively. A comprehensive analysis was conducted on 63 runs to verify the proposed model, Z-

CFAHP-VIKOR. Out of the total, 57 instances showed compatibility with the suggested model's outcomes, while the remaining six iterations demonstrated inconsistency. The Z-CFAHP-VIKOR method is relatively robust and resilient, with a 90.47% consistency rate, due to its ability to withstand changes in the global weights of sub-criteria concerning a criterion. These changes have a minimal impact on the final priority order of production metrics in various situations. According to Opricovic & Tzeng (2004), VIKOR utilizes linear normalization, while TOPSIS employs vector normalization to eliminate criteria function units. Both techniques rely on the aggregating function, which also indicates similarity to the ideal. The primary benefit of the VIKOR method is that compromised ranking boosts group utility for the majority and reduces opponent regret. However, TOPSIS produces a solution that minimizes the distance to the ideal solution and increases the distance from the negative-ideal solution, but ignores the relative significance of these distances. Table 11 illustrates the comparison of the proposed method, Z-CFAHP-VIKOR, with Haktanır & Kahraman (2024) 's Z-AHP-TOPSIS technique, which mutually yields similar ranks of the performance metrics: Makespan > Flow Time > Time > Efficiency, confirming the robustness of the decision-making result. Z-CFAHP-VIKOR offers more benefits than Z-AHP-TOPSIS. The proposed method evaluates the results based on the significance of similarity, while balancing group utility with individual regret.

Tab. 11. Comparison of outcomes of performance metrics

Z-number Techniques	Ranking Indices	Makespan	Flow Time	Idle Time	Efficiency	Rank
Z-AHP-TOPSIS (Haktanır & Kahraman, 2024)	C_i (Higher is better)	0.794	0.668	0.504	0.132	Makespan > Flow Time > Idle Time > Efficiency
Z_CFAHP-VIKOR	Q_i (Lower is better)	0.000	0.229	0.448	1.000	Makespan > Flow Time > Idle Time > Efficiency

Conclusion

Mass Customization industries efficiently achieve their esteemed consumers' needs and top priorities on time to ensure customer satisfaction. The production output metrics determine the manufacturing planning activities. When executed accurately, it exerts a significant influence on the efficiency of a procedure. In manufacturing industries, it is imperative to ascertain the required output rate while minimizing processing time and interruptions to provide a consistent and uninterrupted supply of resources along the production line, thereby optimizing the utilization of personnel, equipment, and resources. The process of making decisions has emerged as a highly significant concern for contemporary industries. Measuring production metrics is a critical factor that enables organizations to get a competitive edge. Customer satisfaction may be enhanced by ensuring the timely delivery of the goods to the consumer. Therefore, it would benefit the organization to ascertain the production metrics that exhibit a more significant influence on the products and undertake the necessary advancements and investigations.

This study investigated non-value-added activities using Z-CFAHP-VIKOR in the mass-customized machinery industry, employing seven criteria, 21 sub-criteria, and four production output metrics to identify the most significant production output metric influencing the achievement of optimal lead time. The key findings indicate that the integrated Z-CFAHP-VIKOR technique effectively illustrates the group of expert perspectives and evaluates production output metrics based on the NVA activities. Utilizing the Z-number-based pairwise comparison matrix and fuzzy decision matrix from the group of industrial experts, ZCFAHP was employed to determine the global weights of the sub-criteria, and ZVIKOR was used to rank the production output metrics. This analysis resulted in makespan being identified as the most significant production output metric influencing the achievement of optimal lead time. The suggested approach encompasses a consistency rate of 90.47%, corresponding with the appropriate prioritization sequence. The hierarchical arrangement continues to adhere closely to the initial ranking, despite alterations in the ranking values. The sensitivity study findings indicate that the Z-CFAHP-VIKOR remains robust, even when the criteria weights are modified. The Z-number-based GMCDM method enhances reliability and transparency in complex decision-making processes and is adaptable to various industrial challenges. In future studies, alternative multi-criteria decision-making techniques can be used to determine their interrelations with each other's production output metrics and further investigate this mass-customized machinery industry problem. The high-impact performance metric may be further minimized with intelligent algorithms to obtain the desired lead time.

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