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CYLINDER AND PISTON: MATERIAL SELECTION IN THE DESIGN PHASE

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The piston and cylinder constitute an inseparable pair, playing a crucial role in both the mechanical and hydraulic industries. They are frequently employed to convert linear motion into rotational motion in various types of engines and are especially valuable for heavy-duty applications. Material selection for these components is conducted during the product design phase. This study aimed to identify the optimal material for each type of product. To determine the best material, a ranking of materials was carried out using the CoCoSo (COmbined COmpromise SOlution) method, with scores for criteria calculated using the Entropy method. Nine materials for cylinder construction were evaluated, including S355JR, S275JR, S235JR, BS97007M20, R35, R45, IS1030GRADE, AISI304, and 60-40-18. Additionally, seven materials for piston construction were considered: 332-T5, A336, 242-T5, 333.0-F, A213.0 F, AISI308, and A319.0F. The Entropy-CoCoSo approach was employed to rank the materials for each case (cylinder material and piston material). The results indicated that AISI304 is the optimal material for cylinder manufacturing, while A336 is the best material for piston manufacturing. Furthermore, the study extensively examined the impact of different weighting methods (Entropy, WENSLO, CRITIC, ROC, RS, EW) and normalization techniques (sum, vector, max, max-min, peldschus, decimal) on CoCoSo method results using an innovative sensitivity analysis approach, analyzing the techniques according to their sensitivity levels.

Keywords: material for cylinder and piston manufacturing, MCDM, CoCoSo, sensitivity analysis

1 INTRODUCTION

The process of selecting materials plays a vital role in engineering applications, as it significantly influences a product's performance, durability, and cost. Choosing the right materials is essential for ensuring the final product’s efficiency, functionality, and lifespan. Selecting the right materials is essential for ensuring both structural integrity and functionality, whereas inappropriate material choices can result in quality defects, higher expenses, and greater environmental consequences. Moreover, assessing various material options is vital in achieving long-term sustainability and cost-effectiveness for products. Cylinders and pistons are critical components commonly used in various fields. When a substance (liquid or gas) is compressed into the cylinder through one end of the piston, the energy of this substance is converted into kinetic energy, which is then transmitted to the executing mechanisms. Although the material requirements for these components vary depending on their specific applications, in general, the materials used for manufacturing cylinders and pistons must meet stringent standards compared to many other mechanical parts [1-3]. Cylinder materials must be strong enough to withstand the high pressures of the gas or liquid contained within them and must also have high rigidity to prevent deformation during assembly and operation. In addition, these materials should possess good weldability, heat resistance, and thermal conductivity, among other characteristics [4-5]. Similarly, materials used in piston manufacturing need to exhibit high hardness, heat resistance, and fatigue strength [3,6-7]. The selection of materials for manufacturing components, particularly cylinders and pistons, is a critical aspect of the product design phase [8]. This selection process depends on the specific properties of the materials [6,9-10]. Consequently, choosing a suitable material is inherently a Multi-Criteria Decision-Making (MCDM) process [11-15].

MCDM methods have been widely applied by researchers to address various decision-making challenges across different engineering fields [16]. Given the vast number of materials available, each with unique properties suitable for piston manufacturing, selecting the optimal material can be a complex task. To tackle this complexity, several studies have employed MCDM methods for piston material selection, including the use of the TOPSIS method [6], the Fuzzy TOPSIS method [17], the MAIRCA method [18], the VIKOR method [19], the AHP method [20], and the combined application of SAW, WPM, and AHP methods [21] among others. Perhaps selecting materials for cylinder construction is even more complex than for piston materials. Cylinders consist of multiple sections with varying thicknesses, each playing a different role, making the choice of materials extremely crucial. Currently, the selection process for cylinder materials typically involves three stages: (1) simulation, (2) manufacturing, and (3) testing [22]. This process can be time-consuming and resource-intensive if simulations, manufacturing, and testing are needed for a wide range of materials. By introducing MCDM methods as an initial stage (before stage 1), the complexity of the entire process can be significantly reduced. However, there is a noticeable lack of literature on using MCDM methods for selecting cylinder materials. While applying MCDM methods for selecting piston materials aligns with current research trends, utilizing these methods for cylinder material selection represents a novel aspect explored in this work.

The CoCoSo (COmbined COmpromise SOlution) method, developed from the well-known VIKOR method, stands out due to its unique feature of comparing alternatives using three different strategies, an approach not found in any other MCDM method [23]. Many scholars have applied the CoCoSo method in their research, including assessing the operational efficiency of private firms in Turkey's electricity production sector [24], material selection for construction activities [25], selecting solutions for medical waste treatment [26], choosing suppliers for construction companies in Madrid [27], evaluating financial risk in enterprises [28] and selecting transportation companies for businesses [29] among others. In this study, the CoCoSo method is applied to select materials for cylinder and piston construction. The third part of this article outlines the steps involved in applying this method.

When using the CoCoSo method to rank alternatives, it is essential to determine the criterion weights. This study employed the Entropy method, an objective, widely used, and reliable technique for determining weights. Additionally, the effects of various weighting and normalization techniques on the CoCoSo method's outcomes were examined using an innovative sensitivity analysis approach, employing six different normalization techniques and seven different weighting methods. The contributions of this research to the existing literature can be summarized as follows: i) The selection of materials for the cylinder and piston assembly, which plays a critical role in the product design process, has been comprehensively addressed using MCDM methods. ii) The application of MCDM methods for selecting cylinder materials represents a novel research area explored in this work. iii) The effects of weights derived from seven different techniques, including Entropy, WENSLO, CRITIC, LOPCOW, ROC (Rank Order Centroid), RS (Rank Sum), and EW (Equal Weight), as well as six different normalization techniques such as Sum, Vector, Max, Max-Min, Peldschus, and Decimal, on CoCoSo results have been thoroughly examined. iv) An innovative sensitivity analysis approach was used to measure the sensitivities and correlation degrees of weighting and normalization techniques based on the CoCoSo method. v) The weighting and normalization techniques that either enhance or diminish the performance of the CoCoSo method have been evaluated within the scope of two different real-life applications.

The remainder of the article is structured as follows: The second section presents a literature review, focusing on studies related to MCDM in material selection. The third section provides detailed explanations and methodologies of the employed methods. Parts four of this article focus on selecting materials for cylinder and piston construction, respectively. The fifth section is dedicated to the innovative sensitivity analysis. The final part of this article presents the findings and outlines future research directions.

2 LITERATURE REVIEW ON MATERIALS SELECTION

Selecting materials is a complex process involving multiple stakeholders and various conflicting criteria. The application of MCDM methods to identify the optimal material for specific applications has become increasingly prevalent in literature. For instance, [30] employed the Fuzzy TOPSIS method for material selection for flywheels, with criterion weights subjectively determined by three decision-makers. Their analysis resulted in the selection of maraging steel 18Ni for flywheel manufacturing, while carbon steel 1065 was the least preferred. [31] employed a MCDM approach in the selection of engineering materials used for the development of wing structures in flying robots. [32] applied the Entropy-MOOSRA model for gear material selection, comparing the results with EXPROM-2, ORESTE, and OCRA methods, concluding that the EXPROM-2 and OCRA methods were superior. [33] investigated the use of Q-analysis as an MCDM tool for optimal material selection. [34] proposed a MCDM approach based on Graph Theory and Matrix methods for the selection of high-temperature thermochemical storage materials. [35] simultaneously selected materials and geometric variables within Hazelrigg's decision-based design framework using Suh's design axioms, MABAC, and AHP methods. [36] applied the COPRAS-G method to address two material and design selection project examples, finding significant effects of the number of criteria and alternatives, as well as normalization methods, on the results. [37] employed AHP-MOORA, TOPSIS, and VIKOR methods to select the most suitable material for brake support valve bodies, identifying PET-gf35 (PET reinforced with 35% glass fiber) as the optimal material. [38] used the TODIM method to select the most suitable materials for motor flywheels and metal gears. [39] employed Entropy, MEREC, LOPCOW, CRITIC, and MEAN-based MARA, RAM, and PIV models for lubricant selection for two-stroke engines, material selection for screw shafts, and material selection for gear production. [40] addressed coating material selection for sheet metal forming applications using MEREC-based WASPAS, TOPSIS, CODAS, and MARCOS models. [41] utilized the Entropy-TOPSIS-GRA model to select appropriate matrix phase materials with various (organic and inorganic) fillers to achieve the optimal multi-stimulus response in shape memory polymer (SMP) composite systems. [42] proposed an integrated MCDM and mathematical dual-objective model for material selection, including a mathematical dual-objective model to determine the best purchasing item using TOPSIS. [43] applied a DEA-MCDM approach for material selection in the automotive parts manufacturing industry. [44] utilized the CRITIC, Entropy, MEREC, SV-based ARAS, CoCoSo, MABAC, ROV, and TOPSIS models for material selection problems. In addition, there are studies in literature that examine operational reliability as a solution to problems encountered in reciprocating compressors. [45] investigated diagnostic parameters such as axial clearance and temperature on tested ball bearings located on the compressor's crankshaft. The research results indicated that the axial clearance dimensions and temperature values were consistent with those observed before the onset of the condition, and these parameters were recognized as reliable indicators of the technical system's overall reliability.

3 METHODS

3.1 CoCoSo method

To select the best option among the available alternatives, the application of the CoCoSo method is carried out following the following sequence [23]:

Step 1. With m alternatives and n criteria, a matrix is constructed as in formula (1).

$$X = [x_{ij}]_{n\times m} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & x_{ij} & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

In which: x_{ij} represents the value of criterion *j* for the alternative *i*, *i= 1-m*, *j = 1-n*.

Step 2. Normalize the data using the two formulas (2) and (3). Formula (2) is applied to criteria where larger values are better, and formula (3) is applied to criteria where smaller values are better.

$$r_{ij} = \frac{x_{ij} - min\, x_{ij}}{max\, x_{ij} - min\, x_{ij}} \quad (2)$$

$$r_{ij} = \frac{max\, x_{ij} - x_{ij}}{max\, x_{ij} - min\, x_{ij}} \quad (3)$$

Step 3. Calculate the two quantities, S_i and P_i using the respective formulas (4) and (5). Where w_j represents the weight of criterion *j*.

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \quad (4)$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \quad (5)$$

Step 4. Calculate the values k_{ia}, k_{ib}, k_{ic} using the respective formulas (6), (7), and (8).

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)'} \quad (6)$$

$$k_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min P_i} \quad (7)$$

$$k_{ic} = \frac{\lambda S_i + (1-\lambda)P_i}{\lambda \max S_i + (1-\lambda)\max P_i} \quad (8)$$

Where (8), λ is a coefficient, typically chosen as 0.5 [21].

Step 5. Calculate the values k_i according to the formula.

$$k_i = (k_{ia}k_{ib}k_{ic})^{1/3} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \quad (9)$$

3.2 Determination of weights for the criteria

Employing MCDM approaches is a highly effective way to make well-informed decisions [46]. The weights of criteria reflect their importance in decision-making processes. There are fundamentally two approaches to determining criterion weights: direct and indirect explication. Direct explication involves obtaining weights through expert interviews, surveys, and predefined rules, with weights assigned prior to gathering data for each alternative. In contrast, indirect explication derives weights from the data itself, assigning them after data collection, which is why these are referred to as a posteriori weights. While direct explication captures expert priorities, indirect assessment represents the relative importance of the evaluated alternatives. This latter method is often considered more robust, as the weights are based directly on the collected data [47-48].

In this study, seven distinct objective methods were employed to calculate the criteria weights. The Entropy method, widely used in recent research [49-51], is also recommended for its reliability [51]. The Equal method, the simplest of the weight determination methods, is also employed [53]. CRITIC is the only method that considers the relationships between criteria, offering a more nuanced approach [54]. ROC and RS are two methods that account for the degree of preference between criteria, though they employ different formulas [55]. The LOPCOW method provides notable advantages, including the ability to manage negative values within the initial decision matrix [56]. A primary benefit of the WENSLO method is that it ensures criteria weights are not influenced by personal judgments or expert opinions. Moreover, this method does not allow the nature of the criteria (whether they are benefits or costs) to affect the calculation process [57].

By using these six weighting methods (with the EW-CoCoSo ranking determined as a fixed factor) and six normalization techniques in combination with the CoCoSo method, 72 different scenarios for ranking materials for cylinder and piston manufacturing can be generated. The weighting techniques utilized in this study are presented in Table 1.

Table 1. Criteria weighting techniques

Method/Reference	Steps	Equation
EW [58]	1: Calculation of criteria weights	$w_j = \frac{1}{n}\ j \in \{1,2,\dots,n\}$ (10) n is the number of criteria
Entropy [59]	1: Normalize the decision matrix	$v_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$ (11)
	2: Calculate the entropy value of the j[th] criterion	$e_j = -k\sum_{i=1}^{m} v_{ij}\,\mathrm{In}(v_{ij}) = -\frac{1}{\mathrm{In}(m)}\sum_{i=1}^{m} v_{ij}\mathrm{In}(v_{ij})$ (12) m is the total number of evaluated alternatives
	3: Calculate the degree of diversification dj	$d_j = 1 - e_j, j \in [1,\dots,n]$ (13)
	4: Calculation of criteria weights	$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$ (14)
WENSLO [57]	1: Normalization of input data	Similar to step 1 of the Entropy method
	2: Calculation of criterion class interval	$\Delta_{z_j} = \frac{\max\limits_{i=1,2,\dots,m} z_{ij} - \min\limits_{i=1,2,\dots,m} z_{ij}}{1 + 3.322 * log(m)}, \forall_j \in [1,2,\dots,n]$ (15) Zij represents the element of the normalized decision matrix
	3: Calculation of the criterion slope	$\tan\phi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1) * \Delta z_j} \forall_j \in [1,2,\dots,n]$ (16)
	4: Determination of the criterion envelope	$E_j = \sum_{i=1}^{m-1} \sqrt{(z_i + 1, j - z_{i,j})^2 + \Delta z_j^2}$ (17)
	5: Define the envelope–slope ratio	$q_j = \frac{E_j}{tan\phi_j}\ \ \forall_j \in [1,2,\dots,n]$ (18)
	6: Calculation of criteria weights	$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j}\ \forall_j \in [1,2,\dots,n]$ (19)
CRITIC [58]	1: Normalize the decision matrix	Similar to step 1 of the CoCoSo method.
	2: Determine the linear correlation matrix	$p_{jk} = \frac{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)^2 \sum_{i=1}^{m}(r_{ik} - \bar{r}_k)^2}}$ (20) $j, k = 1,\dots,n$ p_{jk} *is the* correlation coefficient between the vectors rj and rk
	3: Calculate the key indicator and weight of criteria	$c_j = \sigma_j \sum_{k=1}^{n}(1 - p_{jk})$ (21) $w_j = c_j / \sum_{k=1}^{n} ck\ \ j = 1,\dots,n$ (22) cj is the information given by j th indicator
LOPCOW [60]	1: Normalization of input data	Similar to step 1 of the CoCoSo method

Method/Reference	Steps	Equation	
	2: Calculate the percentage values (PV) of each criterion	$PV_{ij} = \left\| \ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^2}{m}}}{\sigma}\right).100 \right\|$	(23)
	3: Compute the objective weights.	$w_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}}$	(24)
ROC and RS methods [55]	1: Compute the objective weights.	$w_j = \frac{1}{n}\sum_{k}^{n}\frac{1}{k}$	(25)
		$w_j = \frac{2\,(n+1-k)}{n(n+1)}$	(26)

3.3 Normalization methods

The MCDM process primarily helps decision-makers improve the consistency of their decisions by drawing on historical data and information during the decision-making phase [61]. The initial step in most MCDM methods is the normalization process [62]. Normalization is a scaling technique that ensures the comparability of criteria by eliminating differences in optimization direction, measurement units, and ranges of variation. Through normalization, data is transformed to a specific norm or standard [63]. In multi-criteria evaluation, this process is essential for making diverse criteria comparable, as it accounts for both quantitative and qualitative factors, which are often measured in different units. The choice of normalization technique can significantly influence ranking outcomes, underscoring its critical role in solving decision problems. The application of different normalization techniques may result in varying rankings or orderings of alternatives, potentially causing deviations from the optimal sequence. Therefore, selecting the appropriate normalization method is vital for ensuring the accuracy of decision-making outcomes [64]. The normalization techniques considered in this study are summarized in Table 2. Techniques such as Z-score and logarithmic normalization, which can produce negative values depending on the optimization direction, were excluded from this study.

Table 2. Normalization methods

Techniques	Benefit Criteria	Cost Criteria	References
Sum-Based Linear Normalization	$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$	$n_{ij} = \frac{1/x_{ij}}{\sum_{i=1}^{m} 1/x_{ij}}$	[65]
Vector Normalization	$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} \lvert x_{ij}\rvert^2}}$	$n_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} \lvert x_{ij}\rvert^2}}$	[66]
Maximum - Linear Normalization	$n_{ij} = \frac{x_{ij}}{\max_i x_{ij}}$	$n_{ij} = 1 - \frac{x_{ij}}{\max_i x_{ij}}$	[67]
Linear max min normalization	$n_{ij} = \frac{r_{ij} - r_j^{min}}{r_i^{max} - r_i^{min}}$	$n_{ij} = \frac{r_i^{max} - r_{ij}}{r_i^{max} - r_i^{min}}$	[68]
Peldschus Normalization	$n_{ij} = (\frac{x_{ij}}{\max_i x_{ij}})^2$	$n_{ij} = (\frac{min\, x_i}{x_{ij}})^3$	[69]
Decimal scaling normalization	$nv = f(v) = \frac{v}{10^c}$		[70]

4 APPLICATION

4.1 Selecting Materials for cylinder

Nine types of materials commonly used in cylinder manufacturing include S355JR, S275JR, S235JR, BS97007M20, R35, R45, IS1030GRADE, AISI304, and 60-40-18. Four criteria, density (C1, kg/dm³), tensile strength (C2, MPa), yield strength (C3, MPa), and carbon content (C4, %), were used to evaluate each material. Criteria C1, C2, and C3 are favorable parameters, meaning higher values are preferred. However, a high carbon content negatively impacts ductility and flexural strength. Given that high ductility and flexural strength are essential for cylinders, materials with lower carbon content are ideal, making C4 a criterion where lower values are better. The values for all four criteria across the different materials are summarized in Table 3 [71].

Table 3. Materials for manufacturing a cylinder [71]

Material	C1	C2	C3	C4
S355JR	7.8	355	490	0.2
S275JR	7.9	275	410	0.21
S235JR	7.8	235	340	0.2
BS97007M20	7.8	210	410	0.24
R35	7.9	235	345	0.16
R45	7.9	255	440	0.22
IS1030GRADE	7.85	280	580	0.25
AISI304	7.9	210	520	0.08
60-40-18	7.1	276	414	3.6

The maximum value for C1 is 7.9 kg/dm³, achieved by the materials S275JR, R35, R45, and AISI304. The maximum value for C2 is 355 MPa, observed in material S355JR. For C3, the maximum value is 580 MPa, found in the material IS1030GRADE, while the minimum value for C4 is 0.08%, corresponding to the material AISI304. This indicates that no single material simultaneously achieves the maximum values for C1, C2, and C3, along with the minimum value for C4. Consequently, determining the best material requires the application of MCDM methods. For this purpose, the CoCoSo method has been employed. However, prior to this, the process of determining the weights for the criteria must be completed.

This section presents the results of the Entropy-CoCoSo model, followed by the results obtained using seven different weighting methods at the end of the fourth section. To rank the materials for cylinder manufacturing, the data in the CoCoSo method is first normalized using formulas (2) and (3). The normalized data values are summarized in Table 4.

Table 4. The normalized values in the CoCoSo method

Material	C1	C2	C3	C4
S355JR	0.8750	1	0.6250	0.9659
S275JR	1	0.4483	0.2917	0.9631
S235JR	0.8750	0.1724	0	0.9659
BS97007M20	0.8750	0	0.2917	0.9545
R35	1	0.1724	0.0208	0.9773
R45	1	0.3103	0.4167	0.9602
IS1030GRADE	0.9375	0.4828	1	0.9517
AISI304	1	0	0.7500	1
60-40-18	0	0.4552	0.3083	0

The values of parameters S_i, P_i, k_{ia}, k_{ib}, k_{ic} và k_i have been calculated according to the respective formulas (4), (5), (6), (7), (8), and (9). Initially, the criterion weights were calculated using the Entropy method using the formulas 11-14. In Table 5, the computed values of these parameters and the ranking results for the materials have been summarized.

Table 5. Result of the Entropy-CoCoSo model (Example 1)

Material	S_i	P_i	k_{ia}	k_{ib}	k_{ic}	k_i	Rank
S355JR	0.9614	3.9601	0.1290	95.3906	0.9955	34.4770	2
S275JR	0.9468	3.9363	0.1280	93.9602	0.9878	33.9738	4
S235JR	0.9418	2.9443	0.1019	92.9683	0.7861	33.2380	7
BS97007M20	0.9327	2.9383	0.1015	92.0798	0.7830	32.9294	8
R35	0.9532	3.9016	0.1273	94.5615	0.9820	34.1681	3
R45	0.9441	3.9339	0.1279	93.6906	0.9867	33.8797	5
IS1030GRADE	0.9463	3.9436	0.1282	93.9135	0.9891	33.9605	6

AISI304	0.9835	2.9959	0.1043	97.0434	0.8050	34.6632	1
60-40-18	0.0103	1.9732	0.0520	2.0000	0.4012	1.1646	9

According to Table 5, the AISI304 material ranks first in cylinder manufacturing, while the 60-40-18 material ranks last. The overall ranking is as follows: AISI304 > S355JR > R35 > S275JR > R45 > IS1030GRADE > S235JR. The ranking of the various cylinder manufacturing materials was also carried out similarly when the weights of the criteria were calculated using the other six methods (WENSLO, CRITIC, LOPCOW, ROC, RS, EW).

4.2 Selecting materials for piston manufacturing

There are seven types of materials commonly used for piston manufacturing, each corresponding to specific alloy designations: 332-T5, A336, 242-T5, 333.0-F, A213.0 F, AISI308, and A319.0F. Ten criteria (C1 - g/cm^3, C2 - BHN, C3 - GPa, C4 - MPa, C5 - MPa, C6 - %, C7 - w/mk, C8 - μm/m.k, C9 - J/g.C, and C10 - MPa) have been used to describe each material. Detailed information about these seven materials has been summarized in Table 6 [21]. Among the ten criteria mentioned, C1, C2, C3, C4, C5, C7, C9, and C10 are such that higher values are preferred, while the remaining two criteria (C6 and C8) are such that lower values are preferred.

Table 6. Materials for piston manufacturing [21]

Material	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
332-T5	2.76	110	73	250	190	1	105	20.7	963	90
A336	2.72	100	73	214	193	0.5	117	19.8	963	85
242-T5	2.81	85	71	200	205	0.5	134	22.7	963	75
333.0-F	2.80	90	73	230	130	2	100	21	880	96
A213.0 F	3.20	85	73	190	130	1.5	130	23	850	93
AISI308	2.90	78	72	190	110	2	140	20	870	89
A319.0F	2.90	78	72	190	110	2	110	22	880	77

Material 332-T5 excels in criteria C2, C3, C4, and C9. Material A336 performs best in three criteria: C3, C8, and C9. Material 242-T5 is superior in three criteria: C5, C6, and C9. Material 333.0-F stands out in two criteria: C3 and C10. Material A213.0 F excels in two criteria: C1 and C3. Material AISI308 is the top performer in criterion C7. Notably, A319.0F is the only material that does not excel in any of the criteria. Consequently, no single material outperforms others across all ten criteria. To determine the most suitable material, the use of MCDM methods is necessary. The CoCoSo method has been selected for this analysis. The ranking of piston manufacturing materials using the CoCoSo method, with Entropy criterion weights as described in Section 4, is presented and summarized in Table 7.

Table 7. Result of the Entropy-CoCoSo model (Example 2)

	S_i	P_i	k_{ia}	k_{ib}	k_{ic}	k_i	Rank
332-T5	0.6987	9.6259	0.1874	38.3644	0.9801	15.0946	3
A336	0.9082	8.8883	0.1778	49.2525	0.9300	18.7989	1
242-T5	0.9054	7.8531	0.1590	48.9305	0.8314	18.5036	2
333.0-F	0.0994	7.6862	0.1413	6.5316	0.7391	3.3510	5
A213.0 F	0.3242	6.1657	0.1178	18.0926	0.6161	7.3706	4
AISI308	0.0643	5.9718	0.1096	4.3967	0.5730	2.3442	6
A319.0F	0.0190	5.8751	0.1070	2.0000	0.5595	1.3817	7

According to Table 7, the A336 material ranks first in piston manufacturing. On the other hand, the overall ranking is as follows: A336 > 242-T5 > 332-T5 > A213.0 F > 333.0-F > AISI308 > A319.0F.

5 INNOVATIVE SENSITIVITY APPROACH

Sensitivity analysis, which helps determine and manage uncertainties in data inputs such as sampling errors, measurement errors or missing data, enables obtaining more accurate and reliable predictions. This, in turn, leads to more informed decisions and enhances the reliability of the tool [72]. In the literature, sensitivity analysis can be conducted in various ways, such as by employing different normalization techniques, varying criteria weights, using different MCDM methods, or altering the values within the algorithms of the methods. This approach aims to assess the reliability of the employed method, as MCDM results are sensitive to these factors. However, there is no consensus on how to determine the quality of an MCDM method or the reliability of its results. Furthermore, there is also no agreement on the exact limits of sensitivity analysis and how these limits should be defined [73]. According to [74], focusing solely on the change in the rank of a single alternative (usually the top-ranked one) without considering the overall ranking and defining the minimum fluctuation in ranking results obtained through various MCDM methods as "stability" is a controversial and critique-prone approach. The authors suggest that by utilizing data analytics, dynamic MCDM results should be compared to a static external arrangement, and sensitivity should be observed.

In this section, the degree, direction, and nature of sensitivity have been explored using the innovative sensitivity analysis approach proposed by [74]. Accordingly, the impact of different normalization and weighting techniques on the results of the CoCoSo method was assessed, using the EW-CoCoSo scores as the fixed external factor (Table 8). An innovative sensitivity analysis was conducted using the weights obtained from the six different methods specified in Table 9, along with the normalized decision matrices derived from the sum, vector, max, min-max, Peldschus, and decimal normalization techniques. Tables 9 display the Spearman Correlation (rho) results between the actual EW-CoCoSo scores and MCDM rankings for the CoCoSo method, reflecting the impact of different normalization methods and weights on the results. The variation in all correlations is measured using standard deviation, providing an innovative measure of sensitivity [74]. Additionally, the average correlations between the fixed external factor and the methods are presented in Tables 10 and 12 for the first and second applications, respectively.

According to the innovative sensitivity analysis approach, low sensitivity (standard deviation) in an MCDM ranking is equivalent to a high correlation (rho) with a fixed external factor [73]. Based on this premise, techniques with low standard deviation are considered to provide the highest correlation with the compared factor and better MCDM rankings exhibit lower sensitivity. Conversely, sensitivity is influenced by various components, including the chosen MCDM method, problem characteristics, data type, and normalization and weighting coefficients within MCDM integrity [75]. The results obtained in this section, which uses six different data sets, also vary. For instance, based on the row results in Table 10, the min-max technique, with the lowest standard deviation under different weights, shows the highest correlation with the EW-CoCoSo results. Conversely, normalization techniques such as peldschus, max, vector exhibit high sensitivity and low correlation. When evaluated on a column basis, the ROC method, based on different normalization techniques, demonstrates the lowest sensitivity and highest correlation with the fixed external factor. In contrast, the LOPCOW, Entropy and WENSLO technique results show high sensitivity. Results obtained using the Vector, max, and Peldschus normalization method exhibit negative correlations.

Table 8. Fixed external factors (EW-CoCoSo ranking results)

Selecting Materials for Cylinder			Selecting Materials for Piston Manufacturing		
Materials	k_i	Rank	Materials	k_i	Rank
S355JR	34.4770	2	332-T5	15.0946	3
S275JR	33.9738	4	A336	18.7989	1
S235JR	33.2380	7	242-T5	18.5036	2
BS97007M20	32.9294	8	333.0-F	3.3510	5
R35	34.1681	3	A213.0 F	7.3706	4
R45	33.8797	5	AISI308	2.3442	6
IS1030GRADE	33.9605	6	A319.0F	1.3817	7
AISI304	34.6632	1			
60-40-18	1.1646	9			

Table 9. Weights of the criteria (Example 1)

	C1	C2	C3	C4
Entropy	0.4009	0.2099	0.1983	0.1910
WENSLO	0.0003	0.0080	0.0081	0.9837
LOPCOW	0.3562	0.1270	0.1557	0.3610
CRITIC	0.2510	0.1991	0.2987	0.2512
ROC	0.5208	0.2708	0.1458	0.0625
RS	0.4000	0.3000	0.2000	0.1000
EW	0.25	0.25	0.25	0.25

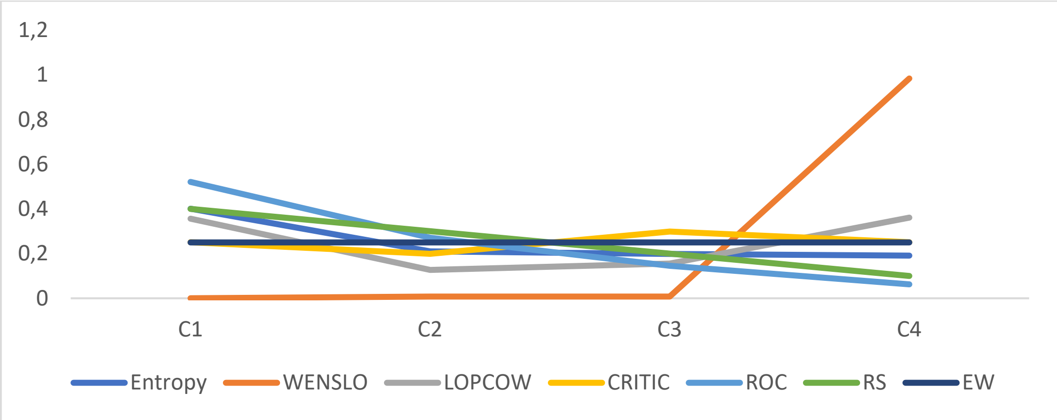

Fig. 1. Criteria Weights (Example 1)

Table 10. CoCoSo results based on different weighting and normalization techniques (Example 1)

	Entropy	WENSLO	CRITIC	LOPCOW	ROC	RS	StDv	Mean
Sum	0.394	0.391	0.712	0.585	0.917	0.882	**0.2307**	**0.6470**
Vector	-0.772	-0.773	-0.549	-0.682	-0.043	-0.227	**0.3054**	**-0.5076**
Max	-0.768	-0.771	-0.344	-0.594	0.321	0.099	**0.4612**	**-0.3428**
Max min	0.800	0.791	0.998	0.958	0.991	0.998	**0.1000**	**0.9227**
Peldschus	-0.772	-0.776	-0.228	-0.521	0.338	0.138	**0.4696**	**-0.3036**
Decimal	0.014	-0.255	0.447	0.467	0.419	0.397	**0.2988**	**0.2482**
StDv	**0.6890**	**0.6804**	**0.6317**	**0.7154**	**0.3937**	**0.4777**		
Mean	**-0.1842**	**-0.2322**	**0.1730**	**0.0355**	**0.4905**	**0.3812**		

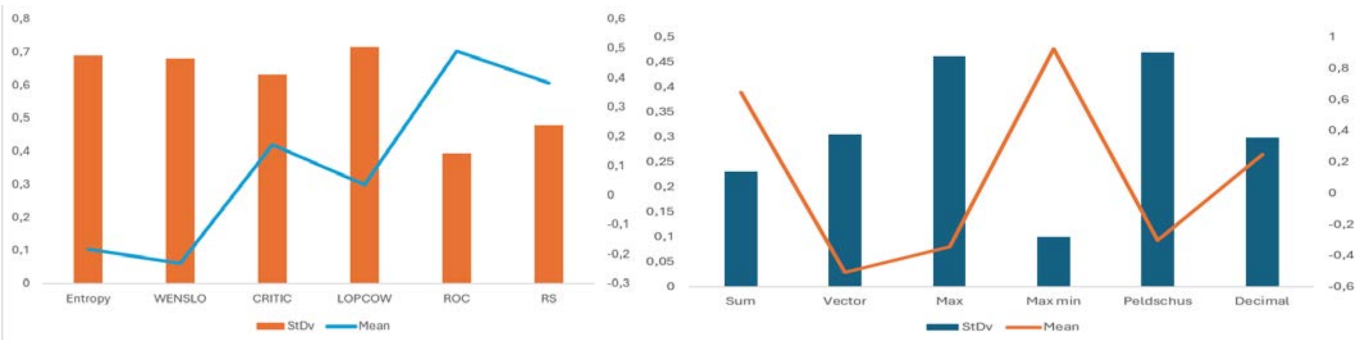

Fig. 2. Sensitivity levels based on weighting and normalization techniques (Example 1)

Similarly to Section 4, the weights of the criteria have also been determined using six different methods, with the values presented in Table 11. The results of the innovative sensitivity analysis, where EW-CoCoSo results are used as the fixed external factor, are shown in Table 12.

Table 11. Weights of the criteria (Example 2)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Entropy	0.1422	0.0881	0.0892	0.0856	0.0862	0.1506	0.0871	0.0988	0.0839	0.0883
WENSLO	0.0265	0.0827	0.0018	0.0598	0.1921	0.4741	0.0767	0.0227	0.0169	0.0468
LOPCOW	0.0697	0.0740	0.1800	0.0530	0.0811	0.0689	0.1130	0.1213	0.1026	0.1365
CRITIC	0.1225	0.0690	0.0942	0.0842	0.0946	0.1028	0.1317	0.1011	0.1013	0.0986
ROC	0.2929	0.1929	0.1429	0.1096	0.0846	0.0646	0.0479	0.0336	0.0211	0.0100
RS	0.1818	0.1636	0.1455	0.1273	0.1091	0.0909	0.0727	0.0545	0.0364	0.0182
EW	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

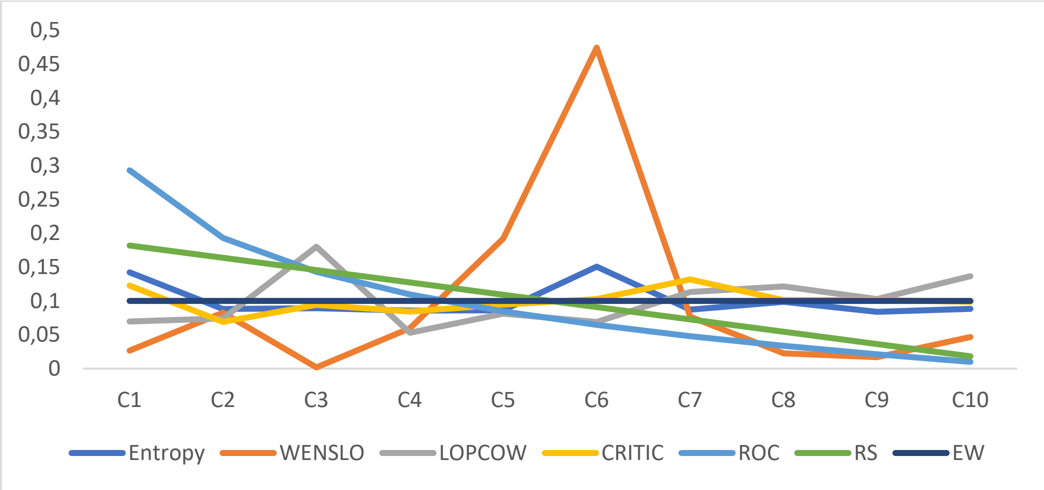

Fig. 3. Criteria weights (Example 2)

Table 12. CoCoSo results based on different weighting and normalization techniques (Example 2)

	Entropy	WENSLO	CRITIC	LOPCOW	ROC	RS	StDv	Mean
Sum	0.608	0.642	0.766	0.831	0.875	0.833	**0.1102**	**0.7591**
Vector	0.740	0.767	0.857	0.910	0.927	0.906	**0.0796**	**0.8513**
Max	0.620	-0.607	0.809	0.894	0.915	0.880	**0.5940**	**0.5853**
Max min	0.782	0.853	0.997	0.990	0.951	0.988	**0.0891**	**0.9267**
Peldschus	-0.729	-0.674	-0.163	0.259	0.644	0.586	**0.6061**	**-0.0130**
Decimal	0.843	0.875	0.897	0.908	0.950	0.938	**0.0396**	**0.9018**
StDv	**0.5983**	**0.7405**	**0.4273**	**0.2693**	**0.1176**	**0.1419**		
Mean	**0.4775**	**0.3092**	**0.6937**	**0.7986**	**0.8771**	**0.8551**		

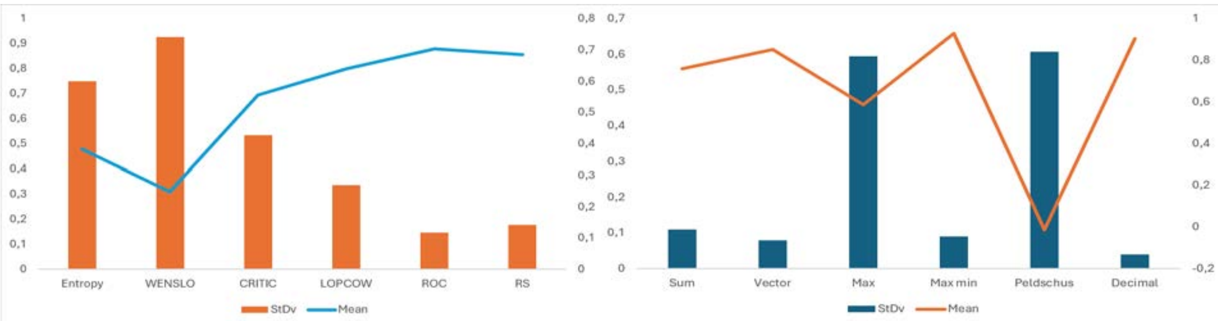

Fig. 4. Sensitivity levels based on weighting and normalization techniques (Example 2)

Examining the results for material selection in piston manufacturing (as indicated in Table 12), it is observed that the normalization method providing the highest correlation with the fixed external factor is Vector, and the weighting technique is ROC. The Peldschus and Max normalization techniques, along with the WENSLO, Entropy, and CRITIC weighting techniques, exhibit the highest sensitivity. On the other hand, the Max min normalization technique with the RS weighting technique can also be readily recommended with the CoCoSo method. Results obtained using the Entropy, WENSLO, and CRITIC techniques based on the Peldschus normalization method exhibit negative correlations, and these techniques have resulted in high sensitivity.

6 CONCLUSIONS

The selection of materials for cylinder and piston assemblies is crucial in the product design process. This research utilized a MCDM approach to rank various materials and identify the optimal material for each application. Specifically, the Entropy method was used to determine criterion weights, and the CoCoSo method was employed to rank the materials. A sensitivity analysis was conducted to assess the impact of weights derived from seven different techniques such as Entropy, WENSLO, CRITIC, LOPCOW, ROC, RS, and EW and six normalization techniques such as Sum, Vector, Max, Max-Min, Peldschus, and Decimal on the CoCoSo results, as well as the sensitivity levels of these methods.

According to the results of the Entropy-CoCoSo model, AISI304 was identified as the best material for cylinder manufacturing among the nine materials considered, S355JR, S275JR, S235JR, BS97007M20, R35, R45, IS1030GRADE, AISI304, and 60-40-18. For piston manufacturing, A336 emerged as the optimal material among the seven materials, 332-T5, A336, 242-T5, 333.0-F, A213.0 F, AISI308, and A319.0F.

The innovative sensitivity analysis compared results obtained using different techniques with the EW-CoCoSo ranking, set as the external fixed factor. Calculations were based on the correlations between these rankings. According to the logic of this approach, an MCDM method with lower sensitivity demonstrates higher performance. The sensitivity analysis applied seven weighting techniques and six normalization techniques, leading to several key conclusions:

i) Methods with low standard deviation indicate low sensitivity and high correlation. For cylinder material selection (Table 12), the Min-Max normalization technique, with the lowest standard deviation (σ=0.1000) among normalization techniques, exhibits the lowest sensitivity and highest performance. Conversely, normalization techniques such as Peldschus, Max, and Vector demonstrate high sensitivity and low correlation, and these techniques reduce the performance of the CoCoSo method. The ROC method, across different normalization techniques, shows the lowest sensitivity and highest performance while the LOPCOW, Entropy, and WENSLO techniques exhibit high sensitivity and low performance ii) For piston material selection problem, the Decimal, Vector, and Min-Max normalization techniques enhance the performance of the CoCoSo method through their demonstrated low sensitivity and high correlation. Normalization techniques with low correlation to the fixed factor results include Peldschus and Max. Among weighting techniques, the ROC method shows the lowest sensitivity, whereas WENSLO, Entropy, and CRITIC techniques demonstrate high sensitivity and low performance. iii) The results obtained in two different real-world problems using the same MCDM methods varied due to differences in parameters such as the data set and the number of alternatives/criteria. iv) Considering both applications, the optimal methods for CoCoSo are min-max and ROC. Conversely, the Peldschus, max, WENSLO, Entropy, and CRITIC techniques decrease the performance of the CoCoSo method. v) The fundamental MCDM algorithm may contain specific cases that prevent generalization [74]. MCDM results are sensitive to the data set, number of criteria, number of alternatives, parameter variations, normalization, and weighting techniques, with results varying based on these factors. For the two real-world problems—cylinder and piston material selection—the Min-Max normalization technique and ROC weighting technique consistently exhibit low sensitivity. In contrast, Peldschus and Max normalization techniques, along with Entropy, WENSLO, and CRITIC weighting techniques, result in high sensitivity. Notably, the Min-Max normalization technique, which shows low sensitivity in both applications, forms a core component of the CoCoSo method.

This study focused on selecting materials based on technical criteria, excluding cost-related and machining capability criteria. Future research should address these aspects to provide a more comprehensive evaluation. Following the use of MCDM methods for material selection, subsequent manufacturing and testing steps are crucial to validate the research results. In summary, this study offers valuable insights into material selection for cylinder and piston manufacturing, highlighting the importance of MCDM methods in making informed decisions. Further research should build upon this work, considering additional criteria and practical aspects, followed by manufacturing and testing to validate the chosen materials. Also, in the innovative sensitivity analysis approach, it is anticipated that a larger dataset will yield more accurate results. In future studies, sensitivity analysis could be conducted for various MCDM methods using a broader dataset.

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