Development of a Novel Integrated MCDM Framework as a Decision-Support Tool for Lathe Selection

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Abstract

This study aims to develop a novel Multi Criteria Decision Making (MCDM) methodological model for use as a decision support tool in industrial machine selection problems. To this end, a new integrated MCDM model consisting of Logarithmic normalization and Standard Deviation (LOGSTA), Logarithmic Percentage Change-driven Objective Weighting (LOPCOW), Logarithmic Decomposition of Criteria Importance (LODECI), and Evaluation by Distance from Ideal Solution of Alternatives (EDISA) methods has been designed for a real-world lathe selection problem faced by a manufacturing company in Turkiye. The criterion weights obtained according to the three methods (LOGSTA, LOPCOW, and LODECI) were combined, and the combined criterion weights were transferred to the EDISA method to create an alternative lathe ranking. According to the combined criterion weights, the criterion with the highest importance level was failure frequency (C1), while the criterion with the lowest importance level was active working time (C5). According to the ranking obtained as a result of transferring the combined criterion weights to the EDISA method, the lathe with the highest performance was determined to be Doosan PUMA VT 900 (A2), while the lathe with the lowest performance was determined to be Doosan Puma 300 LM (A1). The comparison analysis shows that the EDISA method produces the same rankings as the ARAS, COPRAS, and RAWEC methods. It is believed that this framework enables manufacturing managers to compare acquisition cost, reliability, operating characteristics, and resale value within a transparent decision process.

Keywords: EDISA, industrial machine selection, MCDM, LODECI, LOGSTA, LOPCOW.

1. Introduction

A country's economic competitiveness worldwide is mostly determined by the relative cost of manufacturing. Several factors, such as productivity, resource accessibility, operation cost, affect the relative manufacturing cost. Therefore, the performance of manufacturing sector is always significant for countries. However, it became more crucial in the last centuries because manufacturing sector experienced a fast change with technological improvements since the Industrial Revolution, which transformed production process radically. Growing environmental problems have led consumers and governments to be more aware about the

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sustainability in manufacturing, environmental protection and product recyclability [1]. Therefore, sustainability policies worldwide made manufacturing companies adopt environmental practices [2]. These practices in manufacturing companies are widely discussed in literature. Piyathanavong et al. [3] examined environmental practice adoption in manufacturing sector of Thailand. Ferreira et al. [4] assessed international manufacturing companies in Europe to determine the effect of digital approaches on sustainability. Belhadi et al. [5] analyzed manufacturing companies in North Africa in terms of the hybrid effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the environmental performance. Tao et al. [6] determined the effect of the digital economy on greenhouse gas emissions of manufacturing companies in China.

Machine tools are complex and expensive but a significant part of manufacturing systems. They are specifically important for increasing operational efficiency, quality and consequently manufacturing performance. Productivity in manufacturing has been affected directly by the advancement of machine tools since the Revolution [7]. However, they need to be carefully selected and used as cost, quality, environmental impact, and time depend directly on machine tools in manufacturing. Therefore, machine tool selection in manufacturing is a complicated decision problem, which needs simultaneous assessment of various and often conflicting criteria.

Lathes are among the oldest machine tools. They are designed to do turning operations in which the unwanted material is taken out from the counter with a cutting tool. They are the most flexible and commonly used tools therefore called mother tools. There are various lathe tools in several kinds and sizes, very small bench lathes operated for precision processing and very big ones operated for large steel processing.

The lathe tools are significantly used in metal industry. It is projected that production will increase 200% by 2050 in metal industry and this increase will lead to environmental problems as energy use in metal production is high (around 8% globally) therefore they contribute to carbon emissions significantly (30% of industrial emissions) [8]. Therefore, machine tool selection has always been a common decision problem in literature as they are heavy, significant, and expensive. Multi Criteria Decision Making (MCDM) handles various conflicting criteria even under uncertainty which are prevalent in machine tool selection therefore they are commonly used in previous studies to solve decision problems with various techniques such as the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [9], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [10], [11], Decision Making Trial and Evaluation Laboratory (DEMATEL) [10], fuzzy sets [12]-[14], and Analytical Hierarchical Process (AHP) [15]-[17].

Lathe selection is a significant operation in manufacturing to obtain both productivity increase and sustainability [18]-[20]. Kong et al. [21] states that the main contributors to energy use in manufacturing are the tools thus selecting the most efficient tool is significant. The lathe tool selection needs consideration more than cost and technical aspects. Therefore, selecting the most suitable lathe tool for manufacturing companies in metal industry is a complex task in which MCDM techniques would be helpful. However, there are a few studies about lathe selection, and these mostly focus on criteria like price or measurements [18], [22], thus not considering the environmental effect which is needed for applying sustainability in manufacturing. There is overdependence on subjective opinions of experts with pairwise comparisons. This may increase bias in decisions and lead to inconsistent weights. There is a lack of comparative analysis in lathe selection studies. Comparative analysis shows the reliability of developed models. Therefore, in this study, it is aimed to assess lathe machine tools for a heavy equipment and construction machinery plant in Turkiye from a technical-cost-environmental perspective using the recent MCDM techniques, Logarithmic normalization and Standard deviation (LOGSTA), Logarithmic Percentage Change-driven Objective Weighting (LOPCOW), Logarithmic Decomposition of Criteria Importance (LODECI), and Evaluation by Distance from Ideal Solution of Alternatives (EDISA) methods. The LOGSTA technique was developed by Stević et al. [23] to solve the inconsistency issue. It considers both cost and benefit criteria, creates a separate normalization for benefit and cost criteria, and a different normalization process compared to Criteria Importance Through Intercriteria Correlation (CRITIC), Entropy, and Method based on the Removal Effects of Criteria (MEREC) methods, applies natural logarithm two times, and combines standard deviation. The LOPCOW technique was created by Ecer and Pamucar [24]. It eliminates the gap because of the data size, produces more feasible weights, and considers both positive and negative values in determining weights. Pala [25] produced the LODECI method by combining the MEREC and Entropy methods. It eliminates big differences found between significant levels of criteria in MEREC and Entropy with logarithmic operation and maximum dispersion levels. Puška et al. [26] developed the EDISA technique. One of the main advantages of the EDISA method lies in its simple and computationally efficient structure, as it relies on linear deviation measures from ideal and anti-ideal solutions rather than Euclidean distance calculations. This simplicity significantly reduces computational burden and facilitates practical implementation. In addition, EDISA allows decision-makers to easily distinguish strong alternatives from weak ones. Unlike methods such as Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) and Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS), EDISA does not require additional utility or compromise functions, which further streamlines the ranking process and enhances methodological transparency [26].

This study contributes to literature in several ways. First, a novel integrated MCDM approach is developed using the recent MCDM techniques; LOGSTA, LOPCOW, LODECI, and EDISA methods. With developed model, it will benefit from diverse mathematical features (distribution basis, proportion basis, and decomposition basis calculation) of LOGSTA, LOPCOW, and LODECI. With this integration better stability and low bias in weight calculation are achieved in comparison to one method applications.

Second, the EDISA method is combined with three weight calculation methods which provides a consistent and consolidated approach. It supports steadiness and interpretability in MCDM problems.

Third, the developed model is applied to a real case study in manufacturing sector therefore results will reflect applicability in the real world. Fourth, sensitivity analysis with Monte Carlo and comparative analyses with various other commonly used methods (Additive Ratio Assessment (ARAS), Complex Proportional. Assessment (COPRAS), MARCOS, Simple Additive Weighting (SAW), Weighted Aggregated Sum Product Assessment (WASPAS), Evaluation based on Distance from Average Solution (EDAS), Multi-Attributive Border Approximation area Comparison (MABAC), CRADIS, Combined Compromise Solution (CoCoSo), Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN-M), and Ranking of Alternatives with Weights of Criterion (RAWEC)) presented that the results of the model deliver accurate and robust information. Fifth, the developed model with a straightforward assessment procedure will be used by managers and practitioners from diverse backgrounds to make better investment decisions.

Abbreviations and Acronyms

AI	Artificial Intelligence
AHP	Analytical Hierarchical Process
ARAS	Additive Ratio Assessment
AROMAN	Alternative Ranking Order Method Accounting for Two-Step Normalization
BN	Benefit
BWM	Best-Worst Method
CIMAS	Criteria Importance Assessment
CNC	Computer Numerical Control
CoCoSo	Combined Compromise Solution
COPRAS	Complex Proportional Assessment
CORASO	Compromise Ranking from Alternative Solutions
CS	Cost
CRITIC	Criteria Importance Through Intercriteria Correlation
CURLI	Collaborative Unbiased Rank List Integration
DOBI	Dombi Bonferroni
DEMATEL	Decision Making Trial and Evaluation Laboratory
DV	Decomposition Value
EDAS	Evaluation based on Distance from Average Solution
EDISA	Evaluation by Distance from Ideal Solution of Alternatives
ERUNS	Enhanced Relative Utility and Nonlinear Standardisation
EU	European Union
FUCA	Faire Un Choix Adéquat
GRA	Grey Relational Analysis
LDV	Logarithmic Decomposition Values
LODECI	Logarithmic Decomposition of Criteria Importance
LOGSTA	Logarithmic normalization and Standard Deviation
LOPCOW	Logarithmic Percentage Change-driven Objective Weighting
MARA	Magnitude of the Area for the Ranking of Alternatives

MAXC	Maximum of Criterion
MCDM	Multi Criteria Decision Making
MCRAT	Multiple Criteria Ranking by Alternative Trace
MEREC	Method based on the Removal Effects of Criteria
MULTIMOORA	Multi-Objective Optimization Ratio Analysis
PIPRECIA	Pivot Pairwise Relative Criteria Importance Assessment
PIV	Proximity Indexed Value
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
PSI	Preference Selection Index
RADAR	Ranking based on the Distances and Range
RAWEC	Ranking Alternatives with Weights of Criterion
RPM	Revolutions Per Minute
ROC	Rank Order Centroid
SITDE	Skewness Impact Through Distributional Evaluation
SWARA	Subjective Weight Assignment by Ratio Analysis
SIWEC	Simple Weight of Criteria
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje

2. Background

There are various lathe tools on the market with all sorts of configurations, and several criteria sometimes conflicting to consider. Therefore, selecting the most suitable lathe tool is a complicated task. In literature, there are a variety of studies to solve this complexity with MCDM. In this section, first a general look at machine tool selection will be conducted and then lathe tool selection will be reviewed. Finally, the studies using LOGSTA, LOPCOW, LODECI, and EDISA methods will be summarized.

2.1. Machine tool selection

Li et al. [27] created a new integrated MCDM framework using fuzzy DEMATEL, Entropy, and later defuzzification VIKOR to choose a machine tool. “Max spindle torque” is determined as the most crucial factor. Cioca et al. [28] evaluated CNC (Computer Numerical Control) machine tools from the safety perspective with AHP and TOPSIS techniques. The most significant factor in CNC machine tool selection was “quality of programming”. Sahin and Aydemir [29] integrated the Best-Worst Method (BWM), Grey Relational Analysis (GRA), Complex Proportional Assessment (COPRAS), and Multi-Objective Optimization Ratio Analysis (MULTIMOORA) techniques to choose best CNC machine tool. It was found that “price” is the most important criterion in machine tool selection. Son et al. [30] used Faire Un Choix Adéquat (FUCA) and Collaborative Unbiased Rank List Intergration (CURLI) techniques to choose the best grinding machine, drilling machine and milling machine. Trung et al. [31] applied CRITIC, Proximity Indexed Value (PIV), Preference Selection Index (PSI), FUCA and CURLI techniques to choose molding machines. “The screw diameter” was determined as the most critical criterion in plastic molding machine selection. Yin et al [32] used the AHP, TOPSIS, and EDAS techniques for analyzing machine tools in manufacturing. They determined that “the motor output power” is the most significant factor. Van Dua [33] developed a novel method to calculate criteria weights by integrating Skewness Impact Through Distributional Evaluation (SITDE) and Rank Order Centroid (ROC) techniques. “The machine tool power” was found to be the most important criterion.

2.2. Lathe selection

Lata et al. [34] utilized fuzzy AHP and TOPSIS techniques to rank CNC lathe tools. Trung et al. [35] used an integrated MCDM model including the Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA) and the modified FUCA techniques to choose the best lathe tool in two cases: brand new CNC lathe selection and preowned lathe selection. In first case, “max turning length” criterion was determined the most critical factor while “accuracy, stability, and safety” criterion was found to be the most significant in second case. Wofuru-Nyenke [18] evaluated five lathe tools using the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) technique. It was determined that price is the most significant factor in lathe selection. Rakshit [22] ordered lathe tools using the TOPSIS technique. “Swing over bed” criterion was determined as the most significant. Nhu et al. [36] ranked CNC lathes with fuzzy EDAS. They determined that the MICROTURN300DX lathe tool is the most suitable one. Polley et al. [37] used TOPSIS and MATLAB to select the most optimal CNC lathe tool. Table 1 presents the criteria used in the literature.

Table 1. The criteria employed in previous studies for machine tool or lathe selection.

Criterion	Studies
Price/Cost	[18], [35], [36]
Power	[18]
Complexity	[18]
Weight	[18]
Spindle RPM	[35]
Centre height	[22], [36]
Swing over bed	[22]
Swing over cross slide	[22]
Swing in gap	[22]
Max Turning Diameter	[35], [36]
Max Turning Length	[35], [36]
Chuck Size	[35]
Rapid Travel (X)	[35]
Rapid Travel (Z)	[35]
Spindle Torque	[35]
Slide Type	[35]
Travel (X)	[35], [36]
Accuracy, Stability, and Safety	[35]
Travel (Z)	[35], [36]
No. of Tools	[35]
Bed width	[22]

2.3. LOGSTA, LOPCOW, LODECI, and EDISA studies

As the LOGSTA technique is new, it was only used by Stević et al. [23], who applied it in two simulation cases to prove the usability of developed model. The LOPCOW technique is commonly used in literature for calculating criterion weights. Ecer and Pamucar [24] created a new MCDM model using LOPCOW and Dombi Bonferroni (DOBI) techniques for evaluating sustainability performance of banks in developing nation. Biswas and Joshi [38] evaluated initial public offerings (IPOs) in the period of 2020-2021 in India using the LOPCOW technique. Ecer et al. [39] evaluated micro-mobility solutions with interval-valued fuzzy neutrosophic Delphi, LOPCOW, and CoCoSo techniques. Ulutaş et al. [40] determined the best natural fibre material used in insulation using PSI, MEREC, LOPCOW and Multiple Criteria Ranking by Alternative Trace (MCRAT) techniques. Jiang et al. [41] utilized the intuitionistic fuzzy LOPCOW, Subjective Weight Assignment by Ratio Analysis (SWARA), and Enhanced Relative Utility and Nonlinear Standardisation (ERUNS) techniques to determine performance of food supply chains. Dhruva et al. [42] applied fuzzy LOPCOW and COPRAS techniques to rank waste management approaches. Şimşek et al. [43] evaluated electric vehicles using CRITIC and LOPCOW techniques integrated with machine learning. Pala [25] ranked European Union (EU) countries based on social progress with LODECI and CoCoSo techniques. Oztemiz et al. [44] analyzed financial performance of logistics firms based on sustainability using the Simple Weight of Criteria (SIWEC), MEREC, LODECI, and CoCoSo techniques. Ulutaş et al. [45] assessed suppliers from environmental perspective with fuzzy LODECI, Maximum of Criterion (MAXC), and Magnitude of the Area for the Ranking of Alternatives (MARA) techniques. Yalçın [46] used the Criteria Importance Assessment (CIMAS), LODECI, and Ranking based on the Distances and Range (RADAR) techniques to choose the best tractors. Tufan and Ulutaş [47] assessed supplies of food companies with LODECI and Compromise Ranking from Alternative Solutions (CORASO) techniques. The EDISA technique is recently developed by Puška et al. [26] and applied to select electrical vehicles.

Although MCDM techniques have been frequently used in past studies on lathe selection, these studies have mostly determined criterion weights using only one objective or subjective weighting method. Therefore, the resulting criterion weight value is dependent on the assumptions of a single method, which can affect the accuracy and robustness of the decisions. To overcome this, this study uses three different objective criterion weighting methods to obtain an integrated result. This integrated criterion weighting method reduces the bias caused by relying on a single method and yields more robust criterion weights.

The selection of LOGSTA, LOPCOW, and LODECI as the weighting components of the proposed framework is motivated by a deliberate methodological design principle: each method operationalizes a distinct and non-redundant source of criterion importance information. LOGSTA evaluates the significance of a criterion through the logarithmic standard deviation of its normalized distribution, thereby capturing how broadly and unevenly alternatives are spread across each criterion's scale. LOPCOW, by contrast, derives weights from the magnitude of proportional percentage changes across alternatives, making it sensitive to relative differences rather than absolute dispersion. LODECI operates through a decomposition mechanism that isolates the maximum pairwise gap between alternatives for each criterion, prioritizing those criteria that offer the greatest discriminative resolution between competing options. These three perspectives (distributional, proportional, and decomposition-based) are epistemologically complementary: a criterion may exhibit low distributional spread yet carry high proportional variability, or vice versa. Relying on any single method therefore risks systematically underweighting criteria that are salient under alternative information lenses. This design logic distinguishes the proposed framework from ad hoc multi-method combinations and positions it as a theoretically motivated integration architecture. The proposed integration also differs from existing hybrid frameworks that combine LOPCOW or LODECI with a limited number of complementary techniques. Ecer and Pamucar [24] paired LOPCOW with the Dombi Bonferroni operator for ranking, and Pala [25] paired LODECI with CoCoSo for ranking, in both cases relying on a single weighting mechanism. Oztemiz et al. [44] combined SIWEC, MEREC, and LODECI for weighting but relied on CoCoSo for ranking. Yalçın [46] combined CIMAS and LODECI for criterion weighting before applying RADAR for ranking, which similarly fuses two weighting sources rather than relying on a single method. Tufan and Ulutaş [47], by contrast, relied on LODECI alone for weighting and paired it with CORASO for ranking. Among these frameworks, the dual-source fusion adopted by Yalçın [46] comes closest in logic to the present approach, yet it is still limited to two weighting mechanisms. The present study extends this fusion logic further by combining three structurally distinct weighting mechanisms (LOGSTA, LOPCOW, and LODECI) before the ranking stage, which reduces the sensitivity of the final weight vector to the idiosyncrasies of any single method more thoroughly than the two-source combinations reported in the literature. In addition, the ranking stage adopted here, EDISA, does not require the auxiliary compromise or utility functions that CoCoSo, MCRAT, and RADAR depend on, which keeps the overall model computationally simpler while still allowing the tri-method weight fusion to be independently verified, as demonstrated by the Spearman rank correlation of 1.000 obtained against eleven established ranking methods in Section 5.

3. Methodology

In this study, the lathe selection problem for a manufacturing plant in Turkiye was solved by integrating the LOGSTA, LOPCOW, LODECI, and EDISA methods.

3.1. LOGarithmic normalization and STAndard deviation (LOGSTA) method

The steps of the LOGSTA method, developed by Stević et al. [23] for determining the weights of the evaluation criteria, are as follows [23].

Step 1. A decision matrix consisting of alternatives and criteria is established, the relevant matrix is expressed as Eq. (1).

$$F = [f_{ij}]_{n\times m} \tag{1}$$

Step 2. The decision matrix is normalized by the operations performed within Eqs. (2) and (3).

$$d_{ij} = \left|\frac{In\, f_{ij}}{In\left(\prod_{i=1}^{n} f_{ij}\right)}\right| \qquad if\ \ j \in BN \tag{2}$$

$$d_{ij} = \left|\frac{1 - \dfrac{In\, f_{ij}}{In\left(\prod_{i=1}^{n} f_{ij}\right)}}{n-1}\right| \qquad if\ \ j \in CS \tag{3}$$

Step 3. The standard deviation (σ_j) of the values obtained after normalization is multiplied by the sum of f_{ij} and the inverse of the In function, thus forming the P matrix.

$$P = [p_{ij}]_{1\times m} \tag{4}$$

$$p_j = \sigma \times \left(\left|\sum_{i=1}^{n}(In(d_{ij}))\right|\right)^{-1} \tag{5}$$

Step 4. Using Eq. (6), the final value of the weights for each criterion is calculated as follows.

$$w_{jLOGSTA} = \frac{p_j}{\sum_{j=1}^{n} p_j} \tag{6}$$

3.2. LOgarithmic Percentage Change-driven Objective Weighting (LOPCOW) method

The processes of the LOPCOW method proposed by Ecer and Pamucar [24] for objectively calculating criterion weights are described below [24]:

Step 1: A decision matrix consisting of alternatives and criteria is established, the relevant matrix is expressed as Eq. (1).

Step 2: The values in the decision matrix given in Eq. (1) are normalized by applying the processing steps defined in Eqs. (7) and (8).

$$r_{ij} = \frac{f_{ij} - f_{ij_{min}}}{f_{ij_{max}} - f_{ij_{min}}} \qquad if \ \ j \in BN \tag{7}$$

$$r_{ij} = \frac{f_{ij_{max}} - f_{ij}}{f_{ij_{max}} - f_{ij_{min}}} \qquad if \ \ j \in CS \tag{8}$$

Step 3: Finding the % indicators (PVI_{ij}) based on the criteria.

$$PVI_{ij} = \left| ln \left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^2}{m}}}{\sigma} \right) .100 \right| \tag{9}$$

In Eq. (9), (σ_j) represents the standard deviation.

Step 4: The weight values of the criteria are calculated using Eq. (10).

$$w_{jLOPCOW} = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}} \tag{10}$$

3.3. LOgarithmic DEcomposition of Criteria Importance (LODECI) method

The processes of the LODECI method proposed by Pala [25] for objectively calculating criterion weights are described below [46], [48]:

Step 1: A decision matrix consisting of alternatives and criteria is established, the relevant matrix is expressed as Eq. (1).

Step 2: The values in the decision matrix given in Eq. (1) are normalized by applying the processing steps defined in Eqs. (11) and (12).

$$b_{ij} = \frac{f_{ij}}{max(f_{ij})} \qquad if \ \ j \in BN \tag{11}$$

$$b_{ij} = 1 - \frac{min(f_{ij})}{f_{ij}} \qquad if \ \ j \in CS \tag{12}$$

Step 3: The Decomposition Value (DV) is calculated from the normalized dataset using Eq. (13).

$$DV_{ij} = maks\{|b_{ij} - b_{rj}|\} \, r \neq i \tag{13}$$

Step 4: Logarithmic Decomposition Values (LDV) of the criteria are calculated using the formula given in Eq. (14).

$$LDV_j = In \left(1 + \frac{\sum_{i=1}^{n} DV_{ij}}{m} \right) \tag{14}$$

Step 5: The weight values of the criteria are calculated using Eq. (15).

$$w_{jLODECI} = \frac{LDV_j}{\sum_{i=1}^{n} LDV_j} \tag{15}$$

The criterion weights found by LOGSTA, LOPCOW and LODECI methods are combined using Eq. (16).

$$w_j^{CM} = \frac{w_{jLOGSTA} + w_{jLOPCOW} + w_{jLODECI}}{3} \tag{16}$$

The LOGSTA, LOPCOW, and LODECI methods used in this study calculate criterion weights based on different statistical and structural characteristics. The LOGSTA method integrates the normalization process, which considers benefit and cost-oriented criteria, with natural logarithms and standard deviations; the LOPCOW method aims to eliminate differences arising from data size; and the LODECI method focuses on the level of discrimination between alternatives. In this respect, these methods offer different information perspectives that evaluate criterion importance through complementary dimensions such as data distribution, variability, and discriminative power. There is no superiority relationship between the methods, however the arithmetic means is a commonly used approach in literature. It produces more balanced results by limiting the effect of deviations in the dataset; therefore, the simple arithmetic mean approach was preferred in this study.

3.4. Evaluation by Distance from Ideal Solution of Alternatives (EDISA) method

The EDISA method developed by Puška et al. [26] is based on evaluating alternatives in multi-criteria decision-making problems according to weighted criteria, within the framework of their distances from ideal and anti-ideal points. The steps of the method are described below [26].

Step 1. A decision matrix is created based on the data. The created decision matrix is shown in Eq. (1).

Step 2. The values in the decision matrix given in Eq. (1) are normalized by applying the processing steps defined in Eqs. (17) and (18).

$$k_{ij} = \frac{f_{ij}}{max(f_{ij})} \quad if \;\; j \in BN \tag{17}$$

$$k_{ij} = \frac{min(f_{ij})}{f_{ij}} \quad if \;\; j \in CS \tag{18}$$

Step 3. Normalized values are weighted.

$$t_{ij} = k_{ij} \times w_j^{BR} \tag{19}$$

Step 4. Ideal and anti-ideal solutions are determined.

$$t_{ij}^{+} = maxt_{ij}, \quad ideal\ solution \tag{20}$$

$$t_{ij}^{-} = mint_{ij,} \quad anti-ideal\ solution \tag{21}$$

Step 5. Deviations from the ideal and anti-ideal solutions are calculated.

$$S_i^{+} = \sum_{j=1}^{n} (t_{ij} - t_{ij}^{-}) \tag{22}$$

$$S_i^{-} = \sum_{j=1}^{n} (t_{ij}^{+} - t_{ij}) \tag{23}$$

Step 6. The value of the EDISA method is calculated.

$$R_i = \frac{S_i^{+} - S_i^{-}}{S_i^{-}} \tag{24}$$

Within the EDISA methodology, the most suitable alternative is determined as the option with the highest performance R_i value, while the least suitable alternative is defined as the option with the lowest performance R_i value.

4. Application

In this study, the lathe selection problem for a manufacturing plant in Turkiye will be solved by integrating LOGSTA, LOPCOW, LODECI, and EDISA methods. During the analysis process, three lathes (Doosan Puma 300 LM (A1), Doosan PUMA VT 900 (A2), and Tezsan SN50C (A3)) determined by the factory management as alternatives due to their planned future investment and they were evaluated with seven criteria. These criteria are failure frequency (number) (C1), troubleshooting time (hour) (C2), investment cost (EUR) (C3), noise (dB) (C4), active working time (%) (C5), rated motor current (ampere) (C6), and second-hand market value (EUR) (C7). Of the evaluation criteria, failure frequency (C1), troubleshooting time (C2), investment cost (C3), and noise (C4) were considered cost criteria, while active working time (C5), rated motor current (C6), and second-hand market value (C7) were evaluated as benefit criteria. It should be noted that rated motor current (C6) is specified under standard operating load, which functions as a proxy for spindle motor power and machining capacity rather than for the machine's operational energy consumption.

Lathes with a higher rated current are equipped with more powerful motors, translating into greater torque and the capacity to process larger or harder workpieces at higher material removal rates. For this reason, and consistent with how the criterion was operationalized by the participating factory management, C6 was classified as a benefit criterion, distinct from energy efficiency, which was not part of the evaluation framework.

The criteria used in this study were selected through a selection process based on expert opinions, using a list of criteria derived from previous studies. Criterion data was obtained from the company's maintenance and production records, in addition to machine documentation between July 2025 and November 2025. Failure frequency (C1), which refers to the number of failures recorded during given period, troubleshooting time (C2), which refers to the total downtime, active working time (C5) was calculated as the ratio of productive operating time to total available production time, and rated motor current (C6) were collected from the company's production and maintenance records. Second-hand market value (C7) and investment cost (C3) were obtained from purchasing department records and current market data. Noise level (C4) was calculated from the company's occupational health and safety measurements records taken during normal daily production conditions.

A decision matrix was created based on the opinions of the factory management. Then, the LOGSTA, LOPCOW, and LODECI approaches were applied to calculate the weights of the criteria. Based on these calculated criterion weights, the lathes were ranked using the EDISA method. The decision matrix, prepared in accordance with the opinions of the factory management with a survey, is presented in Table 2.

Table 2. Decision matrix for lathe selection problem.

	C1	C2	C3	C4	C5	C6	C7
A1	8	1500	100000	79.7	83.3	8.1	20000
A2	2	550	180000	78.5	82.7	9.9	36000
A3	4	515	55000	85.8	88.8	6.2	11000

4.1. Determining the criterion weights for lathe selection

After the decision matrix is created, criterion weights are calculated to prioritize the criteria that influence the selection of lathes. In this study, criterion weights were determined using the LOGSTA, LOPCOW, and LODECI methods.

4.1.1. Application process of the LOGSTA method

The normalized decision matrix is obtained by considering the criteria directions of the values in Table 3 and using Eqs. (2) and (3). Table 3 shows the normalized decision matrix values obtained by the LOGSTA method.

Table 3. Normalized decision matrix obtained using the LOGSTA method.

	C1	C2	C3	C4	C5	C6	C7
A1	0.2500	0.3159	0.3333	0.3341	0.3319	0.3369	0.3334
A2	0.4167	0.3412	0.3248	0.3346	0.3314	0.3692	0.3532
A3	0.3333	0.3429	0.3419	0.3313	0.3367	0.2939	0.3133

By applying Eqs. (4)–(6) to the values in Table 4, the criterion weights are obtained according to the LOGSTA method. Table 4 shows the LOGSTA method results.

Table 4. LOGSTA method results.

	C1	C2	C3	C4	C5	C6	C7
g_{ij}	0.0248	0.0046	0.0026	0.0005	0.0009	0.0114	0.0061
$w_{jLOGSTA}$	0.4872	0.0904	0.0511	0.0098	0.0177	0.2240	0.1198
Rank	1	4	5	7	6	2	3

According to the application results of the LOGSTA approach shown in Table 4, the criterion weighting order is as follows: C1>C6>C7>C2>C3>C5>C4. According to the LOGSTA method, the criterion with the highest level of importance is failure frequency (C1), while the criterion with the lowest importance level is noise (C4).

4.1.2. Application process of the LOPCOW method

The normalized decision matrix is obtained by considering the criterion directions of the values in Table 4 and using Eqs. (7) and (8). Table 5 shows the normalized decision matrix values obtained by the LOPCOW method.

Table 5. Normalized decision matrix obtained using the LOPCOW method.

	C1	C2	C3	C4	C5	C6	C7
A1	0.0000	0.0000	0.6400	0.8356	0.0984	0.5135	0.3600
A2	1.0000	0.9645	0.0000	1.0000	0.0000	1.0000	1.0000
A3	0.6667	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000

By applying Eqs. (9) – (10) to the values in Table 6, the criterion weights are obtained according to the LOPCOW method. Table 6 shows the results of the LOPCOW method.

Table 6. Results of the LOPCOW method.

	C1	C2	C3	C4	C5	C6	C7
PVI_{ij}	52.84	56.51	51.281	58.583	21.237	42.768	32.351
$w_{jLOPCOW}$	0.1674	0.1791	0.1625	0.1856	0.0673	0.1355	0.1025
Rank	3	2	4	1	7	5	6

According to the application results of the LOPCOW approach shown in Table 6, the criterion weighting ranking is as follows: C4>C2>C1>C3>C6>C7>C5. According to the LOPCOW method, the criterion with the highest importance level is noise (C4), while the criterion with the lowest importance level is active working time (C5).

4.1.3. Application process of the LODECI method

The normalized decision matrix is obtained by considering the criterion directions of the values in Table 7 and using Eqs. (11) and (12). Table 7 shows the normalized decision matrix values obtained by the LODECI method.

Table 7. Normalized decision matrix obtained using the LODECI method.

	C1	C2	C3	C4	C5	C6	C7
A1	0	0	0.4444	0.0711	0.9381	0.8182	0.5556
A2	0.7500	0.6333	0	0.0851	0.9313	1	1
A3	0.5000	0.6567	0.6944	0	1	0.6263	0.3056

The LODECI-based criterion weights were calculated by applying the operations between Eqs. (13) and (15), and the results are shown in Table 8.

Table 8. Criteria weights according to the LODECI method.

	C1	C2	C3	C4	C5	C6	C7
LDV_j	0.2231	0.2178	0.2064	0.0298	0.0246	0.1110	0.2064
$w_{jLODECI}$	0.2189	0.2137	0.2025	0.0292	0.0241	0.1089	0.2025
Rank	1	2	3	6	7	5	3

According to the application results of the LODECI approach shown in Table 8, the criterion weighting ranking is as follows: C1>C2>C3=C7>C6>C4>C5. According to the LODECI method, the criterion with the highest importance level is failure frequency (C1), while the criterion with the lowest importance level is active working time (C5).

4.1.4. Combining criterion weights

The criterion weights obtained from the LOGSTA, LOPCOW and LODECI methods are combined using Eq. (16). The combined weights of the criteria (w_j^{CM}) results are shown in Table 9. According to the combined criterion weighting results in Table 9, the criterion weight ranking is as follows: C1>C2>C6>C7>C3>C4>C5. Based on the combined criterion weights, failure frequency (C1) has the highest importance level, while active working time (C5) has the lowest importance level.

Table 9. Combined criterion weights.

	C1	C2	C3	C4	C5	C6	C7
$w_{jLOGSTA}$	0.4872	0.0904	0.0511	0.0098	0.0177	0.2240	0.1198
$w_{jLOPCOW}$	0.1674	0.1791	0.1625	0.1856	0.0673	0.1355	0.1025
$w_{jLODECI}$	0.2189	0.2137	0.2025	0.0292	0.0241	0.1089	0.2025
w_j^{CM}	0.2912	0.1611	0.1387	0.0749	0.0364	0.1561	0.1416
Rank	1	2	5	6	7	3	4

It is worth noting that the three methods yield divergent weight profiles, particularly for C1 and C4. This divergence reflects the different mathematical foundations of each method rather than inconsistency in the underlying data. Averaging weights mitigates the effect of method-specific extremes and produces a more balanced combined weight vector, as evidenced in Table 9. The dominance of failure frequency (C1) in the combined weight vector follows directly from the structure of the decision matrix rather than from an arbitrary methodological artifact. As shown in Table 2, the three lathes differ by a factor of four in recorded failure frequency (A1: 8, A2: 2, A3: 4), whereas most other criteria, such as active working time (C5: 83.3%, 82.7%, 88.8%) or current draw (C6: 8.1, 9.9, 6.2 A), vary only modestly across alternatives.

LOGSTA and LODECI both assign weight in proportion to how strongly a criterion discriminates between alternatives, so the comparatively large relative dispersion in C1 causes both methods to rank it first, with LOGSTA in particular assigning it a weight of 0.4872, well above any other criterion. LOPCOW, which is driven by proportional percentage change rather than dispersion, instead ranks noise (C4) first, but its maximum weight (0.1856 for C4) is substantially smaller in magnitude than LOGSTA's weight for C1. As a result, when the three weight vectors are averaged, C1 retains the highest combined weight (0.2912) despite not being ranked first by LOPCOW, because its dominance under LOGSTA and LODECI outweighs its comparatively modest third-place position under LOPCOW. The simple arithmetic mean was adopted as the default aggregation rule for three interrelated reasons. First, it does not require introducing additional meta-weights or auxiliary judgments to express the relative importance of LOGSTA, LOPCOW, and LODECI.

Table 10. Normalized decision matrix and obtained results using EDISA method.

	C1	C2	C3	C4	C5	C6	C7	S_i^+	S_i^-	R_i	Rank
A1	0.2500	0.3433	0.5500	0.9849	0.9381	0.8182	0.5556	0.1047	0.4813	-0.7820	3
A2	1	0.9364	0.3056	1	0.9313	1	1	0.4770	0.1090	3.3760	1
A3	0.5000	1	1	0.9149	1	0.6263	0.3056	0.2774	0.3086	-0.1010	2

Since none of the three methods is assumed a priori to be more reliable than the others, equal weighting is the aggregation rule that introduces the least additional subjectivity into the criterion weight determination process. Second, the arithmetic mean preserves the additive scale of the individual weight vectors and guarantees that the combined weights sum to one without requiring renormalization, unlike geometric averaging, which compresses the influence of near-zero weights such as those observed for C4 and C5 in Table 9. Third, and most importantly, the choice of the arithmetic mean was not treated as a fixed methodological commitment but was itself subjected to empirical verification. Section 5 compares the arithmetic mean against three alternative fusion strategies (entropy-based fusion, variance-based fusion, and Borda rank aggregation) and shows that all four strategies yield an identical alternative ranking, with a Spearman rank correlation of 1.000 in every comparison. This result indicates that the final ranking is not an artifact of the specific aggregation rule chosen, which justifies retaining the arithmetic mean for its simplicity and transparency rather than adopting a more complex aggregation scheme that offers no measurable improvement in ranking accuracy. The robustness of the final ranking under varying weight assumptions is further confirmed by the sensitivity analysis in Section 5.

4.2. Arrangement of lathe machines

After obtaining the criterion weights, the ranking of alternative lathes was performed using the EDISA method. The decision matrix in Table 2 was normalized by applying Eqs. (17) and (18) taking into account the criterion directions. The calculated values are shown in Table 10. Alternative scores for the EDISA method were calculated in accordance with the procedures given in Eqs. (19) – (23) and the results are reported in Table 10.

The lathe ranking obtained from the EDISA method was A2>A3>A1. According to this ranking, the lathe with the highest performance was the Doosan PUMA VT 900 (A2), while the lathe with the lowest performance was the Doosan Puma 300 LM (A1). Table 11 represents comparative representation of normalization transformation of the first criterion.

Table 11. Comparative Representation of Normalization Transformation of C1.

	Original Values	LOGSTA	LOPCOW	LODECI	EDISA
A1	8	0.2500	0.0000	0	0.2500
A2	2	0.4167	1.0000	0.7500	1
A3	4	0.3333	0.6667	0.5000	0.5000

The methods used in this study are each based on different normalization approaches. This difference stems from the theoretical foundations of the methods, requiring each method to transform the decision matrix according to its own mathematical framework. In particular, the different transformation formulas used for benefit and cost criteria, the standardization methods, and the effects of data distribution and outliers on the normalization process constitute the main reasons for the differences in the results. In this context, each of the methods used performs an evaluation within its own internal consistency, and the final ranking is obtained not from a single common normalized matrix, but from method-specific transformations.

5. Verification Tests and Discussion

The comparison findings presented in Figure 1 show that the EDISA method produces the same rankings as the Additive Ratio Assessment (ARAS) [49], COPRAS [50], MARCOS [51], SAW [52], WASPAS [53], EDAS [54], MABAC [55], [56], CRADIS [57], CoCoSo [58], AROMAN-M [59] and RAWEC [60] methods. To further validate the robustness of the proposed weighting framework, a supplementary quantitative comparison was conducted in which the identical EDISA ranking procedure was applied under six different weighting configurations on the same decision matrix: (i) the proposed LOGSTA–LOPCOW–LODECI combination, (ii) CRITIC alone, (iii) Entropy alone, (iv) MEREC alone, (v) CRITIC–Entropy combination, and (vi) CRITIC–Entropy–MEREC combination.

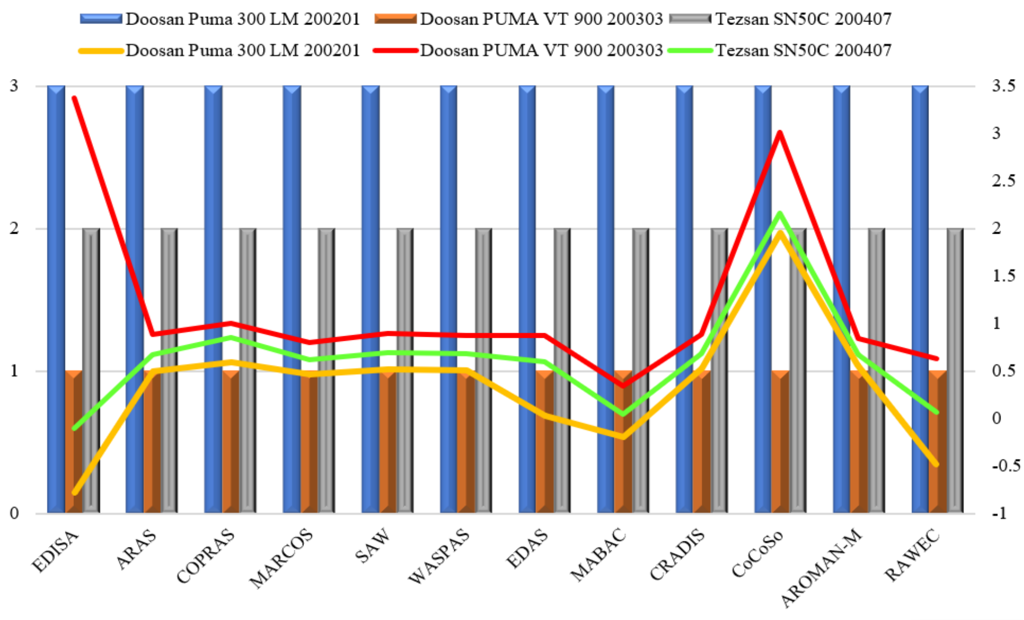

Figure 1. Comparison with other MCDM approaches.

These methods were selected as benchmark comparators because they represent the three most widely adopted objective weighting in the MCDM literature: correlation-based (CRITIC), information-theoretic (Entropy), and removal-effect-based (MEREC). The results are presented in Table 12.

As evidenced in Table 12, despite substantial divergence in the weight vectors across methods; with individual criterion weights differing by as much as 0.195 (e.g., C1: 0.105 under CRITIC vs. 0.291 under the proposed scheme), the final EDISA ranking remained invariant across all six configurations, yielding a Spearman rank correlation of 1.000 in every pairwise comparison. This result confirms that the performance superiority of A2 (Doosan PUMA VT 900) reflects genuine alternative quality rather than a methodological artifact of the chosen weighting approach.

To statistically evaluate this relationship, a correlation analysis was performed between the results obtained from the EDISA and other methods. Correlation analyses revealed a correlation coefficient of 1 in comparative analysis. This result indicates that the rankings produced by the methods completely overlap, and there is a complete linear relationship between the methods in terms of evaluating alternatives.

To examine the robustness of the ranking results, a sensitivity analysis was conducted using a Monte Carlo simulation framework. In this context, 1000 different weighting scenarios were randomly generated to reflect possible variations in criterion importance. For each scenario, criterion weights were randomly assigned while satisfying the constraint $\Sigma w_j = 1$. For each scenario, the EDISA method was employed to determine the alternative rankings of the lathe machine options.

Table 12. Criteria weights and EDISA rankings under alternative weighting schemes.

Weighting Scheme	C1	C2	C3	C4	C5	C6	C7	Rankings
Proposed (LOGSTA+LOPCOW+LODECI)	0.2912	0.1611	0.1387	0.0749	0.0364	0.1561	0.1416	A2 > A3 > A1
CRITIC alone	0.1050	0.1261	0.1921	0.1530	0.1785	0.1256	0.1198	A2 > A3 > A1
Entropy alone	0.1235	0.1177	0.1247	0.1188	0.2313	0.1329	0.1511	A2 > A3 > A1
MEREC alone	0.1496	0.1530	0.2064	0.1215	0.1314	0.0693	0.1688	A2 > A3 > A1
CRITIC + Entropy	0.1142	0.1219	0.1584	0.1359	0.2049	0.1292	0.1354	A2 > A3 > A1
CRITIC + Entropy + MEREC	0.1260	0.1323	0.1744	0.1311	0.1804	0.1093	0.1466	A2 > A3 > A1

The resulting rank distributions, summarized in Table 13, demonstrate that Alternative A2 (Doosan PUMA VT 900) consistently maintains its top-ranked position across almost all scenarios, achieving rank 1 in 797 out of 1,000 scenarios (79.7%). This indicates a high level of stability and robustness against changes in criterion weights, suggesting that A2's performance is not overly sensitive to weighing uncertainty and can be considered a reliable choice. Alternative A3 achieves the top rank in the remaining 203 scenarios (20.3%), while A1 does not rank first in any scenario. Alternatives A1 and A3 exhibit noticeable rank fluctuations across scenarios, implying that their relative performance is more sensitive to changes in the weighting structure. Overall, the sensitivity analysis confirms that the EDISA-based ranking results are robust, especially for the best-performing alternative. The limited rank reversals and the dominant stability of A2 validate the reliability of the proposed evaluation framework under uncertainty. Consequently, the integration of Monte Carlo simulation with the EDISA method provides strong evidence supporting the credibility and consistency of the lathe machine selection results.

To further characterize the robustness of the rankings, rank probability distributions, R score confidence intervals, and rank variance were computed across all 1,000 scenarios (Table 13 and Table 14). A1 achieved rank 1 in zero scenarios and occupied rank 3 in 86.6% of cases, with a 95% confidence interval for its R score entirely in the negative range (−0.917 to −0.406). A3 exhibited the highest rank variance (0.321), indicating sensitivity to weight assumptions, while A2 maintained the lowest instability (variance = 0.188). The complete main ranking (A2 > A3 > A1) was preserved in 673 out of 1,000 scenarios (67.3%).

To assess the sensitivity of the final ranking to the choice of weight aggregation strategy, the simple arithmetic mean (Eq. 16) was compared against three alternative fusion approaches: entropy-based fusion, variance-based fusion, and Borda rank aggregation. The criterion weights and EDISA rankings obtained under each strategy are presented in Table 15.

Spearman r values represent the rank correlation between each fusion strategy and the Simple Arithmetic Mean baseline. All strategies satisfy $\Sigma w_{\mathrm{j}} = 1$. Entropy-based fusion assigns meta-weights inversely proportional to Shannon entropy; variance-based fusion assigns meta-weights proportional to weight vector variance; Borda rank aggregation converts weights to ranks and averages Borda scores.

Table 13. Rank probability distribution across 1,000 Monte Carlo scenarios.

Alternatives	P(Rank 1)	P(Rank 2)	P(Rank 3)
A1 (Doosan Puma 300 LM)	0.0%	13.4%	86.6%
A2 (Doosan PUMA VT 900)	79.7%	19.3%	1.0%
A3 (Tezsan SN50C)	20.3%	67.3%	12.4%

Table 14. R score descriptive statistics across 1,000 Monte Carlo scenarios.

Alternatives	Mean	Std. Dev.	95% CI (Lower)	95% CI (Upper)	Rank Variance
A1 (Doosan Puma 300 LM)	−0.6855	0.1421	−0.9172	−0.4063	0.1160
A2 (Doosan PUMA VT 900)	5.0828	8.3760	−0.3944	23.7465	0.1876
A3 (Tezsan SN50C)	0.4369	1.5508	−0.7939	4.1600	0.3208

Table 15. Criteria weights and EDISA rankings under alternative weight fusion strategies.

Fusion Strategy	C1	C2	C3	C4	C5	C6	C7	Ranking	Spearman r
Simple Arithmetic Mean (Eq. 16)	0.2912	0.1611	0.1387	0.0749	0.0364	0.1561	0.1416	A2 > A3 > A1	1.000
Entropy-based Fusion	0.3084	0.1556	0.1319	0.0673	0.0342	0.1615	0.1411	A2 > A3 > A1	1.000
Variance-based Fusion	0.4168	0.1198	0.0874	0.0226	0.0215	0.1963	0.1357	A2 > A3 > A1	1.000
Borda Rank Aggregation	0.2262	0.1905	0.1429	0.1190	0.0476	0.1429	0.1310	A2 > A3 > A1	1.000

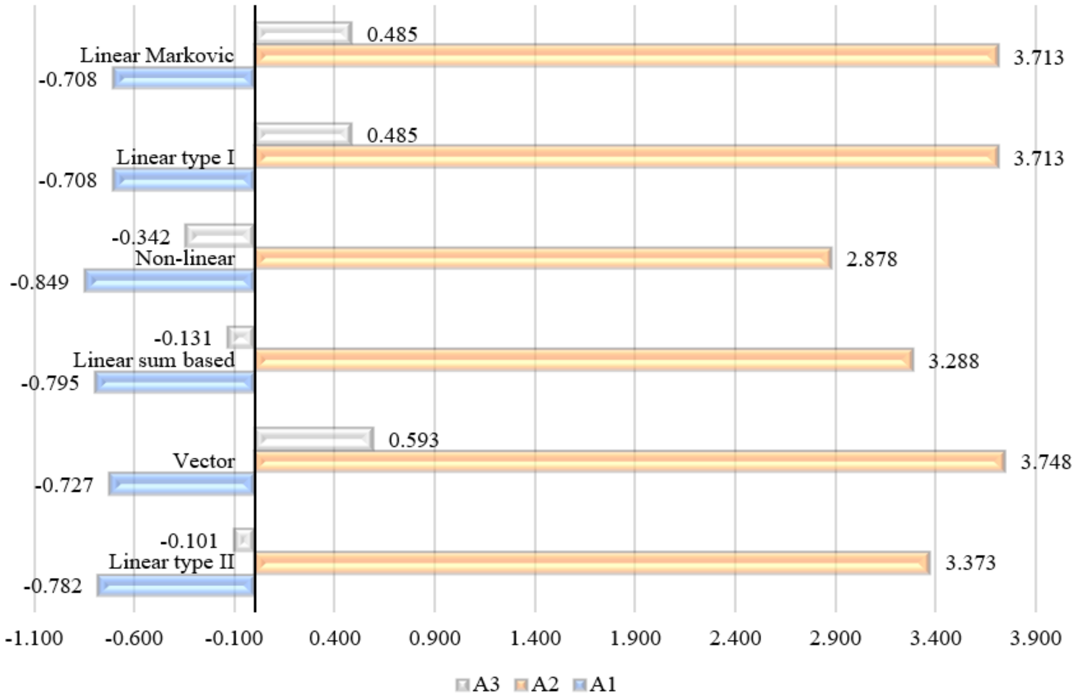

Figure 2. The results of normalization change procedure in EDISA method.

In the next part of the paper, we have checked the obtained results of the EDISA method in a way that we have applied different types of normalization. In the original version, EDISA method uses linear type II normalization, while in the verification test, we have applied six more normalization types presented in Table 16, while the results of this analysis are presented in Figure 2.

Table 16. Different types of normalization.

Vector	$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}$	$r_{ij} = 1 - \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}$
Linear sum-based	$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}^2}$	$r_{ij} = \frac{1/a_{ij}}{\sum_{i=1}^{m} 1/a_{ij}}$
Non-linear	$r_{ij} = \left(\frac{a_{ij}}{a_j^{max}}\right)^2$	$r_{ij} = \left(\frac{a_j^{min}}{a_{ij}}\right)^3$
Linear type I	$r_{ij} = \frac{a_{ij}}{a_j^{max}}$	$r_{ij} = 1 - \frac{a_{ij}}{a_j^{max}}$
Linear max-min	$r_{ij} = \frac{a_{ij} - a_j^{min}}{a_j^{max} - a_j^{min}}$	$r_{ij} = \frac{a_j^{max} - a_{ij}}{a_j^{max} - a_j^{min}}$
Markovic	$r_{ij} = \frac{a_{ij}}{a_j^{max}}$	$r_{ij} = 1 - \frac{a_{ij} - a_j^{min}}{a_j^{max}}$
Linear type II	$r_{ij} = \frac{a_{ij}}{a_j^{max}}$	$r_{ij} = \frac{a_j^{min}}{a_{ij}}$

Computed results shown in Figure 2 are identical to the original results from the rank aspect, while we have shown final values of alternatives to better understand possible changes. Finally, after three verification tests, we can conclude that results are very stable.

To further assess the robustness of the final ranking under data uncertainty, a decision matrix perturbation analysis was conducted across 1,000 independent simulation runs at four noise levels (±5%, ±10%, ±15%, and ±20%). In each run, the values of the three uncertainty-bearing criteria (failure frequency (C1), troubleshooting time (C2), and noise (C4)) were perturbed by multiplying each entry by a factor $(1 + \varepsilon)$, where ε was drawn independently and uniformly from $[-\delta, +\delta]$. The same experiment was subsequently repeated for all seven criteria simultaneously. The EDISA ranking procedure was applied in each run using the original combined criterion weights. The results are presented in Table 17. The main ranking (A2 > A3 > A1) was preserved in all 1,000 runs across every noise level and perturbation scope, with A2 retaining the top position in every scenario and Spearman rank correlation equaling 1.000 throughout. This outcome is attributable to the substantial R score margin separating A2 (R = 3.373) from A3 (R = −0.101) and A1 (R = −0.782), confirming that the ranking is insensitive to realistic levels of measurement uncertainty in the input data.

Table 17. Decision matrix perturbation experiment results (1,000 runs per noise level).

Noise Level	Criteria Perturbed	Stable Ranking (%)	A2 Rank-1 (%)	Mean Spearman r
±5%	C1, C2, C4 only	100.0%	100.0%	1.0000
±10%	C1, C2, C4 only	100.0%	100.0%	1.0000
±15%	C1, C2, C4 only	100.0%	100.0%	1.0000
±20%	C1, C2, C4 only	100.0%	100.0%	1.0000
±5%	All criteria	100.0%	100.0%	1.0000
±10%	All criteria	100.0%	100.0%	1.0000
±15%	All criteria	100.0%	100.0%	1.0000
±20%	All criteria	100.0%	100.0%	1.0000

Taken together, these six verification procedures point to the same practical conclusion: the ranking advantage of A2 (Doosan PUMA VT 900) is not an artifact of a particular weighting choice, normalization scheme, or noise assumption. This has a direct implication for practitioners. In lathe procurement decisions, managers often hesitate between competing MCDM outputs because different weighting techniques can produce contradictory rankings, which undermines confidence in the final choice. Here, the invariance of the ranking across CRITIC, Entropy, MEREC, and their combinations, together with its stability under ±20% data perturbation, means that the selection of Doosan PUMA VT 900 can be defended to plant management independently of which weighting technique was used to justify it. For companies without in-house MCDM expertise, this suggests that the specific choice of subjective or objective weighting method is less critical than ensuring that at least one robustness check, such as a Monte Carlo simulation or a normalization comparison, is performed before finalizing a high-value equipment investment. While the verification tests confirm the robustness of the proposed framework under multiple weighting, normalization, and noise conditions, several limitations should be acknowledged at this stage. All six verification procedures were conducted on the same case study data used to derive the criterion weights, so the robustness they demonstrate reflects internal consistency within this dataset rather than external validity across different manufacturing contexts, criteria sets, or company scales. Furthermore, the verification tests assume that the underlying decision matrix structure remains fixed, and the degree of ranking stability observed here may not generalize to problems involving a larger number of alternatives or criteria with more heterogeneous value distributions. A detailed discussion of these limitations, together with directions for future research, including extensions to fuzzy, grey, or rough-set based uncertainty modeling and validation across multiple manufacturing settings, is provided in the Conclusion.

6. Conclusion

In this study, the lathe selection problem for a manufacturing plant in Turkiye was solved using a new model integrating LOGSTA, LOPCOW, LODECI, and EDISA methods. LOGSTA, LOPCOW, and LODECI approaches were applied to calculate the weights of the criteria. Based on these calculated criterion weights, the lathes were ranked using the EDISA method. The ranking of the criteria obtained by combining the criterion weights calculated with LOGSTA, LOPCOW, and LODECI approaches was C1>C2>C6>C7>C3>C4>C5. Based on the combined criterion weights, failure frequency (C1) was determined to have the highest importance level, while active working time (C5) had the lowest importance level. After transferring the combined criterion weights to the EDISA method, the lathe ranking was A2>A3>A1. According to this ranking, the lathe with the highest performance was the Doosan PUMA VT 900 (A2), while the lathe with the lowest performance was the Doosan Puma 300 LM (A1). The ranking findings obtained with the EDISA method were compared with other alternative evaluation methods accepted in the literature, such as ARAS, COPRAS, and RAWEC. The comparison findings show that the EDISA method produces the same rankings as the ARAS, COPRAS, and RAWEC methods.

The robustness of the ranking results was evaluated through a sensitivity analysis based on a Monte Carlo simulation framework, in which 1,000 weighting scenarios were generated through Dirichlet sampling to capture potential variations in criterion importance. The findings indicate that Alternative A2 (Doosan PUMA VT

900) consistently preserves its top-ranked position in 797 out of 1,000 scenarios (79.7%), demonstrating a high degree of stability against weighting uncertainty and confirming its reliability as the most suitable lathe machine option. Alternative A3 achieves rank 1 in the remaining 203 scenarios (20.3%), while A1 does not rank first in any scenario, further reinforcing the robustness of the main ranking result (A2 > A3 > A1). The 95% confidence interval for A1's R score is entirely negative (−0.917 to −0.406), confirming its consistent underperformance across the full weight space. Overall, the limited occurrence of rank reversals and the dominant stability of A2 confirm the robustness and credibility of the EDISA-based evaluation framework under uncertainty.

The limited number of studies in the literature addressing the LOGSTA method, a new criterion weighting method, and the almost complete absence of integrated criteria weighing method using LOGSTA, LOPCOW, LODECI, and EDISA together with a holistic approach, make this study a unique contribution to the field. This study contributes to literature theoretically by presenting an integrated weighting method, which yields a more accurate and robust criterion weight compared to using a single weighting method.

From a managerial perspective, the developed decision model provides production managers with a transparent and analytical solution for analyzing lathe machine decisions using objective data. The model allows managers in decision-making positions to simultaneously evaluate multiple, diverse, and sometimes conflicting criteria within the evaluation process. Because this evaluation process is based on objective, measurable data rather than the subjective judgments of managers, it ensures that the developed integrated decision model is transparent and consistent and therefore can be used repeatedly for different decision problems. Also, comparability and sensitivity analyses show that the alternatives maintain their stability under various weighting changes, thus demonstrating that the developed model can be used practically by managers.

In practical terms, this weighting structure implies that a production manager evaluating these three lathes should treat reliability, rather than purchase price, as the primary decision driver. This is consistent with the final ranking obtained: although the Doosan PUMA VT 900 (A2) carries the highest investment cost among the three alternatives (EUR 180,000, compared to EUR 100,000 for A1 and EUR 55,000 for A3), its markedly lower failure frequency substantially reduces expected downtime and maintenance disruption, which the combined weighting scheme values more heavily than the upfront cost difference. From an investment standpoint, this suggests that the higher acquisition cost of A2 is justified by its superior operational reliability, and that a purchasing decision based on price alone, favoring the lower-cost A3, would overlook the total cost of ownership implications of more frequent machine failures in a production environment.

There are several limitations. First, this study is limited to seven criteria and three different lathes analyzed from data collected from a manufacturing company. Increasing the number of criteria used in the analysis, or diversifying the criteria to address different dimensions, could contribute to obtaining more intensive and comprehensive results regarding the performance of lathes. Second, the study's reliance on data collected only from a specific company, coupled with the limited sample size, restricts the generalizability of the results and reduces its capacity to represent all lathes used in the sector. Therefore, future research involving the collection of data from multiple businesses operating at different scales and in different sectors will ensure that the findings represent a broader production environment. Third, the inclusion of only three lathes in the analysis limits the scope of the model. Including more machine types in future studies would be beneficial both for testing the applicability of the method and for increasing comparative studies in literature. Fourth, only crisp methods are used in this study. Future studies could extend the proposed framework by incorporating uncertainty modeling through fuzzy set theory, grey numbers, or rough sets to handle imprecise or linguistically expressed evaluations. Additionally, probabilistic MCDM approaches and AI-based decision support systems integrating machine learning with multi-criteria ranking could further enhance the framework's applicability to complex, data-rich industrial environments. Fifth, the practical impact of the proposed decision support framework was not formally evaluated through post-deployment monitoring or structured expert feedback surveys. Future studies should incorporate decision-maker satisfaction assessments, implementation tracking, and longitudinal performance comparisons to provide stronger empirical evidence of the model's real-world decision impact.

Competing Interest Statement

Željko Stević serves as a Guest Editor of the Special Issue. He had no involvement in the peer-review process, editorial evaluation, or final decision regarding this manuscript. The other authors declare no competing interest.

Data Availability Statement

Data are available from the corresponding author, Željko Stević, upon reasonable request at zeljkostevic1988@gmail.com

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References

[1] M. A. Ilgin, S. M. Gupta, and O. Battaïa, "Use of MCDM techniques in environmentally conscious manufacturing and product recovery: State of the art," *Journal of Manufacturing Systems*, vol. 37, no. 3, pp. 746–758, 2015, doi: 10.1016/j.jmsy.2015.04.010.

[2] M. S. Kaswan, and R. Rathi, "Green Lean Six Sigma for sustainable development: Integration and framework," *Environmental Impact Assessment Review*, vol. 83, Art. no. 106396, 2020, doi: 10.1016/j.eiar.2020.106396.

[3] V. Piyathanavong, J. A. Garza-Reyes, V. Kumar, G. Maldonado-Guzmán, and S. K. Mangla, "The adoption of operational environmental sustainability approaches in the Thai manufacturing sector," *Journal of Cleaner Production,* vol. 220, pp. 507–528, 2019, doi: 10.1016/j.jclepro.2019.02.093.

[4] J. J. Ferreira, J. M. Lopes, S. Gomes, and H. G. Rammal, "Industry 4.0 implementation: Environmental and social sustainability in manufacturing multinational enterprises," *Journal of Cleaner Production*, vol. 404, Art. no. 136841, 2023, doi: 10.1016/j.jclepro.2023.136841.

[5] A. Belhadi, S. S. Kamble, K. Zkik, A. Cherrafi, and F. E. Touriki, "The integrated effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the environmental performance of manufacturing companies: The case of North Africa," *Journal of Cleaner Production*, vol. 252, Art. no. 119903, 2020, doi: 10.1016/j.jclepro.2019.119903.

[6] J. Tao, X. Xie, R. Peng, and N. Bei, "Digital economy and environmental pollution in the manufacturing sector: Emission reduction effects and mechanisms," *International Review of Economics & Finance,* vol. 96, Art. no. 103737, 2024, doi: 10.1016/j.iref.2024.103737.

[7] X. Xu, "Machine Tool 4.0 for the new era of manufacturing," *International Journal of Advanced Manufacturing Technology*, vol. 92, no. 5, pp. 1893–1900, 2017, doi: 10.1007/s00170-017-0300-7.

[8] D. Raabe, C. C. Tasan, and E. A. Olivetti, "Strategies for improving the sustainability of structural metals," *Nature*, vol. 575, no. 7781, pp. 64–74, 2019, doi: 10.1038/s41586-019-1702-5.

[9] T. Y. Lin, K. C. Hung, J. Jablonsky, and K. P. Lin, "An Enhanced VIKOR and Its Revisit for the Manufacturing Process Application," *Computers, Materials & Continua*, vol. 83, no. 2, pp. 1901–1927, 2025, doi: 10.32604/cmc.2025.063543.

[10] W. Alhakami, "Enhancing Cybersecurity Competency in the Kingdom of Saudi Arabia: A Fuzzy Decision-Making Approach," *Computers, Materials & Continua,* vol. 79, no. 2, pp. 3211–3237, 2024, doi: 10.32604/cmc.2023.043935.

[11] M. Elangovan, P. Ramya, and C. Goswami, "Sustainable Energy Options: Qualitative TOPSIS Method for Challenging Scenarios," in *Decision-Making Techniques and Methods for Sustainable Technological Innovation: Strategies and Applications in Industry 5.0*. Scrivener Publishing LLC, 2025, pp. 45–67. doi: 10.1002/9781394242603.

[12] M. Amin, M. S. Nazeer, K. Ullah, Z. Ali, and Y. Shang, "A Novel Intuitionistic Fuzzy OPARA-Based Multi-Criteria Decision-Making Framework for the Evaluation of AI-Enabled Intelligent Fault Diagnosis Systems," *Applied Soft Computing*, vol. 192, Art. no. 114738, 2026, doi: 10.1016/j.asoc.2026.114738.

[13] P. H. Nguyen, and H. A. Pham, "A Grey Simulation-Based Fuzzy Hierarchical Approach for Diagnosing Healthcare Service Quality," *Computers, Materials & Continua,* vol. 74, no. 2, pp. 3231–3248, 2023, doi: 10.32604/cmc.2023.031428.

[14] A. Farhad, and Y. Shang, "A Human-Centered Evaluation of AI-Augmented Educational Intelligence Ecosystems Using a T-Spherical Fuzzy SWARA–COPRAS Decision Framework," *Journal of Innovative Research in Mathematical and Computational Sciences,* vol. 4, no. 2, pp. 111–133, 2025, doi: 10.62270/jirmcs.v4i2.58.

[15] M. Veljović, T. Jorgaćević, S. Tadić, M. Krstić, and V. Perović, "Multi-Criteria Evaluation of Key Performance Indicators in Pharmaceutical Supply Chains," *Science, Engineering and Technology*, vol. 6, no. S1, pp. 1–20, 2026, doi: 10.54327/set2026/v6.iS1.339.

[16] D. Božanić, A. Puška, D. Tešić, A. Štilić, K. Ullah, Y. R. Muhsen, and I. M. Hezam, "Fuzzy AHP-Fuzzy MABAC model for ranking a combined construction machine-backhoe loader," *Facta Universitatis, Series: Mechanical Engineering*, vol. 23, no. 3, pp. 605–625, 2025, doi: 10.22190/FUME250801030B.

[17] G. Suleiman, M. K. Younes, M. Ergun, M. F. Abushammala, and M. Aljaradin, "Highlighting traffic accidents on roundabouts using mrss-ahp expert system," *Civil Engineering Journal*, vol. 10, no. 4, pp. 1210–1220, 2024, doi: 10.28991/CEJ-2024-010-04-013.

[18] O. Wofuru-Nyenke, "Sustainable lathe machine selection using PROMETHEE," *Future Sustainability*, vol. 2, no. 4, pp. 15–21, 2024, doi: 10.55670/fpll.fusus.2.4.3.

[19] Z. T. Abdullah, E. A. Abdulrazaq, and S. S. Ghazi, "Sustainability modeling approach on remanufacturing conventional lathe into CNC machine tool," *Current Journal of Applied Science and Technology,* vol. 39, no. 23, pp. 1–30, 2020, doi: 10.9734/CJAST/2020/v39i2330853.

[20] I. G. Santosa, "Developing a wood lathe machine with speed control and workers' anthropometry to increase the productivity of broom industry," *International Research Journal of Engineering, IT & Scientific Research*, vol. 8, no. 4, pp. 144–151, 2022, doi: 10.21744/irjeis.v8n4.2156.

[21] T. Q. Kong, D. R. Nhg, and V. T. Shi, "Method for optimizing energy consumption in machining manufacturing process," *Mathematical Problems in Engineering*, vol. 2022, Art. no. 8300666, 2022, doi: 10.1155/2022/8300666.

[22] A. Rakshit, K. Dey, B. Panja, R. Kumar, and A. Das, "Ranking Analysis Based on the Multi-Criteria Optimization of Technical Specifications to select the best Lathe Machine by Topsis Method," in *Innovative Approaches in Engineering Research*. New Delhi: Bright Sky Publications, 2024, pp. 135–146.

[23] Z. Stević, A. Ulutas, A. Topal, D. Marinkovic, and S. Cavoski, "A New Objectıve Method For Determınıng Crıterıa Weıghts in MCDM Models–LOGSTA," *International Journal of Simulation Modelling*, vol. 24, no. 4, pp. 589–600, 2025, doi: 10.2507/IJSIMM24-4-738.

[24] F. Ecer, and D. Pamucar, "A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector," *Omega*, vol. 112, Art. no. 102690, 2022, doi: 10.1016/j.omega.2022.102690.

[25] O. Pala, "Assessment of the social progress on European Union by logarithmic decomposition of criteria importance," *Expert Systems with Applications*, vol. 238, Art. no. 121846, 2024, doi: 10.1016/j.eswa.2023.121846.

[26] A. Puška, J. Bosna, and I. Stojanović, "Application of New Method Evaluation by Distance from Ideal Solution of Alternatives in the Assessment of Electric Vehicles," *Advanced Engineering Letters,* vol. 4, no. 2, pp. 92–103, 2025, doi: 10.46793/adeletters.2025.4.2.

[27] H. Li, W. Wang, L. Fan, Q. Li, and X. Chen, "A novel hybrid MCDM model for machine tool selection using fuzzy DEMATEL, entropy weighting and later defuzzification VIKOR," *Applied Soft Computing*, vol. 91, Art. no. 106207, 2020, doi: 10.1016/j.asoc.2020.106207.

[28] L. I. Cioca, R. E. Breaz, and S. G. Racz, "Selecting the safest CNC machining workshop using AHP and TOPSIS approaches," *Safety*, vol. 7, no. 2, Art. no. 27, 2021, doi: 10.3390/safety7020027.

[29] Y. Sahin, and E. Aydemir, "A comprehensive solution approach for CNC machine tool selection problem," *Informatica*, vol. 33, no. 1, pp. 81–108, 2022, doi: 10.15388/21-INFOR461.

[30] N. H. Son, T. T. Hieu, N. M. Thang, H. N. Tan, N. T. Can, P. T. Thao, and N. C. Bao, "Choosing the best machine tool in mechanical manufacturing," *EUREKA: Physics and Engineering,* no. 2, pp. 97–109, 2023, doi: 10.21303/2461-4262.2023.002771.

[31] D. D. Trung, B. Dudić, D. Van Duc, N. H. Son, and A. Ašonja, "Comparison of MCDM methods effectiveness in the selection of plastic injection molding machines," *Teknomekanik*, vol. 7, no. 1, pp. 1–19, 2024, doi: 10.24036/teknomekanik.v7i1.29272.

[32] R. Yin, M. N. Ab Rahman, H. Hishamuddin, and I. M. Ikram, "Assessing machine tool selection process in sustainable production to address climate change based on hybrid MCDM methods," *Engineering Journal*, vol. 28, no. 9, pp. 67–77, 2024, doi: 10.4186/ej.2024.28.9.67.

[33] T. Van Dua, "A Novel Approach for Criteria Weight Determination: A Case Study in Machine Ranking," *Engineering, Technology & Applied Science Research,* vol. 16, no. 1, pp. 31333–31337, 2026, doi: 10.48084/etasr.15778.

[34] S. Lata, A. K. Sachdeva, and M. K. Paswan, "Selection of Machine Tool by Using FUZZY TOPSIS Method," *AIP Conference Proceedings,* vol. 2341, Art. no. 020015, 2021, doi: 10.1063/5.0053536.

[35] D. D. Trung, N. X. Truong, and H. X. Thinh, "Combined PIPRECIA method and modified FUCA method for selection of lathe," *Journal of Applied Engineering Sciences,* vol. 20, no. 4, pp. 1355–1365, 2022, doi: 10.5937/jaes0-39335.

[36] Q. T. Nhu, D. H. Phan, and N. T. Tran, "Evaluation of CNC Lathe Machine with Fuzzy Linguistic MCDM Methods," *EUREKA: Physics and Engineering,* no. 4, pp. 113–123, 2024, doi: 10.21303/2461-4262.2024.003360.

[37] A. Polley, S. Das, D. Pramanik, N. Roy, A. Chakraborty, and K. Mishra, "Selection of a CNC Lathe by TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) Method under an MCDM (Multi-Criteria Decision Making) Environment Using MATLAB," in *Intelligent Machining. New York: Apple Academic Press*, 2025, pp. 15–25, doi: 10.1201/9781774919590-2.

[38] S. Biswas, and N. Joshi, "A performance based ranking of initial public offerings (IPOs) in India," *Journal of Decision Analytics and Intelligent Computing,* vol. 3, no. 1, pp. 15–32, 2023, doi: 10.31181/10023022023b.

[39] F. Ecer, H. Küçükönder, S. K. Kaya, and Ö. F. Görçün, "Sustainability performance analysis of micro-mobility solutions in urban transportation with a novel IVFNN-Delphi-LOPCOW-CoCoSo framework," *Transportation Research Part A: Policy and Practice,* vol. 172, Art. no. 103667, 2023, doi: 10.1016/j.tra.2023.103667.

[40] A. Ulutaş, F. Balo, and A. Topal, "Identifying the most efficient natural fibre for common commercial building insulation materials with an integrated PSI, MEREC, LOPCOW and MCRAT model," *Polymers*, vol. 15, no. 6, Art. no. 1500, 2023, doi: 10.3390/polym15061500.

[41] Q. Jiang, H. Wang, and L. Tang, "Robust fuzzy decision support framework for comprehensive evaluating of food supply chain performance," *IEEE Access*, vol. 12, pp. 188874–188889, 2024, doi: 10.1109/ACCESS.2024.3471768.

[42] S. Dhruva, R. Krishankumar, K. S. Ravichandran, A. Kaklauskas, E. K. Zavadskas, and P. Gupta, "Selection of waste treatment methods for food sources: an integrated decision model using q-rung fuzzy data, LOPCOW, and COPRAS techniques," *Clean Technologies and Environmental Policy,* vol. 27, pp. 5069–5093, 2025, doi: 10.1007/s10098-025-03160-6.

[43] A. İ. Şimşek, Y. E. Gür, and E. Ünal, "Innovative MCDM-ML algorithms-based decision-support system for electric vehicle selection," *Environment, Development and Sustainability,* 2025, doi: 10.1007/s10668-025-06476-x.

[44] H. H. Oztemiz, K. Vatansever, and T. Bayraktar, "Sustainable Financial Performance Analysis of Logistics Companies Listed on Borsa Istanbul: An Integrated Multi-Criteria Decision-Making Approach," *Sustainability*, vol. 17, no. 20, Art. no. 9243, 2025, doi: 10.3390/su17209243.

[45] A. Ulutaş, A. Topal, A. A. Yürüyen, and Y. Atalay, "An Innovative Fuzzy Multi-Criteria Decision-Making Approach for Solving Green Supplier Selection," *Journal of Intelligent & Fuzzy Systems,* vol. 50, no. 5, pp. 1652–1671, 2026, doi: 10.1177/18758967251381582.

[46] G. C. Yalçın, "Development of a Fuzzy-Based Decision Support System for Sustainable Tractor Selection in Green Ports," *Facta Universitatis, Series: Mechanical Engineering,* vol. 23, no. 3, pp. 579–604, 2025, doi: 10.22190/FUME250610029Y.

[47] D. Tufan, and A. Ulutaş, "Supplier Selection in the Food Sector: An Integrated Approach Using LODECI and CORASO Methods," *Spectrum of Decision Making and Applications,* vol. 3, no. 1, pp. 40–51, 2026, doi: 10.31181/sdmap31202631.

[48] O. Pala, Ö. Atçeken, H. Omurtak, and B. Şimşir, "Financial Performance Analysis with LODECI and CRADIS in BIST Cement Industry," *Alanya Academic Review*, vol. 8, no. 3, pp. 956–970, 2024, doi: 10.29023/alanyaakademik.1452960.

[49] J. Kozoderović, V. Pajić, and M. Andrejić, "A Multi-Criteria Analysis for E-commerce Warehouse Location Selection Using SWARA and ARAS Methods," *Journal of Engineering Management and Systems Engineering,* vol. 4, no. 2, pp. 122–132, 2025, doi: 10.56578/jemse040204.

[50] R. Naserhojjati Rudsari, and S. F. Fakhrhosseini, "Strategic Prioritization of Human Resource Performance Indicators in Power Plants: A Hybrid MCDM Approach Applied to the Nowshahr Combined Cycle Power Plant," *Journal of Organizations, Technology and Entrepreneurship*, vol. 2, no. 4, pp. 208–220, 2024, doi: 10.56578/jote020402.

[51] M. Blagojević, D. Blagojević, A. Danilevičius, E. Krmac, and S. A. Biancardo, "Application of the FUCOM and MARCOS Methods for Selecting Logistics Service Providers," *Journal of Intelligent Management Decision*, vol. 4, no. 4, pp. 288–297, 2025, doi: 10.56578/jimd040404.

[52] A. Cahyapratama, and R. Sarno, "Application of Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW) methods in singer selection process," in *International Conference on Information and Communications Technology (ICOIACT)*, IEEE, Yogyakarta, Indonesia, 2018, pp. 234–239, doi: 10.1109/ICOIACT.2018.8350707.

[53] S. Chakraborty, and E. K. Zavadskas, "Applications of WASPAS method in manufacturing decision making," *Informatica*, vol. 25, no. 1, pp. 1–20, 2014, doi: 10.3233/INF-2014-25(1)01.

[54] A. Zubia, I. Badi, and M. B. Bouraima, "Development of a Hybrid Model for a Single-Machine Scheduling Using Expert Systems and Search Algorithms: A Simulation Study," *Journal of Industrial Intelligence*, vol. 2, no. 3, pp. 132–143, 2024, doi: 10.56578/jii020301.

[55] B. Kizielewicz, and W. Sałabun, "Benchmark study of re-identification methods based on stochastic fuzzy normalization and their application to decision-making problems in engineering," *Facta Universitatis, Series: Mechanical Engineering*, vol. 23, no. 3, pp. 511–532, 2025, doi: 10.22190/FUME240916004K.

[56] T. Wang, X. Wu, H. Garg, Q. Liu, and G. Chen, "A prospect theory-based MABAC algorithm with novel similarity measures and interactional operations for picture fuzzy sets and its applications," *Engineering Applications of Artificial Intelligence*, vol. 126, part A, Art. no. 106787, 2023, doi: 10.1016/j.engappai.2023.106787.

[57] A. Puška, J. Bosna, and D. Božanić, "Evaluation of the Housing Aggregation Model for Young People in Urban Areas," *Journal of Urban Development and Management*, vol. 4, no. 1, pp. 58–70, 2025, doi: 10.56578/judm040105.

[58] G. Wan, Y. Rong, and H. Garg, "An efficient spherical fuzzy MEREC–CoCoSo approach based on novel score function and aggregation operators for group decision making," *Granular Computing*, vol. 8, no. 6, pp. 1481–1503, 2023, doi: 10.1007/s41066-023-00381-2.

[59] F. Balo, A. Ulutaş, Ž. Stević, H. Boydak, and E. K. Zavadskas, "Hybrid Revit and a new MCDM approach of energy effective nursing-home designed by natural stone and green insulation materials," *Journal of Civil Engineering and Management*, vol. 31, no. 4, pp. 318–337, 2025, doi: 10.3846/jcem.2025.23486.

[60] Z. Durmuş, "Assessment of Renewable Energy Performance in Turkey Using a Novel Integrated MSD-CRITIC-RAWEC Model," *Journal of Operational and Strategic Analytics,* vol. 3, no. 1, pp. 49–64, 2025, doi: 10.56578/josa030105.