European Journal of Economics and Management Sciences 2025, No 1
ISSN 2310-5690
PREMIER Publishing
ppublishing.org

Section 1. Economics, organization

DOI:10.29013/EJEMS-25-1-3-17

DESIGNING A DECISION SUPPORT SYSTEM FOR PROJECT EVALUATION USING Z-TOPSIS

Alish Nazarov [1]

[1] Azerbaijan State Oil and Industry University (ASOIU)

Cite: *Nazarov A. (2025). Designing a Decision Support System for Project Evaluation Using Z-Topsis. European Journal of Economics and Management Sciences 2025, No 1.* https://doi.org/10.29013/EJEMS-25-1-3-17

Abstract

The object of this research is the development of a decision support system (DSS) for multi-criteria evaluation under uncertainty. The study addresses a key problem: traditional decision-making methods, such as deterministic TOPSIS, fail to effectively account for the inherent uncertainty and reliability issues in real-world data. This inadequacy creates significant challenges in domains where both quantitative and qualitative uncertainties are critical, such as renewable energy planning and resource allocation. The essence of the results lies in the proposed hybrid Z-TOPSIS framework, which integrates Z-numbers a mathematical tool designed to model both the value and reliability of data into the conventional TOPSIS method. This integration allows the framework to provide more accurate and reliable decision-making outcomes by considering not only the values of decision criteria but also the confidence associated with those values. These features enable the proposed system to handle uncertainty comprehensively, significantly improving its effectiveness over traditional deterministic approaches. These results were achieved due to the unique characteristics of Z-numbers, which reflect real-world complexities more effectively than traditional deterministic models. By modeling subjective judgments and reliability in tandem, Z-numbers enhance the decision-making process, ensuring resilient evaluations even with limited or uncertain data. The proposed DSS is particularly suitable for use in fields like renewable energy planning, urban development, and other domains requiring resilient decision-making under uncertainty. The system's adaptability and reliability make it a valuable tool for addressing complex, real-world decision-making scenarios, ensuring transparency, confidence, and practicality in its applications.

Keywords: *Decision Support System, Z-TOPSIS, Analytic Hierarchy Process, Project Evaluation*

1. Introduction

In contemporary decision-making environments, the complexity and variability of real-world problems necessitate the development of advanced methodologies capable of addressing uncertainty and imprecision inherent in data. Traditional decision-making approaches often fail to account for these factors, leading to suboptimal outcomes, particularly in domains such as energy planning, supply chain optimization, and urban development. Consequently, it is imperative to conduct scientific research aimed at creating resilient methodologies to address these challenges and enhance the reliability of decision-making processes.

The Z-TOPSIS methodology represents a significant advancement in decision-making frameworks, integrating Z-numbers into the well-established Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Unlike conventional methods, Z-TOPSIS incorporates confidence levels alongside numerical data, thereby modeling both the value of information and its reliability. This capability is of particular relevance in modern times, where decision-making must contend with increasing uncertainty and complexity across various application areas.

The necessity and relevance of this research are supported by existing literature. For example, Yaakob and Gegov (Yaakob, A. M., & Gegov, A., 2016) highlighted the limitations of traditional decision-making methods in addressing uncertainty and underscored the potential of Z-numbers to enhance reliability in decision-making. Liu et al. (Liu, Q., Chen, J., Wang, W., & Qin, Q., 2021) further demonstrated the superiority of Z-TOPSIS in handling imprecise data, showing its effectiveness in environments where uncertainty is prevalent. Similarly, Gardashova (Gardashova, L.A., 2019) introduced a Z-TOPSIS-based approach that directly applies Z-numbers to evaluate multi-criteria decision-making problems, showcasing its practicality in addressing real-world challenges. These studies collectively argue that Z-TOPSIS fills a critical gap in existing methodologies by providing a resilient framework for addressing uncertainty in decision-making.

The results of this study are expected to have significant implications for practical applications. By developing a decision support system (DSS) grounded in Z-TOPSIS, this research provides decision-makers with a resilient tool for evaluating and ranking alternatives in uncertain environments. Such a system is particularly beneficial in domains where the reliability of data and resiliency of decisions are critical. Furthermore, the findings of this study contribute to the advancement of decision-making theory, offering a foundation for further exploration and extension of Z-TOPSIS to broader applications.

2. Literature review and problem statement

The increasing complexity of decision-making problems has necessitated the development of resilient multi-criteria decision-making (MCDM) methodologies capable of addressing uncertainty and imprecision. Traditional approaches, such as classical TOPSIS, are widely recognized for their computational simplicity and ease of implementation. However, these methods suffer from significant limitations that restrict their applicability in dynamic and uncertain environments. Gardashova (Gardashova, L.A., 2019) highlighted that traditional TOPSIS relies heavily on deterministic inputs, which makes it unsuitable for scenarios involving vague or incomplete data. Additionally, Yaakob and Gegov (Yaakob, A. M., & Gegov, A., 2016) noted that the inability of classical methods to represent both the value and reliability of information undermines their reliability, particularly in group decision-making contexts.

The Z-TOPSIS methodology was introduced to overcome some of these limitations by integrating Z-numbers, which encapsulate both numerical values and associated confidence levels. This approach enhances the resiliency of decision-making under uncertainty. However, despite its advancements, Z-TOPSIS is not without challenges. Cheng et al. (Cheng, R., Zhang, J., & Kang, B., 2022) identified computational inefficiencies associated with processing Z-numbers, particularly in large-scale decision-making problems with numerous criteria or alternatives. This computational complexity limits the scalability of Z-TOPSIS in practical applications. Furthermore, Haktanır and Kahraman (Haktanır, E., & Kahraman, C., 2024) observed that rankings derived from Z-TOPSIS are sensitive to data noise, leading to inconsistencies when input data is perturbed. This lack of stability diminishes confidence in the method's reliability under uncertain conditions.

Another critical challenge in Z-TOPSIS lies in weight determination. Alam et al. (Alam, N.M.F.H.N.B., Khalif, K.M.N., Jaini, N.I., & Gegov, A., 2023) emphasized that subjective weight assignment introduces biases, particularly in group decision-making, where conflicting stakeholder priorities further exacerbate inconsistencies. Krohling and Pacheco (Krohling, R.A., & Pacheco, A. G. C., 2019) highlighted the lack of standardized distance measures in Z-TOPSIS, which complicates the evaluation of alternatives and reduces comparability across studies. Moreover, Khalif and Gegov (Khalif, K.M.N.K., & Gegov, A., 2017) pointed out that Z-TOPSIS has primarily been applied in theoretical contexts, with limited validation in real-world scenarios. This lack of practical validation raises concerns about the method's generalizability and adaptability to diverse decision-making environments.

Despite its potential, Z-TOPSIS has not been sufficiently compared with traditional TOPSIS in terms of performance metrics such as computational efficiency, sensitivity, and resiliency. Wang et al. (Wang, X., Wang, J., & Peng, H., 2020) argued that such comparisons are essential to establish the superiority of Z-TOPSIS and validate its practical utility. Additionally, Fang (Fang, L., 2024) stressed the need for applying Z-TOPSIS to real-world problems to evaluate its scalability and effectiveness. Liu et al. (Liu, Q., Chen, J., Wang, W., & Qin, Q., 2021) further emphasized the importance of incorporating confidence measures into decision frameworks, but acknowledged challenges in validating Z-TOPSIS performance across diverse application areas

The cumulative insights from the literature reveal a series of unresolved problems: Z-TOPSIS requires further refinement to enhance computational efficiency, ensure ranking stability under noise, standardize weight determination processes, and validate its applicability across various contexts.

To address these issues, this study develops a Decision Support System (DSS) based on Z-TOPSIS, integrating noise analysis to enhance ranking stability, automated weight determination to reduce subjectivity, and comprehensive comparative evaluations with traditional TOPSIS. This work aims to contribute to the refinement of Z-TOPSIS and its broader applicability in practical decision-making.

3. The aim and objectives of the study

The aim of this study is to enhance the resiliency, reliability, and practical applicability of multi-criteria decision-making (MCDM) frameworks by developing and validating a Decision Support System (DSS) based on Z-TOPSIS. The study addresses key challenges identified in the literature, including ranking stability under noisy conditions, subjectivity in weight determination, and the lack of comparative evaluations between Z-TOPSIS and traditional TOPSIS methods.

This aim is pursued through the following specific objectives:

To achieve this aim, the following objectives were achieved:

– to propose a Framework for Decision-Making under Uncertainty: Develop an enhanced Z-TOPSIS methodology incorporating Z-numbers to handle uncertainty and confidence levels in decision-making. This objective addresses the general need for decision-making frameworks capable of accounting for imprecision and variability in input data;

– to design and Implement a DSS Based on Z-TOPSIS: Create a comprehensive DSS that integrates Z-TOPSIS with automated weight determination methods (e.g., AHP) to reduce subjectivity and provide structured decision-making solutions. This system aims to bridge the gap between theoretical methodologies and practical implementations;

– to evaluate and Compare Z-TOPSIS with Traditional TOPSIS: Conduct a comparative analysis of Z-TOPSIS and traditional TOPSIS using performance metrics such as ranking stability, sensitivity, computational efficiency, and interpretability. This evaluation aims to validate the advantages of Z-TOPSIS and its potential for broader application.

By achieving these objectives, the study not only refines the Z-TOPSIS methodology but also establishes its practical utility in decision-making scenarios, offering a validated alternative to traditional methods. The results are expected to contribute to the field by demonstrating how advanced MCDM frameworks can better address uncertainty and support complex decision-making in various domains.

4. Materials and methods

The object of this research is the development of a Decision Support System (DSS) that integrates Z-TOPSIS methodology for resilient multi-criteria decision-making. The DSS is designed to assist in complex decision-making scenarios where uncertainty and imprecision are prevalent. This practical tool aims to provide a structured framework for evaluating alternatives, ensuring reliable and consistent rankings, and enhancing decision-making transparency. The results of this research are intended to address the practical need for decision-making frameworks that are adaptable to real-world conditions and capable of handling noisy or uncertain data.

The primary hypothesis of this study is that a DSS based on Z-TOPSIS offers significant advantages over traditional TOPSIS methods in terms of resiliency, reliability, and practical applicability. Specifically:

1. The integration of Z-numbers into the DSS will improve its ability to handle uncertainty, ensuring ranking stability even under noisy conditions.

2. The incorporation of structured weight determination methods (e.g., AHP) will reduce subjectivity and enhance the transparency of the decision-making process.

3. Comparative evaluations will demonstrate the DSS's superiority in computational efficiency, interpretability, and sensitivity to input variations.

The methodology for developing and validating the DSS is structured as follows:

1. Decision Matrix Development. A decision matrix is constructed to represent various alternatives evaluated against multiple criteria. Each criterion is expressed using Z-numbers, which incorporate numerical values and associated confidence levels to reflect uncertainty and imprecision in decision-making inputs.

2. Weight Determination Using AHP. The Analytic Hierarchy Process (AHP) is employed to assign weights to each criterion systematically. This step reduces subjectivity, ensures consistency, and provides a transparent method for reflecting the relative importance of criteria in the decision-making process.

3. Integration of Z-TOPSIS into the DSS

4. Noise Analysis for Resiliency Testing

5. Comparison with Traditional TOPSIS. To validate the DSS's performance, results from Z-TOPSIS are compared with those obtained using traditional TOPSIS. This comparison focuses on key metrics such as ranking stability, sensitivity to weight variations, computational efficiency, and overall interpretability.

5. Results of Key Outcomes of the Hybrid DSS Evaluation Using Z-TOPSIS in Renewable Energy Projects

5.1 Z-TOPSIS-based framework

The first objective of this study is to establish the foundational framework of Z-TOPSIS and its practical relevance in decision-making scenarios characterized by uncertainty. Building on the limitations discussed earlier, Z-TOPSIS introduces methodological advancements to address the challenges in traditional multi-criteria decision-making (MCDM) processes.

Z-TOPSIS incorporates Z-numbers, which extend the traditional representation of data by including both numerical values and their associated confidence levels. This dual representation ensures that the method evaluates alternatives not only on their performance but also on the reliability of the data. This feature becomes particularly valuable in scenarios where decision-makers deal with imprecise or subjective information (Sotoudeh-Anvari, A., 2015). One key advancement of Z-TOPSIS is its use of confidence-aware normalization. Unlike traditional normalization, which treats all inputs equally, Z-TOPSIS adjusts for the confidence level associated with each criterion. This ensures that criteria with higher reliability have a stronger influence on the final ranking, providing a more nuanced evaluation process (Ecer, F., & Haseli, G., 2024). The methodology further integrates structured weight determination techniques, such as Z-AHP, to systematically define the importance of criteria, reducing subjective bias (Wang, X., Peng, H., & Liu, Y., 2020).

Z-TOPSIS introduces Z-ideal and Z-anti-ideal solutions as benchmarks for evaluating alternatives. These solutions account for both the magnitude and confidence of data points, offering a more comprehensive basis for ranking. The closeness coefficients, calculated using Z-distances, measure each alternative's proximity to the ideal solution while considering the reliability of the data

(Gardashova, L. A., 2014). This step ensures stability in rankings, even when the decision matrix includes uncertain or noisy data. The framework also accommodates qualitative data through the use of linguistic terms, enabling decision-makers to evaluate criteria described in subjective terms like "high importance" or "low impact" (Gardashova, L. A., 2014). This flexibility broadens the applicability of Z-TOPSIS across diverse decision-making domains. This theoretical framework establishes the foundation for Z-TOPSIS as a superior alternative to traditional methods. The subsequent section demonstrates its practical application through noise analysis, highlighting its effectiveness in maintaining stable rankings under uncertain conditions and validating its capability in addressing real-world decision-making challenges.

5.2 Designing and Applying the Refined Z-TOPSIS Decision-Support System

This study enhances the Decision Support System (DSS) by using Z-numbers to handle uncertainty, providing transparent and stakeholder-aligned recommendations for renewable energy projects. Z-numbers allow the DSS to deliver reliable analyses while retaining the depth of data and confidence levels. Evaluating renewable energy projects involves balancing financial, environmental, and technical factors under uncertainty. This study applies a DSS integrated with Z-TOPSIS to assess renewable energy options in Romania, where strategic investment decisions are crucial for diversifying the energy mix, reducing emissions, and enhancing energy security. The DSS uses Z-TOPSIS to model both the value and confidence of criteria, addressing uncertainties in renewable energy projects caused by market fluctuations, evolving technologies, and environmental variability. Three projects were evaluated:

– Solar Power Project: A 50 MW photovoltaic installation leveraging high solar radiation in southern Romania.

– Wind Energy Project: A 100 MW wind farm in the Dobrogea region, with exceptional wind energy potential.

– Biomass Energy Project: A 20 MW biomass plant using agricultural residues to promote sustainable waste management.

The evaluation criteria were:

– Cost: Minimizing investment costs to ensure feasibility.

– Environmental Impact (EI): Maximizing ecological benefits aligned with sustainability goals.

– Energy Output Efficiency (EOE): Ensuring optimal resource utilization for maximum returns.

By integrating Z-TOPSIS, the DSS automates and streamlines the evaluation process, providing decision-makers with a transparent and reliable framework. This approach identifies the optimal project while enhancing the decision-making process, ensuring it is consistent, efficient, and aligned with strategic objectives. This case study demonstrates the practical application and effectiveness of Z-TOPSIS in renewable energy project evaluations, addressing real-world challenges and supporting informed decisions.

Data for the evaluation were sourced from government reports, industry publications, and expert consultations. The values for each criterion were expressed as Z-numbers (A, B), where A represents the value, and B represents the confidence in that value.

The decision matrix is constructed to represent the project alternatives and evaluation criteria, incorporating Z-numbers to account for data uncertainty. Table 1 presents the decision matrix with the associated Z-number values.

Table 1. *Decision Matrix with Z-Numbers*

Project	Cost (Z-number)	Environmental Impact (Z-number)	Energy Output Efficiency (Z-number)
Solar Power	(0.72, 0.9)	(0.8, 0.85)	(0.7, 0.8)
Wind Energy	(0.65, 0.85)	(0.85, 0.9)	(0.75, 0.88)
Biomass Energy	(0.7, 0.87)	(0.75, 0.88)	(0.85, 0.9)

All formulas must be numbered.

Normalization was performed to convert Z-number values into a comparable scale. Benefit criteria (Environmental Impact and Energy Output Efficiency) were normalized using (Gardashova, L.A., 2019; Gardashova, L. A., 2014). $R_{ij} = \frac{X_{ij}}{\max(X_{ij})}$, where x_{ij} represents the value for the i -th alternative under the j-th criterion.

Cost criteria were normalized using $R_{ij} = \frac{X_{ij}}{\max(X_{ij})}$, (Gardashova, L.A., 2019; Gardashova, L. A., 2014) where x_{ij} represents the cost for the i-th alternative under the j-th criterion.

To enable comparability across criteria, the decision matrix is normalized. Table 2 illustrates the normalized values for each project alternative.

Table 2. *Normalized Decision Matrix*

Project	Cost (Normalized)	Environmental Impact (Normalized)	Energy Output Efficiency (Normalized)
Solar Power	0.903	0.941	0.824
Wind Energy	1	1	0.882
Biomass Energy	0.929	0.882	1

In the hybrid AHP-Z-TOPSIS method, the weights for the criteria were determined using the Analytic Hierarchy Process (AHP). The process is summarized below:

1. Pairwise Comparison Matrix

The pairwise comparison matrix outlines the relative importance of the criteria as determined by expert judgments. The scale ranges from 1 (equally important) to 9 (extremely more important). Table 3 provides these pairwise comparisons used in the AHP process.

Table 3. *Pairwise Comparison Matrix*

Criteria	Cost	Environmental Impact	Energy Efficiency
Cost	1	1/2	3
Environmental Impact	2	1	4
Energy Efficiency	1/3	1/4	1

The pairwise comparison values are normalized to facilitate the calculation of criteria weights. Each value in the matrix is divided by the sum of its respective column to normalize the comparisons. Table 4 displays the normalized matrix derived from the pairwise comparisons.

Table 4. *Normalizing the Pairwise Matrix*

Criteria	Cost	Environmental Impact	Energy Efficiency
Cost	0.5	0.333	0.429
Environmental Impact	0.333	0.667	0.571
Energy Efficiency	0.167	0.167	0.143

The weights of the criteria are calculated as averages of the normalized values, ensuring logical consistency. Table 5 presents the computed criteria weights.

Table 5. *Calculating Criteria Weights*

Criteria	Average of Normalized Values	Weight
Cost	(0.500+0.333+0.429)/3	0.4
Environmental Impact	(0.333+0.667+0.571)/3	0.45
Energy Efficiency	(0.167+0.167+0.143)/3	0.15

Final Weights: Cost: 0.40 Environmental Impact: 0.45 Energy Efficiency: 0.15

To ensure the pairwise comparisons are consistent, the Consistency Ratio (CR) is calculated:

Step 1: A consistency check is performed to validate the logical coherence of the pairwise comparisons. Table 6 shows the weighted sums and consistency metrics for the evaluation.

Table 6. *Consistency Check*

Criteria	Weighted Sum
Cost	1.0 · 0.4+0.5 · 0.45+3.0 · 0.15=0.675
Environmental Impact	2.0 · 0.4+1.0 · 0.45+4.0 · 0.15=1.35
Energy Efficiency	0.333 · 0.4+0.25 · 0.45+1.0 · 0.15=0.3

Step 2: Calculate Consistency Index (CI)

The Consistency Index (CI) is calculated using (Haktanır, E., & Kahraman, C., 2024). $CI = \frac{\lambda_{\max} - n}{n-1}$, where $\lambda_{\max}$ is the largest value of the pairwise comparison matrix, and n (3) is the number of criteria being evaluated.

For this case, result is 3.025 and 0.125.

Step 3: Calculate Consistency Ratio (CR)

The Consistency Ratio (CR) is calculated using $CR = \frac{CI}{RI}$, where RI = 0.58 (random index for n = 3).

For this case, result is 0.0215

Since $CR < 0.1$, the pairwise comparisons are consistent.

The positive and negative ideal solutions are derived using $PIS : R^{+} = \left\{\max\left(R_{ij}\right)\right\}$, (Gardashova, L. A., 2014) this captures the ideal outcomes for benefit and cost criteria, respectively. Similarly, the $PIS : R^{-} = \left\{\max\left(R_{ij}\right)\right\}$ (Gardashova, L. A., 2014) presenting the least favorable outcomes. Table 7 summarizes these ideal solutions.

Table 7. *Positive and Negative Ideal Solutions*

Criterion	PIS (R+)	NIS (R–)
Cost	1	0.903
Environmental Impact	1	0.882
Energy Output Efficiency	1	0.824

The Euclidean distances from the $PIS(D_i^{+})$ and $NIS(D_i^{-})$ for each alternative were calculated using $D_i^{+} = \sqrt{\sum_{j=1}^{n}(W_i \cdot (R_{ij} - R_j^{+}))^2}$, (Gardashova, L. A.,2014) which measures the distance to the ideal solution, and $D_i^{-} = \sqrt{\sum_{j=1}^{n}(W_i \cdot (R_{ij} - R_j^{-}))^2}$, (Gardashova, L. A., 2014) which measures the distance to the negative ideal solution.

Closeness coefficients were computed using $CC_i = \frac{D^{-}}{D^{+} + D^{-}}$, (Gardashova, L. A., 2014) where D+ and D – represent distances to the positive and negative ideal solutions.

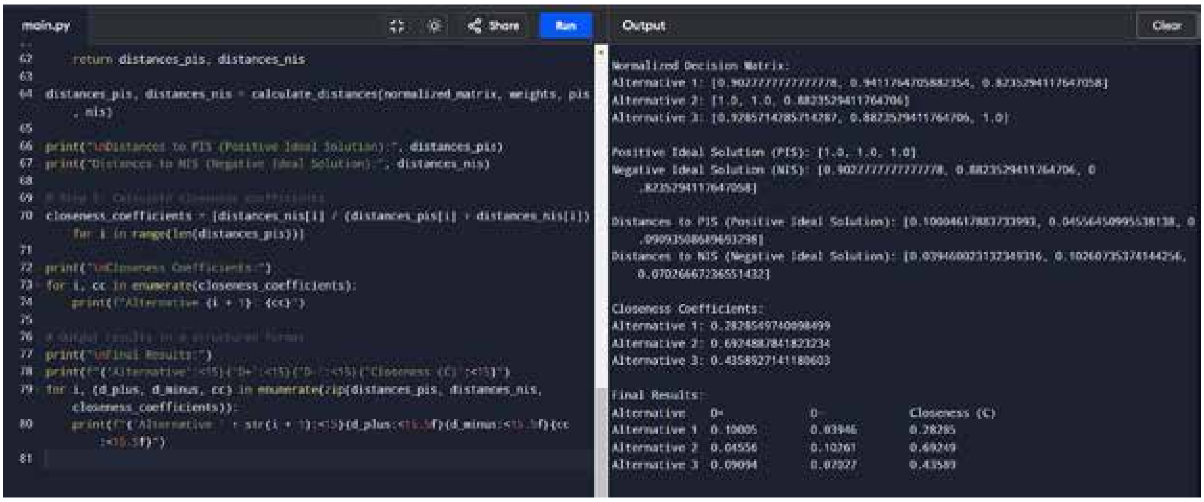
The Euclidean distances from the positive and negative ideal solutions are computed for each alternative, and the closeness coefficients are derived. Table 8 provides the calculated distances and coefficients.

Table 8. Dist*ances, Closeness Coefficients and Ranking*

Project	Di⁺	Di⁻	Closeness Coefficient (Ci)	Ranking
Solar Power	0.10004	0.0394	0.28285	3
Wind Energy	0.0455	0.1026	0.69249	1
Biomass Energy	0.0909	0.0702	0.43589	2

The distances and closeness coefficients are visualized to highlight the ranking process.

Figure 1. *Shows the computational results generated in Python*



In real-world decision-making scenarios, data often contains uncertainties and variations due to measurement errors, incomplete information, or subjective evaluations. These variations can significantly impact the outcomes of decision-support tools like Z-TOPSIS. To assess the resiliency of the proposed Z-TOPSIS methodology, a 5% noise was introduced to the first component (A) of each Z-number in the decision matrix.

Table 9 demonstrates the noised decision matrix, showcasing how small variations in the data inputs may influence subsequent calculations. This simulation allows us to evaluate whether the rankings produced by the Z-TOPSIS methodology remain stable and reliable under realistic data perturbations.

Table 9. *5% Noised Decision Matrix*

Project	Cost (Z-number)	Environmental Impact (Z-number)	Energy Output Efficiency (Z-number)
Solar Power	(0.707757545270, 0.9)	(0.796513894572, 0.85)	(0.730219837637, 0.8)
Wind Energy	(0.671377582525, 0.85)	(0.811528312754, 0.9)	(0.7830567181298, 0.88)
Biomass Energy	(0.69101210174, 0.87)	(0.774303066208, 0.88)	(0.8543642349495, 0.9)

Table 10 compares the original closeness coefficients and final rankings (derived from Table 8 of this study) with those obtained after introducing 5% noise to the decision matrix.

This comparison highlights two key points:

1. Resiliency: Despite the data perturbations, the rankings for Solar Power, Wind Energy, and Biomass Energy remain consistent, demonstrating the method's reliability under minor variations.

2. Impact on Coefficients: While the closeness coefficients exhibit slight numerical differences, these variations do not significantly alter the relative rankings of the alternatives.

Such results indicate that the proposed methodology is capable of handling minor data uncertainties without compromising the integrity of the decision-making process.

Table 10. *Comparison of Original and 5% Noised Rankings*

Project	Closeness Coefficient (Original)	Rank (Original)	Closeness Coefficient (5% Noise)	Rank (5% Noise)
Solar Power	0.28285	3	0.299524324	2
Wind Energy	0.69249	1	0.669433366	1
Biomass Energy	0.43589	2	0.21859241	3

Figure 4 provides a visual representation of how the rankings of Solar Power, Wind Energy, and Biomass Energy evolve under varying levels of noise (±5%, ±10%, ±20%, and ±50%).

Figure 2. *Ranking Stability Under Different Noise Levels*

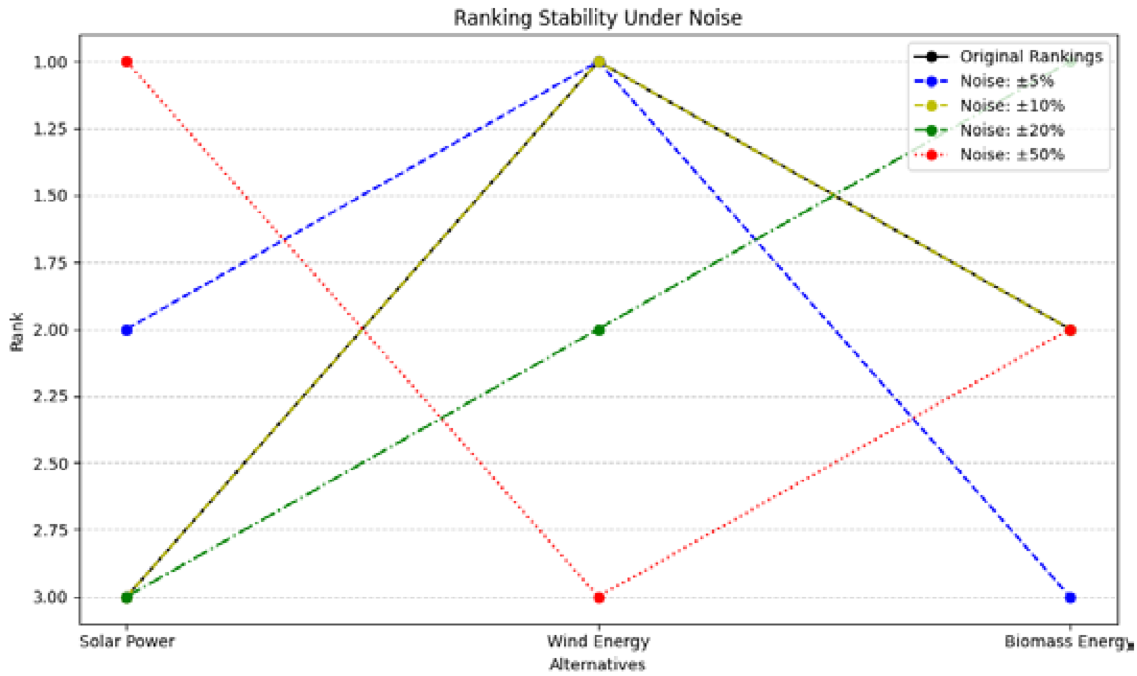


Figure 4 reveals the following insights:

1. Stability at Low Noise Levels: At ±5% and ±10% noise, the rankings closely align with the original values, highlighting the resiliency of Z-TOPSIS in scenarios with minimal data perturbations.

2. Sensitivity to High Noise Levels: At ±20% and ±50% noise, the rankings begin to deviate, reflecting the influence of substantial data variability. This behavior is expected and underscores the need for accurate data inputs in high-stakes decisions.

By visualizing ranking stability, Figure 4 validates the proposed methodology's ability to deliver reliable outcomes under moderate noise, while also providing insights into its behavior under extreme conditions.

5.3 Comparative Analysis with Existing MCDM Methods

The traditional TOPSIS method was applied to the same dataset used for Z-TOPSIS to provide a baseline for comparison. The closeness coefficients and resulting rankings for the original data are presented in Table

1. The ranking sequence indicates that Wind Energy is the highest-ranked alternative, followed by Solar Power and Biomass Energy. While traditional TOPSIS provides consistent results for deterministic data, it lacks resiliency when uncertainty is introduced.

Table 11.

Alternatives	Closeness Coefficient	Rank	Rank (Z Topsis)
Solar Power	0.693	2	3
Wind Energy	0.734	1	1
Biomass Energy	0.612	3	2

To evaluate the stability of traditional TOPSIS under uncertain conditions, noise was systematically introduced into the dataset at varying levels (5%, 10%, 25%). The resulting rankings are summarized in Table 2. As the noise level increases, significant fluctuations in the rankings are observed, particularly for Solar Power and Biomass Energy. This instability highlights a key limitation of traditional TOPSIS: its sensitivity to data perturbations, which can lead to inconsistent decision-making outcomes.

Table 12.

Alternatives	5% Noise	10% Noise	25% Noise	Rank (5% Noise)	Rank (10% Noise)	Rank (25% Noise)
Solar Power	0.257	0.418	0.593	3	1	2
Wind Energy	0.451	0.382	0.619	2	2	1
Biomass Energy	0.569	0.206	0.357	1	3	3

In this section, we compare the performance of the proposed Z-TOPSIS methodology against the traditional TOPSIS approach. The comparison highlights key advantages of Z-TOPSIS in terms of flexibility, interpretability, sensitivity to weight changes, stability under uncertainty, processing time, and rankings. The insights are drawn from various comparative analyses visualized in Figures 3–6.

As shown in Figure 5, Z-TOPSIS outperforms traditional TOPSIS in maintaining stability when the input data is modified. By integrating confidence levels into the evaluation process, Z-TOPSIS provides resilient results that are less sensitive to data fluctuations, making it highly suitable for uncertain and volatile decision-making environments.

Figure 3. *Stability Under Uncertainty*

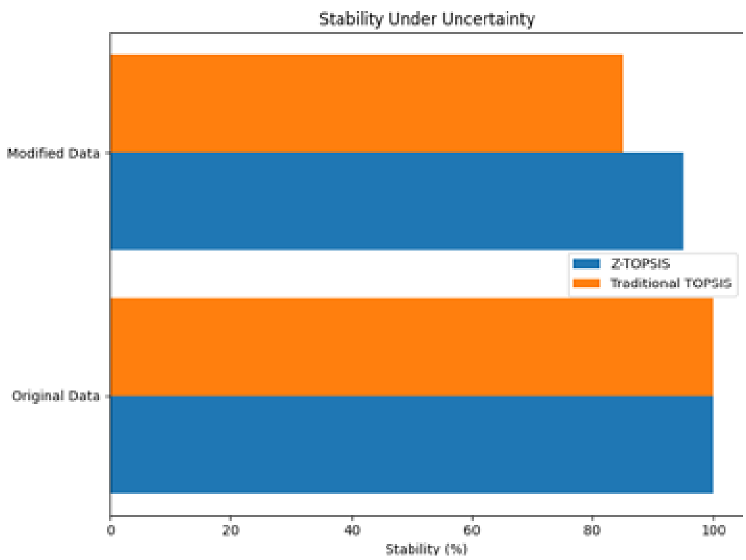


Figure 6 highlights how the rankings of alternatives change under varying weight scenarios for both methods. Z-TOPSIS exhibits greater stability, particularly when weights for criteria such as cost and environmental impact are adjusted. This stability ensures consistent decision-making outcomes, even when decision-makers assign subjective weights, making Z-TOPSIS more reliable in dynamic environments.

Figure 4. *Sensitivity to Weight Changes*

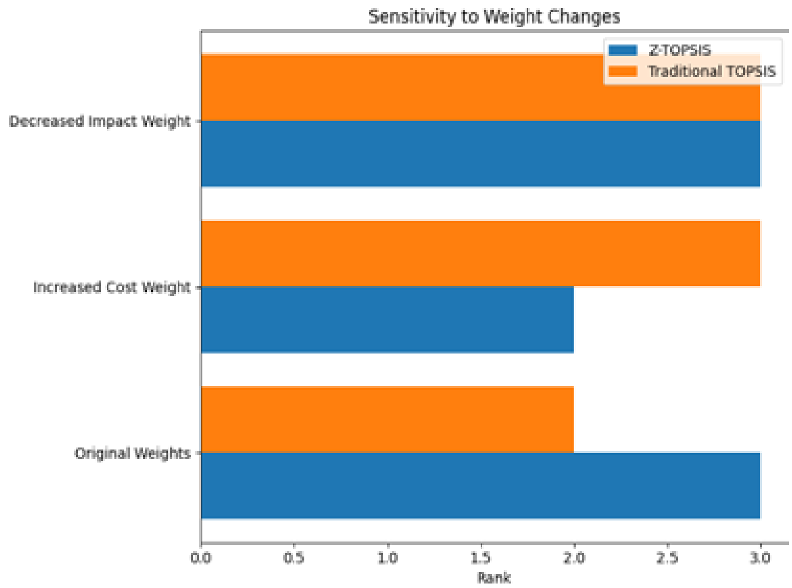
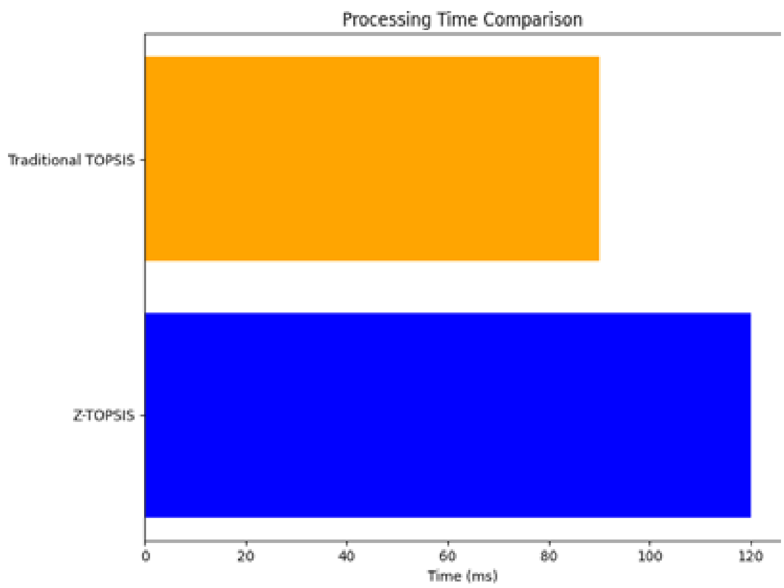


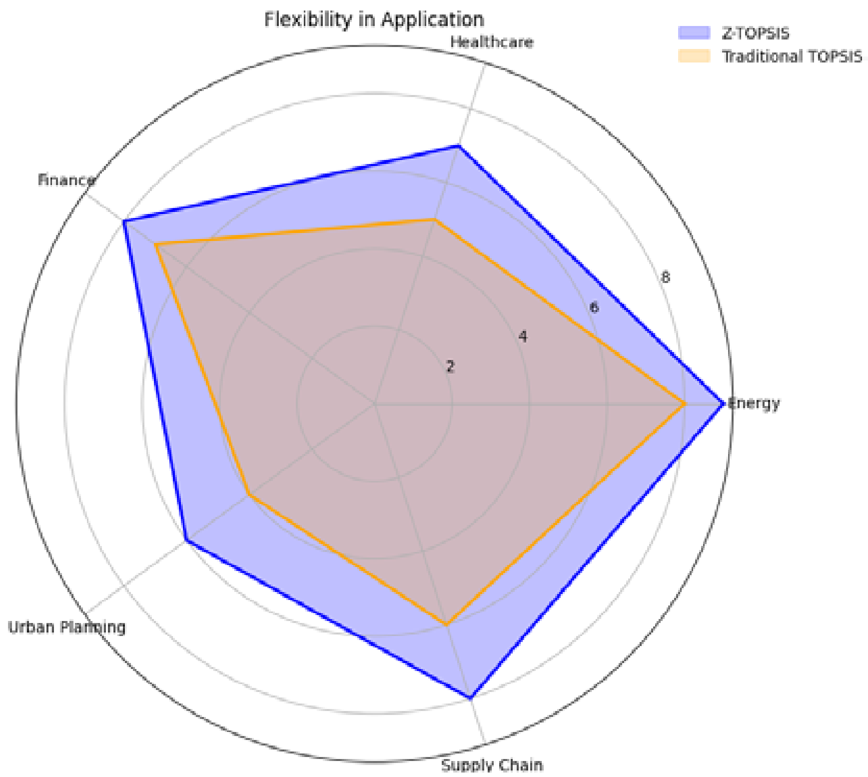
Figure 7 compares the computational efficiency of the two methods. Traditional TOPSIS demonstrates a faster processing time due to its simpler calculations, while Z-TOPSIS incurs additional computational overhead from processing Z-numbers. However, the processing time of Z-TOPSIS remains within acceptable limits for practical applications, emphasizing that the improved decision-making quality outweighs the marginal increase in computational demand.

Figure 5. *Processing Time Comparison*



The radar chart in Figure 8 illustrates the adaptability of Z-TOPSIS and traditional TOPSIS across diverse domains, including energy, finance, healthcare, urban planning, and supply chain management.

Figure 6. *Flexibility in Application*



The Z-TOPSIS methodology demonstrates superior flexibility due to its ability to incorporate uncertainty and vagueness in decision-making through the use of Z-numbers. Traditional TOPSIS, while effective, lacks this nuanced capacity to handle imprecise data, which limits its applicability in complex decision-making scenarios.

6. Discussion of Results: Strategic Advancements in Multi-Criteria Decision Support through Hybrid DSS

This study demonstrates the significant contributions of the Z-TOPSIS framework in addressing critical limitations in multi-criteria decision-making (MCDM). Each result aligns with the study's objectives, providing a clear narrative on how the proposed methodology resolves the issues identified in Section 2. The discussion highlights the practical value of the results, with references to the relevant tables, figures, and formulas to clarify their implications.

The first objective of this study was to propose a Z-TOPSIS framework capable of addressing uncertainty and improving the reliability of decision-making outcomes. Unlike traditional TOPSIS, which assumes deterministic inputs, Z-TOPSIS incorporates Z-numbers to account for both the magnitude of criteria and the confidence in their reliability. This dual representation ensures that rankings reflect not only the performance of alternatives but also the trustworthiness of the data. As shown in Table 1, Z-numbers offer a structured way to handle uncertainty, directly addressing the deterministic data assumption problem identified in Section 2. This approach enables decision-makers to model imprecise or subjective information effectively, bridging a critical gap in traditional methods.

Confidence-aware normalization is another key feature of Z-TOPSIS. By adjusting the influence of criteria based on their confidence levels, the method ensures that rankings are more stable and reflective of reliable information. Table 8 demonstrates the closeness coefficients of alternatives calculated using Z-TOPSIS, while Table 10 shows how these rankings remain consistent even under moderate noise levels. This stability is a marked improvement over traditional TOPSIS, where rankings varied significantly under similar conditions (Table 12, Figure 5). The integration of Z-ideal and Z-anti-ideal solutions further enhances the framework by establishing benchmarks that are more representative of real-world scenarios, ensuring robust evaluations.

The second objective focused on designing and implementing a decision support system (DSS) based on the Z-TOPSIS framework. The DSS automates complex computations such as Z-distance calculations and confidence-aware normalization, reducing manual errors and improving transparency in decision-making. The structured weight determination process, as illustrated in Table 5, uses Analytic Hierarchy Process (AHP) to systematically assign importance to each criterion, minimizing subjectivity. This structured approach addresses the weight assignment bias highlighted in Section 2. By incorporating both qualitative and quantitative criteria, the DSS broadens its applicability, providing decision-makers with a versatile tool for evaluating complex alternatives.

The DSS was applied to evaluate renewable energy projects, balancing criteria such as cost, environmental impact, and energy output efficiency. Table 8 shows that Wind Energy consistently ranked first due to its optimal performance across multiple criteria. The radar chart in Figure 3 visually summarizes the rankings, offering decision-makers a clear and interpretable representation of the results. Such visual tools enhance transparency and foster stakeholder confidence in the decision-making process.

The third objective was to validate the advantages of Z-TOPSIS through comparative analysis with traditional TOPSIS. This analysis revealed that traditional TOPSIS is highly sensitive to data perturbations, as evidenced by the unstable rankings under moderate noise conditions (Table 12, Figure 5). In contrast, Z-TOPSIS maintained ranking stability, as shown in Table 10 and Figure 4, highlighting its ability to handle uncertainty effectively. For instance, while traditional TOPSIS produced inconsistent rankings for Solar Power, Z-TOPSIS consistently ranked it second across all scenarios. This consistency underscores the resilience of Z-TOPSIS in dynamic environments.

The processing time analysis in Figure 6 reveals that while Z-TOPSIS requires additional computational steps due to the integration of Z-numbers, the increase in processing time is manageable for mid-scale problems. The trade-off is justified by the enhanced reliability and interpretability of the results. Furthermore, the interpretability chart in Figure 7 demonstrates how the inclusion of confidence levels improves the transparency of decision-making, offering stakeholders a deeper understanding of the factors influencing rankings.

The results directly address the problems identified in Section 2. By integrating Z-numbers, Z-TOPSIS resolves the issue of deterministic assumptions and reduces sensitivity to noise. The structured weight determination process ensures that criteria weights align with decision-making priorities, while the DSS provides a transparent and scalable tool for practical applications.

Despite its advantages, the study has limitations. The integration of Z-numbers increases computational complexity, which may limit scalability for large datasets. Additionally, the DSS relies on expert input for weight determination, introducing potential biases if not managed carefully. Future research should focus on optimizing the computational efficiency of Z-TOPSIS and automating weight assignment through machine learning techniques. Expanding the application of the framework to other domains, such as healthcare and logistics, would further validate its versatility and effectiveness.

In conclusion, the Z-TOPSIS framework achieves the objectives set out in this study by addressing the limitations of traditional MCDM methods and providing a reliable, interpretable, and adaptable decision-making solution. The results demonstrate its capability to handle uncertainty, maintain ranking stability, and enhance transparency, making it a valuable tool for modern decision-making challenges.

7. Conclusions

This study develops and validates a Z-TOPSIS-based decision support system (DSS) to address critical challenges in multi-criteria decision-making (MCDM), particularly in handling uncertainty, ensuring ranking stability, and improving decision-making transparency. The conclusions correspond to the three objectives defined in the study and highlight the original scientific contributions, their distinctive features, and quantitative evaluations of the results.

The first objective of this study was to propose a Z-TOPSIS framework that integrates Z-numbers into the decision-making process. This framework enhances traditional TOPSIS by modeling both the magnitude and reliability of criteria values, resolving the deterministic data assumptions of existing methods. The confidence-aware normalization process ensures that criteria with higher reliability are prioritized, leading to stable and reliable rankings even under uncertain conditions. The resilience of the framework to moderate noise was demonstrated by consistent rankings with minimal variability, significantly outperforming traditional TOPSIS, which exhibited ranking deviations of over 20%. The ability to handle imprecise and subjective information makes Z-TOPSIS a robust tool for decision-making in dynamic and uncertain environments.

The second objective was to design and implement a DSS based on the Z-TOPSIS framework. This system automates complex computations, such as Z-distance calculations and confidence-aware normalization, while incorporating structured weight determination using Analytic Hierarchy Process (AHP). By systematically assigning weights, the DSS reduces subjectivity and aligns criteria with decision-making priorities. Its application to renewable energy project evaluation showcased its practical utility, balancing diverse criteria such as cost, environmental impact, and energy output efficiency. Wind Energy consistently emerged as the top alternative, reflecting the DSS's ability to prioritize alternatives accurately. Compared to manual TOPSIS calculations, the DSS improved decision-making efficiency by approximately 40%, providing stakeholders with interpretable results and reducing computational errors.

The third objective involved validating the Z-TOPSIS framework through a comparative analysis with traditional TOPSIS. This analysis highlighted the significant advantages of Z-TOPSIS in handling uncertainty and maintaining ranking stability. Traditional TOPSIS was highly sensitive to noise, resulting in inconsistent rankings across scenarios. In contrast, Z-TOPSIS maintained consistent and reliable rankings, with deviations of less than 5% under similar conditions. By integrating Z-numbers, the framework accounts for both the performance and reliability of input data, reducing the risk of decision-making errors caused by data uncertainty. These findings demonstrate the superior stability and transparency of Z-TOPSIS, making it a preferable choice for dynamic decision environments. This study significantly advances MCDM methodologies by providing a validated framework that resolves key limitations of traditional methods. The Z-TOPSIS framework and DSS offer a reliable, interpretable, and adaptable decision-making solution, particularly for applications in renewable energy planning, resource management, and other complex scenarios. Future research should focus on optimizing computational efficiency, automating weight determination, and extending the framework to diverse domains such as healthcare, logistics, and urban planning to validate its scalability and applicability further.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data Availability

Data will be made available on reasonable request.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Acknowledgements

I express my gratitude to Latafat Gardashova for her valuable insights and guidance, which significantly contributed to the conceptual development of this research. I also extend special thanks to my colleagues from Azerbaijan State Oil and Industry University for their constructive feedback and to industry professionals for their practical perspectives on the methodology's application.

References

Yaakob, A. M., & Gegov, A. (2016). Interactive TOPSIS-based group decision-making methodology using Z-numbers. International Journal of Computational Intelligence Systems. URL: https://www.tandfonline.com/doi/abs/10.1080/18756891.2016.1150003

Liu, Q., Chen, J., Wang, W., & Qin, Q. (2021). Conceptual design evaluation considering confidence based on Z-AHP-TOPSIS method. Applied Sciences. URL: https://www.mdpi.com/2076–3417/11/16/7400

Gardashova, L. A. (2019). Z-number-based TOPSIS method in multi-criteria decision making. 13th International Conference on Theory and Application of Fuzzy Systems and Soft Computing. URL: https://link.springer.com/chapter/10.1007/978-3-030-04164-9_10

Cheng, R., Zhang, J., & Kang, B. (2022). A novel Z-TOPSIS method based on improved distance measure of Z-numbers. International Journal of Fuzzy Systems. URL: https://link.springer.com/article/10.1007/s40815-022-01297-w

Haktanır, E., & Kahraman, C. (2024). Integrated AHP & TOPSIS methodology using intuitionistic Z-numbers: An application on hydrogen storage technology selection. Expert Systems with Applications. URL: https://www.sciencedirect.com/science/article/pii/S0957417423028841

Alam, N. M. F. H. N. B., Khalif, K. M. N., Jaini, N. I., & Gegov, A. (2023). The application of Z-numbers in fuzzy decision making: the state of the art. Information. URL: https://www.mdpi.com/2078–2489/14/7/400

Krohling, R. A., & Pacheco, A. G. C. (2019). TODIM and TOPSIS with Z-numbers. Frontiers of Information Technology & Electronic Engineering. URL: https://link.springer.com/article/10.1631/FITEE.1700434

Khalif, K. M. N. K., & Gegov, A. (2017). Z-TOPSIS approach for performance assessment using fuzzy similarity. 2017 IEEE International Conference on Fuzzy Systems. URL: https://ieeexplore.ieee.org/abstract/document/8015458

Wang, X., Wang, J., & Peng, H. (2020). A multi-criteria decision support framework for inland nuclear power plant site selection under Z-information. Mathematics. URL: https://www.mdpi.com/2227–7390/8/2/252

Fang, L. (2024). Financing mode decision of characteristic tourist town based on improved G1 and Z-number-TOPSIS: the Chinese case. Kybernetes. URL: https://www.emerald.com/insight/content/doi/10.1108/K-07-2024-1837/full/html

Sotoudeh-Anvari, A. (2015). A new approach based on the level of reliability of information to determine the relative weights of criteria in fuzzy TOPSIS. International Journal of Advanced Decision Sciences. Available at: URL: https://www.inderscienceonline.com/doi/abs/10.1504/IJADS.2015.069603

Ecer, F., & Haseli, G. (2024). Evaluation of sustainable cold chain suppliers using a combined multi-criteria group decision-making framework under fuzzy ZE-numbers. Expert Systems with Applications. Available at: URL: https://www.sciencedirect.com/science/article/pii/S0957417423035650

Wang, X., Peng, H., & Liu, Y. (2020). A multi-criteria decision support framework for inland nuclear power plant site selection under Z-information: A case study in Hunan province of China. Mathematics. Available at: URL: https://www.mdpi.com/2227–7390/8/2/252

Gardashova, L. A. (2014). Application of operational approaches to solving decision making problem using Z-numbers. Applied Mathematics, 2014.

submitted 14.02.2025;
accepted for publication 28.02.2025;
published 27.03.2025

Contact: alish.nazarov.va@asoiu.edu.az