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An Integrated AHP-SVNS-TOPSIS Approach and its Application to Efficiency Analysis of Hydropower Plant

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Abstract. Multi-Criteria Decision-Making (MCDM) is a vital tool for handling complex decision problems under uncertainty. Fuzzy set theory and its extensions, such as Single-Valued Neutrosophic Sets (SVNS), enhance decision-making by addressing ambiguity, indeterminacy, and partial information. Among MCDM techniques, TOPSIS has gained prominence for ranking alternatives, and its integration with some MCDM approaches has been widely applied. However, no prior study has combined the Analytic Hierarchy Process (AHP) with Neutrosophic-TOPSIS. This study proposes a hybrid AHP-SVNS-TOPSIS framework, where AHP determines the weights of evaluation criteria, and Neutrosophic-TOPSIS ranks alternatives under uncertain conditions. The model is applied to assess hydropower plant (HPP) performance, considering impacts from urbanization, climate change, and machine failures. The generator's efficiency is the most important parameter, based on the results of the suggested model. Existing research validates the outcomes of the suggested model.

Key words: AHP, single-valued neutrosophic sets, TOPSIS, efficiency, hydro power plant.

1. Introduction

A crucial area of decision-making theory is multi-criteria decision-making (MCDM), which is typically divided into two primary categories based on the characteristics of the problem's solution space: continuous and discrete. While multi-attribute decision-making (MADM) strategies are used to tackle discrete problems, multi-objective decision-making (MODM) approaches are usually used to solve continuous difficulties. However, the terms MCDM and MADM are frequently used interchangeably in the majority of the literature currently in publication, mostly referring to the discrete form of decision analysis (Roberts and Goodwin, 2002).

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In order to better handle uncertainty, vagueness, and expert subjectivity, improved fuzzy set theories and aggregation operators have been the focus of more recent research in risk analysis and decision-making. In 2-tuple linguistic complicated intuitionistic fuzzy aggregation operators are used to solve multiple attribute group decision-making (MAGDM) problems. The suggested geometric and arithmetic operators provide increased accuracy and flexibility in managing multidimensional decision processes. The suggested technique outperforms current methods, especially in complicated two- and three-dimensional decision-making contexts, as shown by a real-world example and comparative analysis (Yasmin *et al.*, 2025).

Risk assessment is further improved by using Q-rung orthopair fuzzy sets (Q-ROFSs) into Failure Modes and Effects Analysis (FMEA). Conventional FMEA models frequently restrict verbal expression and ignore differential expert weights. To attain expert consensus, the suggested Q-ROFSsFMEA model uses dynamic expert weighting and aggregation operators. The model's efficacy is validated by application to COVID-19 risk factors, and comparison analysis reveals stable and consistent ranking outcomes among various models (Abdullah *et al.*, 2025).

A novel family of aggregation procedures under fractional orthotriple fuzzy (FOF) information is created in Qiyas *et al.* (2022). The paper presents Banzhaf Choquet-Copula aggregation operators and operational rules by expanding Archimedean copula and co-copula ideas. By using objective fuzzy measure determination, these techniques reduce subjectivity in decision-making situations including correlated criteria and incomplete or unknown criteria weights.

By suggesting Choquet-Frank averaging and geometric aggregation operators based on Frank t-norm and conorm procedures, the study in Qiyas *et al.* (2023) improves fractional orthotriple fuzzy sets (FOFSs). Comparative results validate the robustness and application of these operators, which improve information aggregation in multi-attribute decision-making issues.

In order to capture probabilistic hesitation in membership and non-membership information, Qiyas *et al.* (2025) presents probabilistic dual hesitant fuzzy sets (PDHFSs) and interval-valued PDHFSs. For MAGDM applications, a partial-knowledge-based weighting framework and a Muirhead mean aggregation operator are suggested. The usefulness and efficiency of the strategy are confirmed by a case study on renewable energy choosing.

When making decisions where there is ambiguity and uncertainty, fuzzy set theory is crucial. It permits elements to have partial membership, which makes it possible to mimic human thinking that is imprecise (Zadeh, 1965). Fuzzy approaches improve consistency and reliability in multi-criteria decision-making (MCDM) by converting qualitative judgments into quantitative values (Chen and Hwang, 1992). This method works well for language evaluations that are hard to quantify, such "high" or "low" (Zimmermann, 2011). In complicated situations with ambiguity, fuzzy-based methods such as fuzzy AHP and fuzzy TOPSIS improve decision accuracy (Mardani *et al.*, 2015). Fuzzy sets thereby improve decision-making by better capturing ambiguity in the real world than conventional techniques.

In many fields, such as management science, operations research, data mining, and medical science, decision-making is crucial. The Analytic Hierarchy Process (AHP)

(Saaty, 1980), Interactive Multi-Criteria Decision-Making (TODIM) (Gomes and Lima, 1991), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon, 1981), Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) (Brauers and Zavadskas, 2006, 2010) are just a few of the many decision-making techniques used today to address Multi-Attribute Decision-Making (MADM) problems under uncertain conditions. Among these, the TOPSIS technique has become incredibly popular over the last ten years and has drawn a lot of scholarly attention for its ability to solve a variety of MADM problems.

Chen (2000) was the first to convert the TOPSIS approach to a fuzzy context, using triangular fuzzy numbers to convey the attribute weights and alternative assessments. This idea was developed for multi-attribute group decision-making (MAGDM) in the intuitionistic fuzzy set (IFS) environment in 2009 by Boran *et al.* (2009), who specifically addressed supplier selection problems. Later, in 2010, Ye (2010) added an interval-valued IFS framework to improve the TOPSIS technique.

In the Single Valued Neutrosophic Set (SVNS) architecture, Pramanik *et al.* (2023) created the Neutrosophic TOPSIS Strategy, a fuzzy version of the TOPSIS approach. The neutrosophic set notion was first presented by Smarandache (1999) to address data inconsistencies, uncertainty, and indeterminacy. This concept was then developed in 2010 by Wang *et al.* (2010) through the definition of the Single Valued Neutrosophic Set (SVNS).

Several hybrid MCDM methods for alternative ranking have been developed in recent years using the Neutrosophic TOPSIS approach. The hybrid approaches that use the Neutrosophic TOPSIS framework are summarized in Table 1.

Although Neutrosophic-TOPSIS has been extensively hybridized with a number of criteria-weighting techniques, including BWM, FUCOM, and OPA, it is clear from the thorough literature review summarized in Table 1 that no previous study has integrated the Analytic Hierarchy Process (AHP) with Neutrosophic-TOPSIS. Given AHP's long-standing reputation for its logical structure, pairwise comparison mechanism, and consistency checking capacity, its omission reveals a glaring methodological research gap. The current study fills this gap by proposing a novel hybrid multi-criteria decision-making (MCDM) framework that integrates the Single-Valued Neutrosophic Set (SVNS) based TOPSIS with the Analytic Hierarchy Process (AHP). Designing, developing, and implementing an AHP-SVNS-TOPSIS hybrid decision-support model that can handle complicated decision-making issues marked by ambiguity, uncertainty, and subjective human assessments is the main goal of this research. In order to ensure methodological rigour and logical coherence in the weighting process, the proposed framework uses AHP to systematically evaluate the relative importance and priority weights of evaluation criteria through structured pairwise comparisons. The Neutrosophic-TOPSIS process then uses these derived weights to rank choice options according to how close they are to ideal and anti-ideal solutions in a neutrosophic setting.

The complimentary advantages of the two approaches serve as the rationale for this integration. The SVNS-based Neutrosophic-TOPSIS approach successfully captures ambiguity, indeterminacy, and incomplete information through its truth, indeterminacy, and falsity membership functions, whilst AHP offers transparency, consistency, and interpretability in criteria weighing. When compared to traditional fuzzy or crisp MCDM models, this

Table 1
Review of neutrosophic-TOPSIS-based hybrid MCDM frameworks.

Hybrid model name	Year	Model selection for criteria	Model selection for alternatives	Application area
BWM-Neutrosophic-TOPSIS (Pramanik *et al.*, 2023)	2023	Best–Worst Method (BWM) (Rezaei, 2015)	Neutrosophic-TOPSIS (Pramanik *et al.*, 2023)	Selection of an appropriate apartment for a customer (Pramanik *et al.*, 2023)
Trapezoidal Neutrosophic FUCOM-TOPSIS in SVNS (Majumder, 2023)	2023	Trapezoidal Fuzzy Full Consistency Method (TrF-FUCOM) (Garg *et al.*, 2022)	Neutrosophic-TOPSIS (Pramanik *et al.*, 2023)	Enhanced seismic hazard evaluation (Paul *et al.*, 2025a) and
				Efficiency analysis of water treatment plant (Majumder, 2023)
Trapezoidal Fuzzy BWM-Neutrosophic-TOPSIS strategy (Debroy *et al.*, 2024)	2024	Trapezoidal Fuzzy BWM (Majumder *et al.*, 2023)	Neutrosophic-TOPSIS strategy (Pramanik *et al.*, 2023)	Effective water quality parameter of aquaponic system (Majumder *et al.*, 2023)
FUCOM-SVNN TOPSIS (Paul *et al.*, 2025b)	2025	Full Consistency Method (FUCOM) (Pamučar *et al.*, 2018)	Neutrosophic-TOPSIS strategy (Pramanik *et al.*, 2023)	Soil liquefaction under seismic risk (Paul *et al.*, 2025b)
Intuitionistic Fuzzy Ordinary Priority Approach (OPA-IF) with the Neutrosophic-TOPSIS strategy (Debroy *et al.*, 2025)	2025	OPA-IF (Majumder and Salomon, 2024)	Neutrosophic-TOPSIS strategy (Pramanik *et al.*, 2023)	Selection of the most effective control strategy for aquaponic system (Debroy *et al.*, 2025)

hybridization improves the decision-making process's flexibility, resilience, and reliability. The study's ultimate goal is to expand the theoretical and practical applicability of Neutrosophic MCDM approaches by providing a more thorough and reliable decision-support framework that enhances ranking accuracy and decision quality in real-world decision making problems where expert subjectivity and uncertainty naturally coexist.

The necessity to methodically address subjective judgments, uncertainty, inconsistency, and indeterminacy in complex multi-criteria decision-making (MCDM) problems led to the choice of the AHP-SVNS-TOPSIS framework. In contrast to techniques like BWM or FUCOM, which rely on fewer comparisons but may be susceptible to expert bias when judgments are highly uncertain, AHP is used for criteria weighting because of its intuitive hierarchical structure and pairwise comparison mechanism, which enables decision-makers to express preferences transparently and check consistency. The model is further strengthened by integrating AHP with the Single Valued Neutrosophic Set (SVNS) environment, which goes beyond fuzzy and intuitionistic fuzzy representations by encapsulating three independent dimensions of information: truth, indeterminacy, and falsity.

TOPSIS is then used for alternative ranking because of its obvious geometric justification of increasing distance from the negative ideal and reducing distance from the ideal solution, which makes the final ranking simple to understand.

The suggested AHP-SVNS-TOPSIS paradigm is different from previous methods in terms of both expressive capability and methodological integration. While intuitionistic fuzzy and interval-valued IFS-based TOPSIS simulate reluctance but are still unable to clearly reflect indeterminacy, traditional fuzzy TOPSIS just takes vagueness into consideration. This constraint is overcome by neutrosophic TOPSIS, and the primary difference between contemporary hybrid models (Table 1) is the method used to compute the criteria weights. AHP-SVNS-TOPSIS, on the other hand, is especially appropriate when criterion interrelationships and expert consensus are crucial since it places an emphasis on hierarchical structuring and consistency validation in criteria weighing. Therefore, compared to current neutrosophic hybrid MCDM techniques, the suggested approach provides a balanced, reliable, and transparent decision-support framework that increases reliability.

2. Background

Changes in climate patterns have had an increasing impact on hydropower generation in recent years. The operational efficiency of hydropower plants have been greatly impacted by changes in river hydrology brought on by climatic variability. The buildup of greenhouse gases like carbon dioxide (CO_2) causes global warming, which traps heat in the atmosphere and interferes with the water cycle. The timing and volume of river flow are changed by these climate changes, which also increase reservoir evaporation and ultimately lower hydroelectric output. These effects are felt in the energy industry as a whole (Arnell, 1996), system operations (Zereini, 2008), and economic performance (Whittington and Gundry, 1998). Furthermore, as rural areas transform into cities and metropolitan areas, the current century's rapid urbanization has increased power demand, placing further strain on conventional and hydroelectric systems (Majumder *et al.*, 2018a).

Urban water supplies enable vital urban services like street cleaning, firefighting, and the upkeep of recreational lakes, swimming pools, and green spaces in addition to providing homes, businesses, and corporations. However, hydropower plants (HPPs) are significantly impacted by urbanization, which has negative effects on the environment (Chaisomphob and Tanutpongpalin, 2004), financial hardship (Wang *et al.*, 2014), and electricity supply variations (Wang *et al.*, 2009).

Machine failure is another important element affecting the production of hydropower. Turbines, generators, transformers, pipelines, and switchgear are examples of essential components that are susceptible to failure as a result of mechanical and electrical stress, overload, or aging. These machines are essential to hydropower technology and control systems, so when they malfunction, significant operational and financial losses result (Majumder *et al.*, 2018a).

Globally, the combined effects of urbanization, climate change, and mechanical breakdowns have drastically decreased HPPs' operational efficiency. In order to ensure safe and

Table 2
Selected performance criteria and associated alternatives for HPP evaluation.

Criteria	Alternatives	Description
Urbanization impact (Whittington and Gundry, 1998; Majumder *et al.*, 2018a; Chaisomphob and Tanutpongpalin, 2004)	Efficiency of transformer (Tuna, 2013)	For long-distance transmission, power plant electricity must first pass through transformers to raise its voltage. Transformers lower the voltage to levels that are safe for houses and appliances at substations and local distribution points.
Climatic impact (Arnell, 1996; Zereini, 2008; Whittington and Gundry, 1998)	Efficiency of turbine (Majumder and Saha, 2018)	A hydroelectric power station is a system in which mechanical energy is transformed into electrical energy by the turbine driving the generator rotor.
Impact of machine failure (Majumder *et al.*, 2018a)	Efficiency of penstock (Majumder *et al.*, 2018b)	A portion of the river's flow is redirected to a turbine via a penstock or channel for run-of-the-river hydroprojects, which causes the river to spin. The motion of the turbine propels a shaft, which can power machinery or use a generator to produce electricity.
	Efficiency of generator (Majumder *et al.*, 2018a,b)	Water pressure is converted by hydroturbines into mechanical shaft power, which powers a generator of electricity.

steady operation, it is now crucial to evaluate and forecast performance degradation in hydropower plants. Creating efficient maintenance plans, enhancing dependability, and optimizing financial gains all depend on accurate performance forecasts. Finding the most important factors impacted by climate change, urbanization, and equipment failures are essential to reduce these difficulties. It is possible to control their influence on plant performance by keeping an eye on these crucial elements. A viable remedy is the use of intelligent soft computing technologies, which make it possible to identify and assess critical performance indicators objectively. These methods offer a scientific basis for improving hydropower systems' operational effectiveness and resilience in an urban and environmental setting that is changing (Majumder *et al.*, 2018a). Table 2 displays the chosen criteria and options in accordance with the literature review mentioned above. Figure 1 represents the decision hierarchy of the current decision making problem.

3. Preliminary of Single Valued Neutrosophic Set (SVNS)

Smarandache developed the fundamental idea of neutrosophic sets in 1998 (Smarandache, 1998). Single-Valued Neutrosophic Sets (SVNS) were later presented by Wang et al. in 2010 to address concerns with uncertainty and missing information (Wang *et al.*, 2010).

The following definition characterizes an SVNS ∂ over a predetermined set E.

A Single-Valued Neutrosophic Set (SVNS) $\boldsymbol{J}$ defined over a specified set $\boldsymbol{G}$ is described as follows:

$$J = \{(j, T_f(j), I_f(j), F_f(j)) : j \in G\},$$

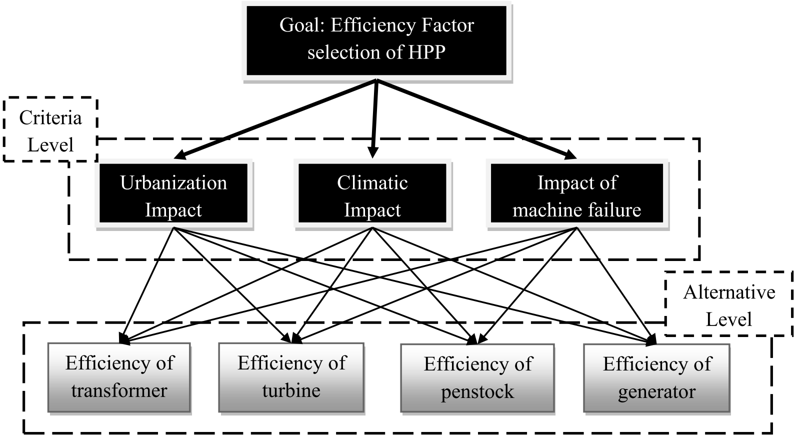

Fig. 1. Decision hierarchy.

where $T_f, I_f, F_f : G \rightarrow [0, 1]$ and so $0 \leqslant T_f(j) + I_f(j) + F_f(j) \leqslant 3$. If $\boldsymbol{J}$ is an SVNS defined over a given set $\boldsymbol{G}$, the triplet $(T_f(j), I_f(j), F_f(j))$ is referred to as a Single-Valued Neutrosophic Number (SVNN).

In order to address Multi-Attribute Decision-Making (MADM) concerns inside the SVNS framework, Mandal and Basu (2019) developed a new scoring mechanism in 2019. The following steps define the scoring procedure:

(i) Let $A = (T_f, I_f, F_f)$, which stands for an SVNN, correspond to a point in a three-dimensional space where 0 is the origin. To get a new point, $\boldsymbol{A}$, translate this point by a vector, $B = (T_h, I_h, F_h)$. Here $T_h = T_f + \varepsilon$, $I_h = I_f + \varepsilon$, $F_h = F_f + \varepsilon$, where $\varepsilon > 0$, and $f_\varepsilon < 1$ and stays unique for a particular issue. Consider another point, $B' = (T_h, -I_h, -F_h)$, which is produced by mirroring $B = (T_h, I_h, F_h)$ across the *x-axis* by reflection.

(ii) The angle created between OB and OB' is shown by γ, thus find the scoring function $U_1(B) = \cos\gamma$.

(iii) If two different SVNNs' score values $B_1 = (T_{h_1}, I_{h_1}, F_{h_1})$ and $B_2 = (T_{h_2}, I_{h_2}, F_{h_2})$, indicated as $U(B_1)$ and $U(B_2)$ accordingly, are equivalent, and ascertain $B_1^{**} = (T_{h_1}, -I_{h_1}, -\sqrt{F_{h_1}})$ and $B_2^{**} = (T_{h_2}, -I_{h_2}, -\sqrt{F_{h_2}})$ respectively for the corresponding translated points $B_1^* = (T_{h_1*}, I_{h_1*}, F_{h_1*})$ and $B_2^* = (T_{h_2*}, I_{h_2*}, F_{h_2*})$ where, $T_{h_1*} = T_{h_1} + \varepsilon$, $I_{h_1*} = I_{h_1} + \varepsilon$, $F_{h_1*} = F_{h_1} + \varepsilon$ and $T_{h_2*} = T_{h_2} + \varepsilon$, $I_{h_2*} = I_{h_2} + \varepsilon$, $F_{h_2*} = F_{h_2} + \varepsilon$.

(iv) Evalute $\cos\gamma_1$ as well as $\cos\gamma_2$, where γ_1 indicates the angle between OB_1^* as well as OB_1^{**}, also γ_2 indicates the angle between OB_2^* and OB_2^{**}, with O denoting the origin.

(v) The score mapping $U(B_1) = \cos\gamma_1$ as well as $U(B_2) = \cos\gamma_2$.

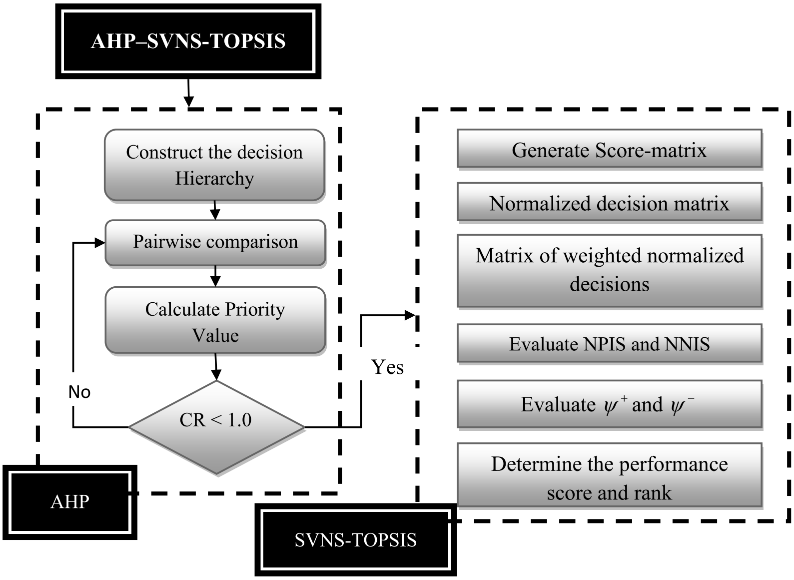

Fig. 2. The comprehensive overview of proposed model.

4. AHP-SVNS-TOPSIS Approach

The SVNS Environment Approach divides strategy into three stages. To determine the weight or priority value (PV) of criteria in phase I, AHP is utilized. In Phase II, Neutrosophic-TOPSIS Strategy under SVNS Environment is implemented so that it can determine the rank of alternates. An index based on the PV of alternatives is generated. Figure 2 illustrates the computational steps of proposed approach.

Phase-I: AHP

The AHP (Saaty, 1980) derives the weights of criteria and alternatives using pairwise comparison matrices. Let M $= \{\vartheta_\alpha : \alpha = 1(1)m\}$ be the set of criteria. Initially, each of the m criteria is compared pairwise to construct the comparison matrix M.

$$M = \begin{pmatrix} \eta_{11} & \eta_{12} & \cdots & \eta_{1m} \\ \eta_{21} & \eta_{22} & \cdots & \eta_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \eta_{m1} & \eta_{m2} & \cdots & \eta_{mm} \end{pmatrix}.$$

Each entry in the comparison matrix $M = [\eta_{ij}]_{m\times m}$ denotes an estimated ratio between the weights of two criteria. For example, η_{23} approximates the ratio p_2/p_3. The Saaty scale, a linear 1–9 scale used for paired comparisons, is displayed in Table 3.

According to the Saaty scale, the following properties hold: $\eta_{ii} = 1$, $\eta_{ij} > 0$, and $\eta_{ji} = \frac{1}{\eta_{ij}}$, $\forall i, j = 1(1)m$. The estimation of the weight vector P from M is shown in

Table 3
Saaty scale (Saaty, 1980; Ishizaka and Nemery, 2013).

Intensity	1	3	5	7	9
Definition	Equal importance	Moderate importance	Strong importance	Demonstrate importance	Absolute importance

Note: Rational numbers from the scale can be used for comparison when more consistency is required.

Eq. (1), where $\lambda_{\max}$ represents the largest eigen value of M.

$$MP = \lambda_{\max} P. \tag{1}$$

AHP's significance in MADM-related research is mostly due to consistency verification, which assesses the dependability of the input data (Ishizaka and Nemery, 2013). Equation (2), where n is the number of pieces compared and RI is the random index, is used to compute the consistency ratio (CR).

$$CR = \frac{\lambda_{\max} - n}{RI(n-1)}. \tag{2}$$

If $\eta_{ij} = p_i/p_j, \forall i, j = 1(1)m$, then $\lambda_{\max} = n$ and $CR = 0$. Otherwise, $\lambda_{\max} > n$ and $CR > 0$. Usually, comparison matrices with $CR \leqslant 0.1$ are accepted according to AHP (Saaty, 1980).

Phase-II: SVNS-TOPSIS Strategy

Consider the set of alternative $\mathrm{B} = \{q_t : t = 1(1)\beta\}, t \geqslant 1$ as well as $\mathrm{M} = \{\vartheta_\alpha : \alpha = 1(1)m\}, \alpha \geqslant 2$ be the set of attributes with weights of criteria $w_\alpha, \alpha = 1(1)m$.

Decision-makers (DMs) provide ratings of alternatives $(q_t, t = 1(1)\beta)$ based on the each attributes $(\vartheta_\alpha, \alpha = 1(1)m)$ and it is denoted by $q^*_{t\alpha} = (m_\alpha, T_{q_t}(m_\alpha), I_{q_t}(m_\alpha), F_{q_t}(m_\alpha))$, where $0 \leqslant T_{q_t}(m_\alpha) + I_{q_t}(m_\alpha) + F_{q_t}(m_\alpha) \leqslant 3$ which are represented using an SVNN. Here, $(T_{t\alpha}, I_{t\alpha}, F_{t\alpha})$ is denoted as an SVNN $q^*_{t\alpha}$, $(t = 1(1)\beta$ and $\alpha = 1(1)m)$. Derive the decision matrix based on the ratings: $\mathrm{E}^* = [q^*_{t\alpha}]_{\beta\times m}$.

Applying the score function on all the entries of the matrix $\mathrm{E}^* = [q^*_{t\alpha}]_{\beta\times m}$ construct the score-matrix represented by $E = [q_{t\alpha}]_{\beta\times m}$ and defined by $q_{t\alpha} = U(q^*_{t\alpha})$.

After formation of the score matrix, construct the Normalized decision matrix $\Im = [y_{t\alpha}]_{\beta\times m}$ with the help of the Eq. (3).

Where

$$y_{t\alpha} = \frac{q_{t\alpha}}{\sqrt{\sum_{\alpha=1}^{m} q_{t\alpha}}}, \quad t = 1(1)\beta. \tag{3}$$

On multiplying normalized value of $\Im$ (found from Eq. (3)) and weights of criteria the weighted normalized decision matrix is constricted and is denoted by $\mathrm{X} = [x_{t\alpha}]_{\beta\times m}$, i.e. $x_{t\alpha} = w_\alpha \otimes y_{t\alpha}, t = 1(1)\beta$ and $\alpha = 1(1)m$.

After construction of normalized decision matrix, the Neutrosophic Positive Ideal Solution (NPIS), as well as Neutrosophic Negative Ideal Solution (NNIS), are evaluated and demoted by ϕ^+, as well as ϕ^-, respectively.

$$\phi^+ = \{x_\alpha^+ : \alpha = 1(1)m\}, \quad \text{where } x_\alpha^+ = \max_\alpha x_{t\alpha}, \alpha = 1(1)m \quad \text{and}$$
$$\phi^- = \{x_\alpha^- : \alpha = 1(1)m\}, \quad \text{where } x_\alpha^+ = \min_\alpha x_{t\alpha}, \alpha = 1(1)m.$$

Determine the difference between each option's NPIS and NNIS parameters using the following formulas (4) and (5):

$$\psi_t^+ = \sqrt{\sum_{t=1}^{n} (x_{t\alpha} - x_\alpha^+)^2}, \quad t = 1(1)\beta, \tag{4}$$
$$\psi_t^- = \sqrt{\sum_{\alpha=1}^{n} (x_{t\alpha} - x_\alpha^-)^2}, \quad t = 1(1)\beta. \tag{5}$$

Use formula (6) to calculate each alternative's performance score:

$$R_t = \psi_t^- / (\psi_t^+ + \psi_t^-), \quad t = 1(1)\beta. \tag{6}$$

Performance scores are used to rank the options; the option with the highest score is given the top rank, while the option with the lowest score is given the lowest rank.

5. Result and Discussion

This section is divided into four parts. The first part shows the results of the proposed model using Table 4 and Table 5. The remaining three parts are used for the validation of the model. The second part compares the results of the proposed model with some existing methods, as shown in Tables 6, 7, 8, and 10. The third part represents the statistical analysis of all the results of the methods shown in Table 11. The fourth part presents the sensitivity analysis of the alternatives with respect to the criteria shown in Fig. 4. Figure 3 represents the outline of the results section of the proposed model.

The goal of the current study is to assess an HPP's performance efficiency utilizing certain metrics under various urbanization and climate change scenario using AHP-SVNS-TOPSIS. So in this study Urbanization Impact (UI), Climatic Impact (CI) and Impact of Machine (MI) are consider as criteria and these are denoted by q_1, q_2 and q_3 respectively. Also Efficiency of Transformer (ETF), Efficiency of Turbine (ET), Efficiency of Penstock (EP) and Efficiency of Generator (EG) are considered as set of alternatives, also denoted by ϑ_1, ϑ_2, ϑ_3 and ϑ_4, respectively. Table 4 displays the criteria comparisons and their weight vector, which is derived from normalizing the direct eigenvector in accordance with the AHP approach.

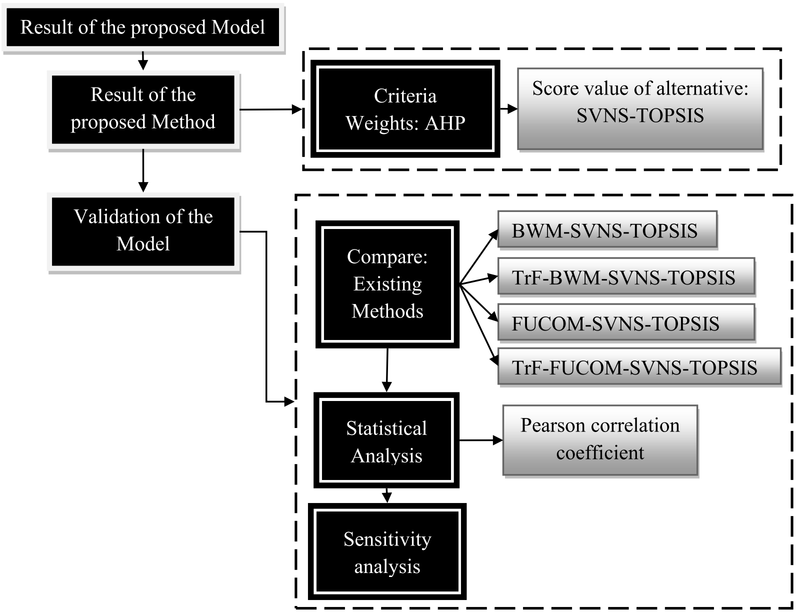

Fig. 3. Outline of the results section.

Table 4
Pairwise comparison matrix and criteria weights.

	q_1	q_2	q_3	Weights
q_1	1	5	4	0.673
q_2		1	1/3	0.101
q_3			1	0.226

Table 5
Decision matrix and performance scores by SVNS-TOPSIS.

	q_1	q_2	q_3	NPIS	NNIS	Performance scores	Rank
ϑ_1	(0.78, 0.34, 0.07)	(0.82, 0.23, 0.08)	(0.74, 0.43, 0.14)	0.385	0.306	0.290	4
ϑ_2	(0.97, 0.43, 0.12)	(0.93, 0.26, 0.09)	(0.83, 0.33, 0.17)	0.060	0.038	0.405	2
ϑ_3	(0.76, 0.31, 0.19)	(0.89, 0.41, 0.21)	(0.89, 0.31, 0.23)	0.131	0.079	0.329	3
ϑ_3	(0.86, 0.28, 0.11)	(0.71, 0.37, 0.12)	(0.77, 0.29, 0.03)			0.812	1

The eigen value of the pairwise comparison matrix shown in Table 4 is roughly 3.086 and Consistency Ratio (CR) is $0.09 < 0.10$. According to AHP standards, the matrix is considered to have an acceptable degree of inconsistency because this is close to the ideal value of 3. According to the result provided by AHP that UI is the most significant criteria.

The decision matrix displayed in Table 5 is the outcomes of the decision maker's evaluation of alternatives using SVNNs. Using SVNS-TOPSIS determines the final score value and based on this score value determine the rank of the alternatives shown in Table 5. The proposed model indicates that Efficiency of Generator is the most responsible parameter for efficiency of the HPP (see Table 5).

Table 6
Pairwise comparison and criteria weights by BWM.

	q_1	q_2	q_3	Weights
q_1	1	5	3	0.650
q_2		1		0.125
q_3		2		0.225

Table 7
Pairwise comparison and criteria weights by TrF-BWM.

	q_1	q_2	q_3	Weights
q_1	(1, 1, 1, 1)	(6, 6.5, 7.5, 8)	(2, 2.5, 3.5, 4)	0.660
q_2		(1, 1, 1, 1)		0.059
q_3		(4, 4.5, 5.5, 6)		0.281

Table 8
Pairwise comparison and criteria weights by FUCOM.

	Importance	Weights
q_1	1	0.559
q_2	3	0.187
q_3	2.2	0.254

Table 9
Pairwise comparison and criteria weights by TrF-FUCOM.

	Importance	Weights
q_1	(1, 1, 1, 1)	0.517
q_2	(2, 2.5, 3.5, 4)	0.223
q_3	(1, 1.5, 2.5, 3)	0.260

Selected comparisons from Table 4 were used to do a BWM application. The necessary pairwise comparisons between size (the worst criterion) and substrate (the best criterion) are shown in Table 6 and Table 7, along with the relevant criteria weights determined using the BWM and Trapezoidal Fuzzy Best Worst Method (TrF-BWM) approach.

Table 8 shows the fuzzy criterion measures for the FUCOM approach. Likewise, the TrF-FUCOM method's related measurements are shown in Table 9. These tables together offer a comparative perspective on the weights evaluation criteria.

The methods BWM, TrF-BWM, FUCOM and TrF-FUCOM proposed that Urbanization Impact is the most significant criteria. Tables 6, 7, 8 and 9 depict the result of BWM, TrF-BWM, FUCOM and TrF-FUCOM, respectively.

To verify the efficacy of the suggested model, its outcomes are contrasted with those of other models, including BWM-SVNS-TOPSIS, TrF-BWM-SVNS-TOPSIS, FUCOM-SVNS-TOPSIS, and TrF-FUCOM-SVNS-TOPSIS. Table 10 displays all corresponding results. All the existing methods also indicate that Efficiency of Generation is the most significant alternative (see Table 10).

Table 10
Results of different existing approaches.

	BWM-SVNS-TOPSIS		TrF-BWM-SVNS-TOPSIS		FUCOM-SVNS-TOPSIS		TrF-FUCOM-SVNS-TOPSIS	
	Performance scores	Rank	Performance scores	Rank	Performance scores	Rank	Performance scores	Rank
ϑ_1	0.315	4	0.230	4	0.372	4	0.408	3
ϑ_2	0.426	2	0.429	2	0.512	2	0.553	2
ϑ_3	0.332	3	0.386	3	0.375	3	0.383	4
ϑ_3	0.773	1	0.888	1	0.684	1	0.638	1

Table 11
Result of Pearson correlation coefficient.

	BWM-SVNS-TOPSIS	TrF-BWM-SVNS-TOPSIS	FUCOM-SVNS-TOPSIS	TrF-FUCOM-SVNS-TOPSIS
AHP-SVNS-TOPSIS	0.9986	0.9870	0.9622	0.8789
BWM-SVNS-TOPSIS		0.9810	0.9733	0.9005
TrF-BWM-SVNS-TOPSIS			0.9458	0.8531
FUCOM-SVNS-TOPSIS				0.9749

The Pearson correlation coefficient (ρ) values between the total HPP efficiency weights derived from AHP-SVNS-TOPSIS, BWM-SVNS-TOPSIS, TrF-BWM-SVNS-TOPSIS, FUCOM-SVNS-TOPSIS and TrF-FUCOM-SVNS-TOPSIS are shown in Table 10. Additionally, Table 11 makes it clear that there is a positive correlation between the weights of the suggested model and the current models.

In order to determine the effects of changing weight coefficient values, some situations, each containing a set, are studied. To ascertain the proportionality of criteria PVs (w_α) (7), sensitivity analysis is used to evaluate the dominating criteria (w_α). The evolution of the dominating criterion is also examined.

$$w'_y = w_y\left(\frac{1 - r_\alpha w_\alpha}{1 - \omega_\alpha}\right), \quad y = 1(1)k. \tag{7}$$

When w'_y presents the criterion's taken-in value; this is its initial value, $w_y(y = 1(1)k)$; w_α presents its initial point; as well as $r_\alpha \in (0, 1) \cup \{0, 1\}$ presents its modified value.

The phrase (7) is used to create 25 situations for this study. It is now possible for R to take any value between 0 and 1 at random. According to Fig. 4, Efficiency of Generator is the most sensitive alternative for efficiency of HPP among all those considered.

6. Conclusion

This paper proposes a novel hybrid decision-making framework that integrates the Analytic Hierarchy Process and the Single-Valued Neutrosophic Set-based TOPSIS to strengthen neutrosophic multi-criteria decision analysis. Although Neutrosophic-TOPSIS

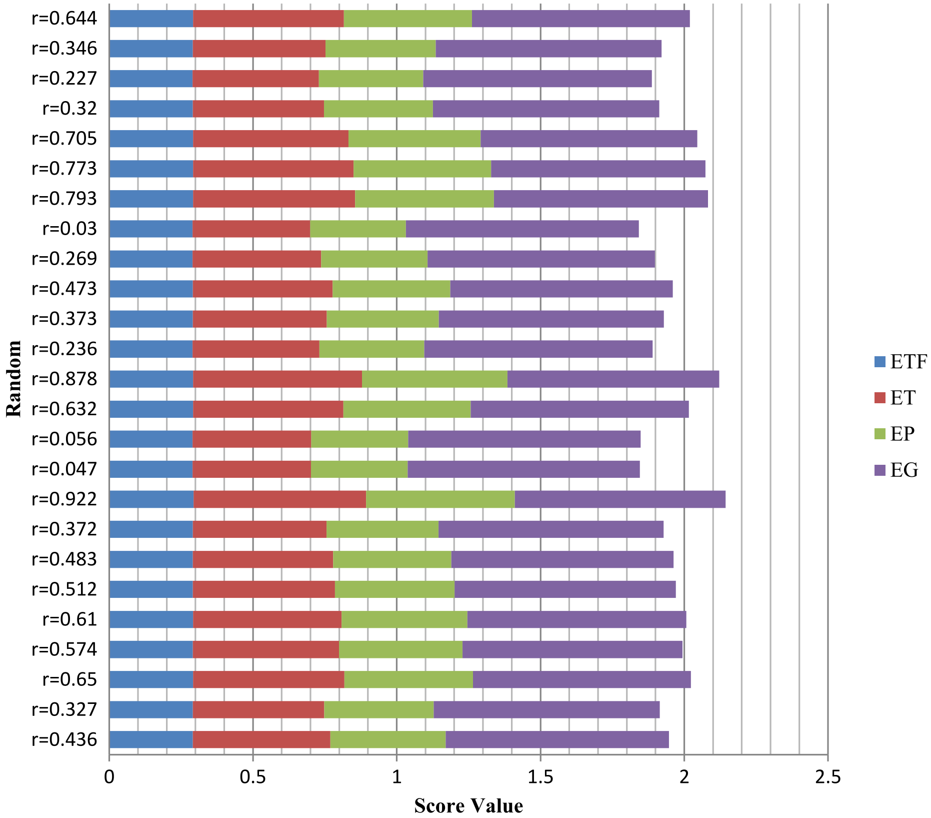

Fig. 4. Sensitivity analysis results.

has been integrated with a number of weighting approaches, including BWM, FUCOM, and OPA, its integration with AHP has not been previously investigated, according to a comprehensive study of the literature. The suggested framework fills a significant methodological gap by introducing a clear hierarchical structure, organized pairwise comparisons, and consistency verification into the criteria-weighting process through the use of AHP. By explicitly modelling uncertainty, indeterminacy, and subjective expert assessments through separate truth, indeterminacy, and falsity membership degrees, the SVNS-TOPSIS component improves the system even more. When compared to traditional fuzzy, intuitionistic fuzzy, and current neutrosophic hybrid techniques, this complementing integration enhances the robustness, dependability, and interpretability of decision outputs.

The implementation of the suggested AHP-SVNS-TOPSIS model for assessing hydropower plant (HPP) performance efficiency under the combined influences of urbanization, climate variability, and machine failure demonstrates its practical usefulness. The most important elements influencing HPP efficiency were determined by analysing four technical options and three key criteria. The findings unequivocally show that the influence of urbanization is the most important factor affecting overall system performance, emphasizing the growing strain that fast urban growth places on hydroelectric infrastructure. The most important aspect influencing HPP performance among the options taken into consideration was generator efficiency, highlighting the significance of preserving and modernizing electro-mechanical components to guarantee effective power generation. These results support the validity of the suggested paradigm by being in line with previously published findings in the literature (Majumder *et al.*, 2018a).

The resultant ranks were verified by comparison with current models to guarantee robustness, and sensitivity analysis was used to further analyse them. The sensitivity results demonstrate the stability and efficacy of the suggested decision-support model by confirming that generator efficiency continues to be the most significant and sensitive metric across different weight situations. Confidence in the framework's potential to facilitate well-informed decision-making in intricate, uncertain operational situations is bolstered by such validation.

The study has some drawbacks despite its efficacy. Because reliability-based analysis of HPP components was not included, the suggested model may show decreased ranking stability as the number of criteria and options increases. Future studies might concentrate on expanding the framework by combining SVNS-TOPSIS with sophisticated or fuzzy AHP variations, adding reliability and risk analysis, and using the model in related fields like thorough hydropower system reliability evaluation and water treatment plant efficiency assessment. All things considered, the suggested AHP-SVNS-TOPSIS framework provides an organized, dependable, and adaptable decision-support method for evaluating hydropower performance in the face of increasing urbanization demands, climate uncertainty, and operational difficulties.

References

Abdullah, L., Awang, N.A., Qiyas, M. (2025). Q-rung orthopair fuzzy sets-enhanced FMEA for COVID-19 risk assessment. *Informatica*, 49(1). https://doi.org/10.31449/inf.v49i1.4791.

Arnell, N.W. (1996). *Global Warming, River Flows and Water Resources*. vii+-224.

Boran, F.E., Genç, S., Kurt, M., Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications*, 36(8), 11363–11368.

Brauers, W.K., Zavadskas, E.K. (2006). The MOORA method and its application to privatization in a transition economy. *Control and Cybernetics*, 35(2), 445–469.

Brauers, W.K.M., Zavadskas, E.K. (2010). Project management by MULTIMOORA as an instrument for transition economies. *Technological and Economic Development of Economy*, 16(1), 5–24.

Chaisomphob, T., Tanutpongpalin, N. (2004). Application of geographic information system to site selection of run-of-river type small hydropower project based on environmental criteria. *Engineering Journal of Research and Development*, 15(4), 37–47.

Chen, C.T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, 114(1), 1–9.

Chen, S.J., Hwang, C.L. (1992). Fuzzy multiple attribute decision making methods. In: *Fuzzy Multiple Attribute Decision Making: Methods and Applications*. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 289–486.

Debroy, P., Majumder, P., Pramanik, S., Seban, L. (2024). TrF-BWM-Neutrosophic-TOPSIS strategy under SVNS environment approach and its application to select the most effective water quality parameter of aquaponic system. *Neutrosophic Sets and Systems*, 70, 217–251.

Debroy, P., Smarandache, F., Majumder, P., Majumdar, P., Seban, L. (2025). OPA-IF-Neutrosophic-TOPSIS strategy under SVNS environment approach and its application to select the most effective control strategy for aquaponic system. *Informatica*, 36(1), 1–32.

Garg, H., Majumder, P., Nath, M. (2022). A hybrid trapezoidal fuzzy FUCOM-AHP approach and their application to identification of monkeypox risk factors. *Computational and Applied Mathematics*, 41(8), 379.

Gomes, L.F.A.M., Lima, M.M.P.P. (1991). TODIMI: basics and application to multicriteria ranking. *Foundations of Computing and Decision Sciences*, 16(3–4), 1–16.

Hwang, C.L., Yoon, K.P. (1981). *Multiple Attribute Decision Making: Methods and Applications*. Springer-Verlag, New York.

Ishizaka, A., Nemery, P. (2013). *Multi-Criteria Decision Analysis: Methods and Software*. John Wiley & Sons.

Majumder, P. (2023). An integrated trapezoidal fuzzy FUCOM-TOPSIS method to determine alternatives' ranking and utilization in the water treatment plant. *Environmental Progress & Sustainable Energy*, 42(4), e14096.

Majumder, P., Saha, A.K. (2018). Efficiency assignment of hydropower plants by DEMATEL-MAPPAC approach. *Water Conservation Science and Engineering*, 3(2), 91–97.

Majumder, P., Salomon, V.A.P. (2024). Intuitionistic fuzzy ordinal priority approach with grey relational analysis. *Mathematics*, 12(19), 3156.

Majumder, P., Majumder, M., Saha, A.K. (2018a). Climate change and urbanization impact on hydropower plant by neural network-based decision-making methods: identification of the most significant parameter. *Water Conservation Science and Engineering*, 3(3), 169–179.

Majumder, P., Saha, A.K., Majumder, M. (2018b). Application of DEMATEL-TOPSIS method to analyze operational efficiency of hydropower plants. *Journal of Civil and Construction Engineering*, 17(2).

Majumder, P., Das, A., Hezam, I.M., Alshamrani, A., Aqlan, F. (2023). Integrating trapezoidal fuzzy best–worst method and single-valued neutrosophic fuzzy MARCOS for efficiency analysis of surface water treatment plants. *Soft Computing*, 1–24.

Mandal, K., Basu, K. (2019). Vector aggregation operator and score function to solve multi-criteria decision-making problem in neutrosophic environment. *International Journal of Machine Learning and Cybernetics*, 10, 1373–1383.

Mardani, A., Jusoh, A., Zavadskas, E.K. (2015). Fuzzy multiple criteria decision-making techniques and applications–two decades review from 1994 to 2014. *Expert Systems with Applications*, 42(8), 4126–4148.

Pamučar, D., Stević, Ž., Sremac, S. (2018). A new model for determining weight coefficients of criteria in MCDM models: full consistency method (FUCOM). *Symmetry*, 10(9), 393.

Paul, A., Ghosh, S., Smarandache, F., Majumder, P. (2025a). Integrating trapezoidal neutrosophic FUCOM-TOPSIS in SVNS for enhanced seismic hazard evaluation of Northeast India. *Informatica*, 37(1), 109–157.

Paul, A., Ghosh, S., Majumder, P., Pramanik, S., Smarandache, F. (2025b). Identification of influential parameters in soil liquefaction under seismic risk using a hybrid neutrosophic decision framework. *Infinite Study*.

Pramanik, S., Das, S., Das, R., Tripathy, B.C. (2023). Neutrosophic BWM-TOPSIS strategy under SVNS environment. *Neutrosophic Sets and Systems*. 56(1). https://digitalrepository.unm.edu/nss_journal/vol56/iss1/13.

Qiyas, M., Abdullah, S., Khan, F., Naeem, M. (2022). Banzhaf-Choquet-Copula-based aggregation operators for managing fractional orthotriple fuzzy information. *Alexandria Engineering Journal*, 61(6), 4659–4677.

Qiyas, M., Naeem, M., Khan, N. (2023). Fractional orthotriple fuzzy Choquet-Frank aggregation operators and their application in optimal selection for EEG of depression patients. *AIMS Mathematics*, 8(3), 6323–6355.

Qiyas, M., Naeem, M., Khan, Z., Okyer, S. (2025). Interval-valued probabilistic dual hesitant fuzzy Muirhead mean aggregation operators and their applications in regenerative energy source selection. *International Journal of Intelligent Systems*, 2025(1), 8892299.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, 53, 49–57.

Roberts, R., Goodwin, P. (2002). Weight approximations in multi-attribute decision models. *Journal of Multi-Criteria Decision Analysis*, 11(6), 291–303.

Saaty, T.L. (1980). *The Analytic Hierarchy Process*. McGraw-Hill, New York, NY, USA.

Smarandache, F. (1998). *Neutrosophy: Neutrosophic Probability Set and Logic: Analytic Synthesis & Synthetic Analysis*. American Research Press.

Smarandache, F. (1999). *A Unifying Field in Logics: Neutrosophic Logic. Neutrosophy, Neutrosophic Set, Neutrosophic Probability and Statistics*.

Tuna, M.C. (2013). Feasibility assessment of hydroelectric power plant in ungauged river basin: a case study. *Arabian Journal for Science and Engineering*, 38(6), 1359–1367.

Wang, Q., Qiu, H.N., Kuang, Y. (2009). Market-driven energy pricing necessary to ensure China's power supply. *Energy Policy*, 37(7), 2498–2504.

Wang, H., Smarandache, F., Zhang, Y., Sunderraman, R. (2010). Single valued neutrosophic sets. In: *Multispace & Multistructure. Neutrosophic Transdisciplinarity*. pp. 410–413.

Wang, S., Fang, C., Guan, X., Pang, B., Ma, H. (2014). Urbanisation, energy consumption, and carbon dioxide emissions in China: a panel data analysis of China's provinces. *Applied Energy*, 136, 738–749.

Whittington, H.W., Gundry, S.W. (1998). Global climate change and hydroelectric resources. *Engineering Science and Education Journal*, 7(1), 29–34.

Yasmin, S., Qiyas, M., Karabasevic, D., Khan, N. (2025). 2-tuple linguistic complex intuitionistic fuzzy aggregation operators and their application in decision making problem. *Engineering Applications of Artificial Intelligence*, 158, 111342.

Ye, F. (2010). An extended TOPSIS method with interval-valued intuitionistic fuzzy numbers for virtual enterprise partner selection. *Expert Systems with Applications*, 37(10), 7050–7055.

Zadeh, L.A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.

Zereini, F. (2008). *Climatic Changes and Water Resources in the Middle East and North Africa*. Hötzl, H. (Ed.). Springer-Verlag, Berlin.

Zimmermann, H.J. (2011). *Fuzzy Set Theory—and Its Applications*. Springer Science & Business Media.

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