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Hybrid Multi-Criteria Decision-Making (MCDM) Approaches with Random Forest Regression for Interval-Based Fuzzy Uncertainty Management

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Abstract. This research presents an innovative framework that combines Hybrid Multi-Criteria Decision-Making (MCDM) approaches with Random Forest Regression to address interval-based fuzzy uncertainty in renewable energy project evaluation. Traditional Fuzzy TOPSIS methods often struggle with the inherent uncertainty and complexity of real-world data, which can lead to suboptimal decision-making. To enhance decision accuracy, we propose a hybrid solution that integrates Higher Interval TOPSIS with Random Forest Regression. This methodology effectively captures intricate interdependencies among project attributes—including cost, energy output, environmental impact, and social acceptance—within an interval-based fuzzy context. We applied our approach to a dataset of renewable energy projects and compared it against conventional Fuzzy TOPSIS methods. Results indicated significant improvements in predictive performance, achieving a Mean Absolute Error (MAE) of 0.045, a Mean Squared Error (MSE) of 0.0029, and an R^2 value of 0.95, highlighting the framework's ability to explain 95% of the variability in outcomes. This research underscores the promise of integrating AI-driven techniques within MCDM frameworks to enhance decision-making under uncertainty in the renewable energy sector.

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1. Introduction

1.1 *Multi-criteria decision making (MCDM)*

Multi-Criteria Decision Making (MCDM) techniques emerged as crucial tools in planning and decision-making across various domains, including economics, environmental management, and renewable energy development. Early contributions, such as Massam's [29] comprehensive study, examined the theoretical underpinnings and practical applications of various MCDM methodologies, illustrating the multifaceted nature of decision-making processes in planning contexts. Massam provided an extensive survey of MCDM techniques, detailing their potential to improve the quality of decisions by integrating multiple conflicting criteria into a structured framework. This foundational work laid the groundwork for subsequent research and advancements in the field.
In the following decades, the framework for MCDM expanded, particularly within computational contexts. Bonissone et al. [6] articulated a systematic approach toward MCDM in their article, highlighting the intersection of computational intelligence with decision-making methodologies. They emphasized the importance of developing robust

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frameworks that catered to diverse applications of MCDM, influencing both theoretical developments and practical implementations across numerous sectors.

Furthermore, Zavadskas and Turskis [57] provided an extensive overview of MCDM methods specifically applied in economics. They categorized various techniques and critically assessed their effectiveness in addressing complex economic problems characterized by uncertainty and multiple decision criteria. The authors underscored the necessity for adaptive methodologies that could capture the dynamic nature of economic evaluation processes.

Over the years, the discourse on MCDM evolved to include a variety of contexts, especially in renewable energy scenarios. Researchers, including Ghasempour et al. [12], conducted reviews focusing on the application of MCDM methods for selecting solar plant sites and technologies. This study highlighted the effectiveness of MCDM in optimizing site selections by balancing technical, economic, and environmental factors, which became increasingly relevant in the context of sustainable energy development.

As the field progressed, reviews such as those conducted by Siksnelyte-Butkiene et al. [46] and Lak Kamari et al. [23] further contributed to understanding specific applications of MCDM in assessing renewable energy technologies and their implementation within households. These reviews synthesized existing literature, providing insights into the diverse methodologies employed and the varying outcomes achieved in different contexts. The emphasis on practical applications reinforced the relevance of MCDM in addressing contemporary energy challenges.

Moreover, Taherdoost and Madanchian [49] compiled recent advancements in MCDM methods and concepts, providing a comprehensive encyclopedia entry that summarized key methodologies utilized in decision-making processes. This synthesis not only updated the academic community about emerging trends but also emphasized the interdisciplinary nature of MCDM, showcasing its application across multiple fields. Kumar et al. [22] presented a critical review of MCDM approaches aimed at promoting sustainable renewable energy development. Their work highlighted the alignment of MCDM methodologies with sustainability goals, advocating for decision-making frameworks that consider long-term impacts and sustainability metrics in energy projects.

1.2 *Uncertainty management*

Uncertainty management has long been a central theme in both theoretical and applied research across various fields, including expert systems, organizational behavior, project management, and innovation ecosystems. As the complexity of systems and environments increases, the need for effective strategies to navigate uncertainty has become paramount. In the early scholarship of the domain, Ng and Abramson [37] laid the groundwork by analyzing how expert systems could address uncertainty. Their work highlighted the importance of integrating uncertainty management techniques within these systems, facilitating better decision-making processes in environments characterized by incomplete or conflicting information.

Building on the foundations laid by earlier research, Brashers [5] emphasized the role of communication in uncertainty management. The study explored how effective communication strategies can mitigate uncertainty and enhance understanding among stakeholders. By framing uncertainty as a communicative challenge, Brashers provided insights into the interpersonal and social dimensions of uncertainty management, stressing its significance in various contexts, including personal and organizational settings.

Grote [13] further contributed to the discourse by placing uncertainty management at the core of system design. His analysis underscored the need for systems to accommodate uncertainty when defining design parameters and objectives. The synthesis of uncertainty into the design process allowed for the construction of more robust systems capable of adapting to changes in their environments while maintaining functionality and performance.

Within project management, Ward and Chapman [54] focused on the dynamics of stakeholder involvement in uncertainty management. They examined how different stakeholders interact with uncertainty and how their perceptions influence project outcomes. Their findings suggested that proactive engagement with stakeholders could significantly improve uncertainty management strategies during the project lifecycle, thereby enhancing project performance and stakeholder satisfaction.

The field saw further advancement with the publication of "Uncertainty in Industrial Practice" by de Rocquigny et al. [11], which provided a comprehensive guide to quantitative uncertainty management. This work enriched practical applications by offering quantitative tools and methodologies designed to quantify and manage uncertainty in industrial contexts. Their approach encouraged practitioners to adopt systematic methods for analyzing uncertainty, which enhanced decision-making and optimized resource allocation.

In more recent contributions, Matsunaga [30] examined the intersection of uncertainty management and transformational leadership in an AI-powered organizational context. His research highlighted how leaders could influence their teams' ability to manage uncertainty, particularly in environments rapidly transformed by technological advancement. The findings indicated that effective leadership played a crucial role in fostering a culture of adaptability, enabling organizations to thrive amidst uncertainty.

In the context of global innovation ecosystems, de Vasconcelos Gomeset al. [10] investigated uncertainty management as a critical factor influencing innovation outcomes. Their study revealed that effective uncertainty management strategies were essential for sustaining innovation in an increasingly interconnected and volatile global environment. They argued that organizations must develop capabilities to anticipate and respond to uncertainties in order to maintain competitive advantage.

Kramer [21] further generalized the discourse on uncertainty management in the "Global Encyclopedia of Public Administration, Public Policy, and Governance." His entry underscored the pervasive nature of uncertainty management across various domains of public administration and governance, emphasizing its relevance in policymaking and public sector performance. Varathan's [50] review on uncertainty management approaches for active distribution system planning marked a significant contribution to the renewable energy sector. This study examined existing strategies in managing uncertainty within electricity distribution, highlighting the role of uncertainty in planning and operational decisions. The review underscored the need for comprehensive frameworks that integrate technical and managerial perspectives on uncertainty.

Iriani et al. [19] delved into the complexities of risk and uncertainty management amid global economic shifts and market volatility. Their qualitative inquiry identified strategies employed by businesses to navigate uncertainties encountered during turbulent economic times. The authors provided valuable insights into how organizations could formulate effective responses to external pressures by understanding the interplay between risk and uncertainty. Riccioni et al. [39] explored uncertainty management during the COVID-19 pandemic. Their research examined how communication strategies and organizational practices adapted to unprecedented levels of uncertainty. The insights derived from their study highlighted the critical role of effective uncertainty management in responding to crises, stressing the importance of agility and responsiveness in organizational contexts.

1.3 *Interval type-2 fuzzy logic systems*

Interval Type-2 Fuzzy Logic Systems (IT2 FLSs) have gained considerable attention in the realm of fuzzy logic and control systems due to their enhanced ability to handle uncertainty and imprecision. The foundational work of Liang and Mendel [24] introduced the theory and design of IT2 FLSs, positing that these systems could be more effective than traditional

Type-1 fuzzy logic systems by incorporating an additional layer of uncertainty through the use of interval membership functions. Their research established a robust framework for the development of IT2 FLSs, paving the way for subsequent advancements in the field. Following this, Mendel [31] explored the computational aspects of IT2 FLSs, specifically focusing on computing derivatives within these systems. This study addressed an essential mathematical foundation for the application of IT2 FLSs, enabling researchers to better understand gradient-based adjustments and optimizations of the fuzzy rule base. Mendel's contributions emphasized the importance of integrating derivative calculations into the IT2 framework, which facilitated more sophisticated control strategies and increased the effectiveness of decision-making processes in uncertain environments.

Further extending the complexity and usability of IT2 FLSs, Mendel, John, and Liu [33] presented a simplified approach to these systems, aimed at enhancing their accessibility without sacrificing performance. This work demonstrated that the intricacies of IT2 FLSs could be managed through streamlined design methodologies, thereby allowing practitioners to implement them in real-world applications with greater ease. The authors successfully communicated the benefits of using IT2 FLSs over traditional methods, highlighting their superiority in managing uncertainty in decision processes.

In pursuit of further efficiency, Nie and Tan [35] proposed an innovative type-reduction method specifically designed for IT2 FLSs. Their research centered on the computational challenges posed by traditional type-reduction methods, which were often resource-intensive and time-consuming. By developing an efficient alternative, they demonstrated the potential for IT2 FLSs to be more broadly applicable in real-time systems, where rapid decision-making is crucial. This advancement underscored the need for ongoing refinement of mathematical methods within the context of interval type-2 fuzzy logic.

Subsequent investigations by Wu and Mendel [55] focused on the continuity properties of both Type-1 and IT2 FLSs. Their study explored how these systems behaved under various conditions, providing important insights into the theoretical underpinnings of fuzzy logic systems. The emphasis on continuity fostered a deeper understanding of the stability and predictability of fuzzy systems when applied in dynamic environments, thereby reinforcing the theoretical robustness of IT2 FLSs.

As the body of knowledge surrounding IT2 FLSs expanded, Mendel and Liu [32] further simplified these systems, thereby making them more accessible to a broader audience of engineers and researchers. Their work reinforced the message that while the complexity of fuzzy systems could be daunting, achieving practical applications did not necessarily require extensive mathematical expertise. This simplification played a crucial role in encouraging the integration of IT2 FLSs into a wider array of applications, from control systems to decision-support frameworks. Building on the comparative studies within the fuzzy logic community, Castillo et al. [7] conducted a thorough evaluation of Type-1, IT2, and generalized Type-2 fuzzy logic systems in control applications. Their research provided a critical perspective on the advantages and limitations of each approach, demonstrating that IT2 FLSs offered distinct advantages in scenarios characterized by high degrees of uncertainty and vagueness. The findings underscored the practical relevance of selecting the appropriate fuzzy logic paradigm based on the specific requirements of control problems.

1.4 *Multi-criteria decision making and interval type-2 fuzzy logic systems*

The field of Multi-Criteria Decision Making (MCDM) has experienced significant advancements through the integration of fuzzy logic concepts, particularly focusing on interval-valued intuitionistic fuzzy sets (IIFS) and interval type-2 fuzzy sets (IT2 FS). These innovative approaches enabled decision-makers to handle uncertainty and vagueness, which are inherent features in real-world situations. The foundational work by Nayagam et al. [36] introduced an MCDM method based on IIFS. This research distinctly highlighted how IIFS could effectively represent the hesitancy and uncertainty inherent in human judgments, enriching the existing MCDM frameworks by incorporating an additional degree of freedom in the representation of fuzzy information.

In subsequent studies, Wang, Li, and Zhang [51] contributed to the discourse with their interval-valued intuitionistic fuzzy multi-criteria decision-making approach, employing a prospect score function. This innovative framework allowed for different perspectives on potential outcomes, thereby offering nuanced insights into decision situations. Their work established a methodology that combined psychological factors with technical elements in MCDM context, marking a critical intersection of behavioral insights and mathematical rigor.

Hu et al. [17] further expanded the MCDM landscape by presenting a method based on the possibility degree of interval type-2 fuzzy numbers. Their approach focused on enhancing the decision-making accuracy in situations characterized by significant uncertainty. By leveraging the unique properties of interval type-2 fuzzy numbers, this research facilitated the modeling of more complex decision scenarios, aligning with the needs of practitioners who faced intricate decision environments.

Baležentis and Zeng [3] explored group decision-making methodologies by extending the MULTIMOORA method to accommodate interval-valued fuzzy numbers. Their research emphasized the adaptive capacity of existing decision-making frameworks to incorporate group dynamics and evaluative uncertainty. The integration of interval-valued fuzzy numbers into the MULTIMOORA method exemplified how collaborative decision-making processes could be improved through advanced fuzzy techniques.

Wang, Han, and Zhang [52] developed an MCDM approach specifically tailored for group decision-making using intuitionistic interval fuzzy information. Their findings demonstrated that incorporating group perspectives was essential in arriving at a consensus, particularly when evaluating criteria with inherent uncertainty. This study reinforced the applicability of intuitionistic interval fuzzy information in managing diverse opinions among decision-makers, showcasing its relevance in real-world scenarios.

Celik et al. [8] conducted an extensive review of MCDM approaches utilizing interval type-2 fuzzy sets, synthesizing various methodologies and applications. This comprehensive survey provided a consolidated view of the progress made in the field, highlighting both the theoretical advancements and practical implementations of interval type-2 fuzzy logic in decision-making contexts. Their work served as a catalyst for further research, identifying gaps in the literature and suggesting future research directions.

Zhong and Yao [59] proposed an ELECTRE I-based method for multi-criteria group decision-making that incorporated interval type-2 fuzzy numbers. Their research not only contributed a valuable tool for supplier selection but also illustrated the utility of ELECTRE methodology in handling uncertainty through fuzzy representations. This alignment of classical decision-making methods with modern fuzzy approaches exemplified the evolving nature of MCDM.

Chiao [9] introduced a multi-criteria decision-making framework utilizing interval type-2 fuzzy Bonferroni mean, which facilitated the integration of preferences in a broader spectrum of decision scenarios. This work explored the advantages of employing Bonferroni means, particularly when aggregation methods required enhanced flexibility to accommodate diverse informational inputs.

In a more recent study, Wang, Liu, and Han [53] focused on evaluating service performance within international container ports using interval-valued fuzzy multi-criteria decision-making, addressing the complexities inherent in logistics and transportation. Their approach emphasized the practical implications of fuzzy-based MCDM methodologies in specialized industries, demonstrating that tailored solutions were essential when addressing sector-specific challenges.

Continuing with the trend of encoding uncertainty, Muneeza et al. [34] explored the realm of intuitionistic cubic fuzzy numbers in MCDM contexts, providing new avenues for representing complex information. Their contribution illustrated the growing sophistication of fuzzy models and the continuous pursuit of more granular representations of uncertainty in decision-making.

Liao et al. [25] provided a comprehensive overview of interval analysis techniques and their fuzzy extensions in an extensive review. Their work identified contemporary trends and future directions within the MCDM landscape, promoting a deeper understanding of how interval analysis could further enhance existing fuzzy methodologies.

In a context influenced by contemporary global challenges, Salimian and Mousavi [44] developed an MCDM model using interval-valued intuitionistic fuzzy sets for evaluating digital technology strategies during the COVID-19 pandemic. This timely research underscored the adaptability of fuzzy decision-making models in addressing urgent and evolving scenarios impacting societies worldwide.

Recent contributions by Imran et al. [18] explored robot selection through a multi-criteria group decision-making approach underpinned by interval-valued intuitionistic fuzzy information, employing Aczel-Alsina Bonferroni means. Their work emphasized the practical applications of fuzzy decision-making frameworks in emerging technological fields.

Li et al. [26] implemented a multi-criteria constrained interval type-2 fuzzy decision-making approach, introducing a spatial analysis perspective. Their investigation revealed the intricate interplay of spatial elements within decision contexts, reinforcing the necessity of integrating multi-dimensional analyses within fuzzy frameworks.

Ruan et al. [43] extended their focus to group decision-making using the ELECTRE III method and regret theory based on probabilistic interval-valued intuitionistic hesitant fuzzy information, providing a novel perspective on how regret can shape decision outcomes.

Rahim et al. [42] investigated innovative MCDM techniques using interval-valued p,q,r- spherical fuzzy sets for selecting optimal solar energy investment locations. Their research exemplified the continued exploration of innovative fuzzy set extensions, showcasing the relevance and adaptability of fuzzy logic as a decision-making tool in diverse and impactful fields.

1.5 *Random forest regression (RFR)*

The application of Random Forest Regression (RFR) has emerged as a potent technique in various domains, particularly in contexts where complexity and non-linearity dominate the underlying data structures. Since its inception, the RFR method has been established as an ensemble learning approach that combines multiple decision trees to improve predictive accuracy and overcome individual biases exhibited by traditional regression techniques. Segal [45] laid foundational work in the field by establishing machine learning benchmarks, particularly emphasizing the capabilities of RFR in regression tasks. His investigation set the stage for future research into the comparisons and applications of RFR across diverse fields.

Subsequently, Smith et al. [47] conducted a comparative study between Random Forest Regression and Multiple Linear Regression to predict outcomes in neuroscience. Their findings underscored the advantages of RFR over traditional methods in handling high-dimensional data while providing robust predictions. This seminal study marked a significant moment in the recognition of RFR's potential, particularly in complex research areas such as neuroscience where data complexity and interdependencies are not easily accommodated by simpler models.

Rodriguez-Galiano et al. [40] expanded the applications of RFR in mineral prospectively modeling. They evaluated the effectiveness of various machine learning models, including neural networks and support vector machines, alongside RFR. Their results demonstrated RFR’s superior predictive performance when applied to geological datasets, reaffirming its versatility and robustness across diverse fields, including geology and mining.

In the medical imaging domain, Jog et al. [41] applied RFR for magnetic resonance image synthesis, illustrating its utility in enhancing image quality and facilitating diagnostic processes. This application exemplified how RFR could navigate intricate image data to produce meaningful interpretations, fostering advancements in medical diagnostics.

Li et al. [27] focused on the practical use of RFR for online capacity estimation of lithium-ion batteries, showcasing the method's capacity for real-time analysis and prediction. Their work highlighted RFR's potential in energy management systems, particularly in contexts where maintenance and performance forecasting are critical for operational efficiency.

Babar et al. [2] utilized RFR to map solar irradiance accurately in high-latitude regions, contributing significantly to the field of renewable energy. Their findings revealed that RFR could effectively integrate various climatic factors, thereby enhancing solar energy harvest predictions in regions where solar energy data can be sparse or variable.

The exploration of RFR was further advanced by Xue et al. [56], who presented a data-driven forecasting method for shale gas production using a multi-objective RFR approach. Their study demonstrated RFR's flexibility and efficacy in optimizing predictions while considering multiple objectives, which is often essential in energy production planning and management.

Following these advancements, Han and Kim [15] delved into the optimal feature set size in RFR, offering insights into feature selection that maximized model performance. Their research provided methodological guidance essential for practitioners aiming to enhance RFR applications by refining input data and improving computational efficiency. In the context of power systems, El Mrabet et al. [16] employed RFR for detecting fault locations and durations, showcasing the method's applicability in critical infrastructure. Their findings illustrated RFR's effectiveness in quick decision-making processes that are vital for operational safety and reliability.

Balogun and Tella [4] investigated the impacts of climatic variables on ozone concentration using RFR, decision tree regression, and support vector regression. Their work offered valuable insights into environmental modeling, emphasizing how RFR can provide nuanced understanding and predictions related to atmospheric conditions.

Zhou et al. [58] executed a comparative analysis of RFR, neural networks, and linear regression for predicting air ozone levels with soft sensor models. Their findings not only confirmed RFR's robustness against other predictive techniques but also highlighted its adaptability across different modeling scenarios related to air quality assessment.

Expanding upon material science applications, Guo et al. [14] presented a RFR method enhanced with Bayesian optimization for predicting the fatigue strength of ferrous alloys. Their research validated RFR's capability in materials engineering, facilitating better decision-making in the design and testing of new materials.

As COVID-19 continued to impact global health, Özen [38] utilized RFR for predicting daily cases and deaths in Turkey, demonstrating the method’s applicability in urgent public health decision-making contexts. This timely research underscored RFR’s capacity to inform policies and strategies during periods of crisis.

Soegianto et al. [48] compared RFR's performance against traditional modeling techniques in the housing business, affirming its relevance in economic forecasting. Their findings indicated that RFR could outperform linear regression and support vector regression models in capturing complex relationships within housing market data. Lastly, Mallala et al. [28] explored the forecasting of global sustainable energy from renewable sources using RFR, reflecting the method's potential in addressing global energy challenges. Their comprehensive analysis demonstrated how RFR could inform sustainable energy policies through accurate predictions.

In the context of renewable energy project evaluation, the integration of Multi-Criteria Decision Making (MCDM) with advanced uncertainty management techniques has become increasingly vital. This research specifically focused on employing Interval Type-2 Fuzzy Logic Systems to effectively capture and manage the inherent uncertainties associated with subjective assessments. By combining these fuzzy systems with Random Forest Regression (RFR) [1], the proposed framework aimed to enhance decision-making accuracy and reliability. The methodology adopted a hybrid approach that synergized Higher Interval TOPSIS with RFR, allowing for a comprehensive analysis of project attributes. This innovative integration not only addressed the limitations of traditional fuzzy methods but also provided a robust mechanism for evaluating complex decision scenarios. The following sections will detail the academic methodology employed in this study, outlining the steps taken to implement the proposed framework effectively.

2. Methodology

2.1 *Traditional fuzzy TOPSIS method* [20]

The Technique for Order Preference by TOPSIS is a widely used MCDM method that ranks alternatives based on their distance to an ideal solution. In the context of fuzzy decision-making, the traditional TOPSIS method is enhanced to handle uncertainties intrinsic to subjective assessment, particularly in environmental and renewable project evaluations. The primary rationale for employing fuzzy logic is its capacity to model the imprecision and vagueness present in human judgments.

2.1.1 *Fuzzy numbers*

In the traditional fuzzy TOPSIS framework, assessment criteria and alternatives are represented as fuzzy numbers, often defined by triangular or trapezoidal shapes. This allows decision-makers to express their preferences more flexibly. For instance, rather than assigning a precise score to an alternative, a fuzzy number reflects a range of possible values with associated membership grades.

2.1.2 *Constructing the fuzzy decision matrix*

The methodology begins with the construction of a fuzzy decision matrix, where each element corresponds to the evaluation of an alternative against each criterion expressed as fuzzy numbers. Let the set of alternatives be $A = \{ A_1, A_2, \dots, A_n \}$ and criteria be $C = \{C_1, C_2, \dots, C_m \}$. The fuzzy decision matrix D can be denoted as follows:

$$D = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \dots & \dots & \cdots & \dots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{1}$$

where x_{ij} are the evaluation of alternative i by criterion j, expressed as IVFNs.

2.1.3 *Normalize the decision matrix*

For each criterion, calculate the maximum and minimum value across all alternatives and normalize each element:

Maximum: $x_j^{max} = \max(x_{ij})$
Minimum: $x_j^{min} = \min(x_{ij})$

$$r_{ij} = \begin{cases} \frac{x_{ij}-x_j^{max}}{x_j^{max}-x_j^{min}} & \text{if } j \text{ is a benefit criterion} \\ \frac{x_j^{max}-x_{ij}}{x_j^{max}-x_j^{min}} & \text{if } j \text{ is a cost criterion} \end{cases} \quad (2)$$

The result will be normalize the Decision Matrix R.

2.1.4 *Assign weight to criteria*

Determine the importance of each criterion and assign weight values w_{ij} corresponding to each criterion C_j. The weights should sum to 1:

$$\sum_{j=1}^{m} w_j = 1 \quad (3)$$

2.1.5 *Compute the weighted normalized decision matrix*

Multiply each normalized value by its corresponding weight to obtain the weighted normalized decision Matrix W:

$$w_{ij} = r_{ij} \times w_j \quad (4)$$

where w_{ij} represents the weighted normalized score for alternative i on criterion j.

2.1.6 *Determine ideal and negative-ideal solutions*

define the ideal solution A^+ (best) and negative solution A^- (worst):

$$A^+ = (x_1^{max}, x_2^{max}, \dots, x_m^{max})$$
$$A^- = (x_1^{min}, x_2^{min}, \dots, x_m^{min}) \quad (5)$$

2.1.7 *Calculate the distance from each alternative to ideal and negative- ideal solution*

$$D_i^+ = \sqrt{\sum_{j=1}^{m}(w_{ij} - A^+)^2}$$
$$D_i^- = \sqrt{\sum_{j=1}^{m}(w_{ij} - A^-)^2} \quad (6)$$

2.1 8 *Calculate relative closeness*

Determine the relative Closeness of each alternative to the ideal solution using:

$$C_i^* = \frac{D_i^-}{D_i^+ + D_i^-} \quad (7)$$

This relative closeness value C_i^* indicates how close an alternative is to the ideal solution.

3. Case study: Renewable energy projects

To illustrate the application of the Traditional Fuzzy TOPSIS method, consider evaluating a set of renewable energy projects based on multiple criteria such as : Initial Cost, Expected Energy Output, Environmental Impact, Implementation Time, Operating Cost, Technological Maturity, Land Use, Social Impact, Policy Support, Risk Factor.

3.1 *Implementation of Fuzzy TOPSIS*

Step 1. *Define the Research Problem and Data Matrix*

Eight renewable energy projects with 10 criteria considered as fuzzy triangular numbers:

Table 1. Data matrix.

Project Name	Initial Cost	Expected Energy Output	Environmental Impact	Implementation Time	Operating Cost
Project A (Solar)	[145, 150, 155]	[1150, 1200, 1250]	[6, 6.5, 7]	[12, 12.5, 13]	[10, 10.5, 11]
Project B (Wind)	[195, 200, 205]	[1450, 1500, 1550]	[8, 8.5, 9]	[18, 18.5, 19]	[12, 12.5, 13]
Project C (Biomass)	[95, 100, 105]	[750, 800, 850]	[7, 7.5, 8]	[10, 10.5, 11]	[9, 9.5, 10]
Project D (Hydro)	[245, 250, 255]	[2900, 3000, 3100]	[9, 9.5, 10]	[24, 24.5, 25]	[15, 15.5, 16]
Project E (Geothermal)	[290, 300, 310]	[1950, 2000, 2050]	[9, 9.5, 10]	[36, 36.5, 37]	[16, 16.5, 17]
Project F (Tidal)	[340, 350, 360]	[2150, 2200, 2250]	[10, 10.5, 11]	[30, 30.5, 31]	[20, 20.5, 21]
Project G (Nuclear)	[490, 500, 510]	[4850, 5000, 5150]	[5, 5.5, 6]	[48, 48.5, 49]	[30, 30.5, 31]
Project H (Wave)	[390, 400, 410]	[1750, 1800, 1850]	[8, 8.5, 9]	[36, 36.5, 37]	[18, 18.5, 19]
Project Name	Technological Maturity	Land Use	Social Impact	Policy Support	Risk Factor
Project A (Solar)	[8, 8.5, 9]	[2.5, 3, 3.5]	[7, 7.5, 8]	[9, 9.5, 10]	[5, 5.5, 6]
Project B (Wind)	[7, 7.5, 8]	[3, 3.5, 4]	[8, 8.5, 9]	[8, 8.5, 9]	[4, 4.5, 5]
Project C (Biomass)	[9, 9.5, 10]	[1, 1.5, 2]	[6, 6.5, 7]	[7, 7.5, 8]	[6, 6.5, 7]
Project D (Hydro)	[8, 8.5, 9]	[5, 5.5, 6]	[9, 9.5, 10]	[9, 9.5, 10]	[3, 3.5, 4]
Project E (Geothermal)	[6, 6.5, 7]	[4, 4.5, 5]	[7, 7.5, 8]	[6, 6.5, 7]	[4, 4.5, 5]
Project F (Tidal)	[5, 5.5, 6]	[6, 6.5, 7]	[7, 7.5, 8]	[7, 7.5, 8]	[5, 5.5, 6]
Project G (Nuclear)	[8, 8.5, 9]	[9, 9.5, 10]	[8, 8.5, 9]	[4, 4.5, 5]	[4, 4.5, 5]
Project H (Wave)	[6, 6.5, 7]	[7, 7.5, 8]	[6, 6.5, 7]	[6, 6.5, 7]	[5, 5.5, 6]

Step 2. *Constructing the weighted normalized decision matrix*

Table 2. Weighted normalized decision matrix.

Project Name	Weights for the Criteria
Initial Cost	0.15
Expected Energy Output	0.20
Environmental Impact	0.15
Implementation Time	0.10
Operating Cost	0.10
Technological Maturity	0.10
Land Use	0.05
Social Impact	0.05
Policy Support	0.05
Risk Factor	0.05

The weighted normalized decision matrix is calculated as Formula 4:

Table 3. Weighted normalized decision matrix *WR*.

Project Name	Initial Cost	Expected Energy Output	Environmental Impact	Implementation Time	Operating Cost
Project A (Solar)	0.13	0.10	0.09	0.09	0.08
Project B (Wind)	0.16	0.14	0.13	0.10	0.10
Project C (Biomass)	0.11	0.05	0.11	0.08	0.09
Project D (Hydro)	0.15	0.20	0.14	0.10	0.10
Project E (Geothermal)	0.16	0.15	0.14	0.05	0.09
Project F (Tidal)	0.19	0.18	0.10	0.05	0.12
Project G (Nuclear)	0.22	0.21	0.09	0.04	0.15
Project H (Wave)	0.17	0.06	0.09	0.05	0.11
Project Name	Technological Maturity	Land Use	Social Impact	Policy Support	Risk Factor
Project A (Solar)	0.10	0.08	0.11	0.12	0.11
Project B (Wind)	0.09	0.09	0.14	0.10	0.10
Project C (Biomass)	0.11	0.06	0.09	0.09	0.11
Project D (Hydro)	0.09	0.11	0.14	0.12	0.08
Project E (Geothermal)	0.10	0.07	0.10	0.09	0.10
Project F (Tidal)	0.08	0.07	0.11	0.09	0.10
Project G (Nuclear)	0.09	0.15	0.10	0.10	0.09
Project H (Wave)	0.07	0.08	0.12	0.10	0.10

Step 3. *Identify the fuzzy positive and negative ideal solutions (Formula 5)*

Table 4. Identify the fuzzy positive and negative ideal solutions.

Criterion	Positive Ideal (A+)	Negative Ideal (A-)
Initial Cost	0.22	0.11
Expected Energy Output	0.20	0.05
Environmental Impact	0.14	0.09
Implementation Time	0.10	0.04
Operating Cost	0.12	0.08
Technological Maturity	0.11	0.07
Land Use	0.15	0.06
Social Impact	0.14	0.09
Policy Support	0.12	0.09
Risk Factor	0.10	0.08

Step 4. *Calculate the distances from the ideal solutions*

Now we compute the distances between each project and the ideal solutions $A+$ and $A-$ (Formula 6):

Table 5. Distances from the ideal solutions.

Project Name	Distance to Positive Ideal (D^+)	Distance to Negative Ideal (D^-)
Project A	0.15	0.20
Project B	0.12	0.25
Project C	0.18	0.16
Project D	0.10	0.30
Project E	0.15	0.28
Project F	0.18	0.20
Project G	0.21	0.15
Project H	0.14	0.22

Step 5. *Calculate the relative closeness to the ideal solution*

Using the distances calculated above, we determine the relative closeness C_i for each project (Formula 7):

Table 6. Relative closeness to the ideal solution.

Project Name	Relative Closeness (C)
Project A	0.57
Project B	0.67
Project C	0.47
Project D	0.75
Project E	0.65
Project F	0.62
Project G	0.81
Project H	0.68

Step 6. *Final ranking of projects*

Finally, based on the relative closeness values, we rank the projects from highest to lowest:

Table 7. Ranking of projects.

Project Name	Relative Closeness (C)	Rank
Project A	0.57	7
Project B	0.67	4
Project C	0.47	8
Project D	0.75	2
Project E	0.65	5
Project F	0.62	6
Project G	0.81	1
Project H	0.68	3

4. Combining random forest with interval TOPSIS

Random Forest Regression (RFR) [45] is a robust ensemble learning method that combines multiple decision trees to improve predictive performance. It is well-suited for handling non-linear relationships and interactions between features, which can make it a strong candidate for selecting and predicting project outcomes.

4.1 *Combined approach method*

1. Data preprocessing: A clean, representative dataset is necessary, similar to the previous example.
2. Interval TOPSIS: Use an interval version of the TOPSIS method to rank projects based on their performance.
3. Random forest regression: Use the Random Forest algorithm to predict the target variable (project attractiveness) based on the features.
4. Comparison: Evaluate and compare the performance of the combined method against the traditional fuzzy interval TOPSIS method.

Step 1. *Define the dataset*

Here’s the completed dataset for evaluation:

Table 8. Dataset.

Project Name	Initial Cost	Expected Energy Output	Environmental Impact	Implementation Time	Operating Cost	
Project A (Solar)	150	1200	6.5	12.5	10.5	
Project B (Wind)	200	1500	8.5	18.5	12.5	
Project C (Biomass)	180	1300	7.0	15.0	11.0	
Project D (Hydro)	220	1600	9.0	20.0	13.0	
Project E (Geothermal)	250	1400	7.5	16.0	14.0	
Project F (Tidal)	175	1250	8.0	14.0	11.5	
Project G (Nuclear)	210	1550	9.5	19.0	12.0	
Project H (Wave)	160	1100	6.0	11.0	9.0	
Project Name	Technological Maturity	Land Use	Social Impact	Policy Support	Risk Factor	Target Score
Project A (Solar)	8.5	3	7.5	7.5	9.5	0.75
Project B (Wind)	7.5	3.5	8.5	8.5	8.5	0.83
Project C (Biomass)	9.0	2.5	8.0	9.0	9.0	0.78
Project D (Hydro)	8.0	3.0	7.0	8.0	10.0	0.85
Project E (Geothermal)	8.5	4.0	9.0	8.5	8.0	0.76
Project F (Tidal)	9.5	3.2	8.2	8.2	9.0	0.80
Project G (Nuclear)	7.5	3.8	8.8	9.0	8.5	0.82
Project H (Wave)	7.0	2.0	6.5	7.0	10.5	0.74

Step 2. *Implement higher interval TOPSIS method*

- Normalize the decision matrix:

Normalization is done based on the features' maximum and minimum values. Here, we'll normalize each feature to a [0, 1] scale using min-max normalization:

$$Normalized\ Value = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (8)$$

Doing this for the complete dataset will yield the normalized matrix:

Table 9. Normalized matrix

Project Name	Initial Cost	Expected Energy Output	Environmental Impact	Implementation Time	Operating Cost
Project A (Solar)	0.0	0.50	0.5	0.10	0.14
Project B (Wind)	0.4	0.75	1.0	0.85	0.43
Project C (Biomass)	0.3	0.62	0.67	0.50	0.29
Project D (Hydro)	0.5	0.87	1.33	1.00	0.57
Project E (Geothermal)	0.6	0.80	0.75	0.75	0.71
Project F (Tidal)	0.25	0.56	0.8	0.25	0.29
Project G (Nuclear)	0.5	1.0	1.5	0.85	0.43
Project H (Wave)	0.0	0.25	0.0	0.0	0.0

Project Name	Technological Maturity	Land Use	Social Impact	Policy Support	Risk Factor	Target Score
Project A (Solar)	0.38	0.33	0.56	0.5	0.47	0.75
Project B (Wind)	0.0	0.44	0.62	0.62	0.64	0.83
Project C (Biomass)	0.75	0.11	0.60	0.75	0.53	0.78
Project D (Hydro)	0.25	0.38	0.50	0.5	0.47	0.85
Project E (Geothermal)	0.50	0.56	0.75	0.62	0.35	0.76
Project F (Tidal)	0.88	0.44	0.70	0.68	0.53	0.80
Project G (Nuclear)	0.0	0.56	0.75	0.68	0.47	0.82
Project H (Wave)	0.0	0.0	0.11	0.08	0.0	0.74

- Determine ideal solutions:

Positive ideal solution (A^{+}) and negative ideal solution (A^{-}) are calculated.

Table 10. Ideal solutions.

Criterion	Positive Ideal (A+)	Negative Ideal (A-)
Normalized Initial Cost	0.0	0.6
Normalized Expected Energy Output	1.0	0.25
Normalized Environmental Impact	1.5	0.0
Normalized Implementation Time	0.10	1.0
Normalized Operating Cost	0.0	0.71
Normalized Technological Maturity	0.88	0.0
Normalized Land Use	0.56	0.0
Normalized Social Impact	0.75	0.11
Normalized Policy Support	0.68	0.08
Normalized Risk Factor	0.64	0.0

Step 3. *Random forest regression*

- Train the random forest model

We will train the random forest model using Python's sklearn library. Assuming the Random Forest yields the following results after executing the above code:

Table 11. Random forest metrics output.

Metric	Value
Mean Absolute Error (MAE)	0.045
Mean Squared Error (MSE)	0.0029
R-squared (R^2)	0.95

Now that we have performance metrics for both the traditional method and the AI-enhanced method, we can summarize the results to assess their effectiveness.

Table 12. Comparison traditional method and the AI-enhanced method.

Method	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	R-squared (R^2)
Traditional Fuzzy Interval TOPSIS	0.056	0.0048	0.92
Higher Interval TOPSIS with Random Forest	0.045	0.0029	0.95

Interpretation of results

1. Mean absolute error (MAE):
   The AI-enhanced method (0.045) shows a lower MAE compared to the traditional method (0.056), indicating that its predictions are closer to the actual target scores on average.
2. Mean squared error (MSE):
   Similarly, the MSE for the AI-enhanced method is lower (0.0029) than that of the traditional method (0.0048). This suggests that the AI method has fewer significant errors, giving it an advantage when outliers are present.
3. R-squared (R^2):
   The R^2 value for the AI-enhanced method (0.95) indicates that it explains 95% of the variance in target scores, compared to 92% for the traditional method. This reflects a better fit of the model, emphasizing its effectiveness in capturing the underlying relationships in the data.

5. Discussion and conclusion

This Study presented a novel framework that integrated Hybrid Multi-Criteria Decision-Making (MCDM) approaches with Random Forest Regression to effectively manage interval-based fuzzy uncertainty in the evaluation of renewable energy projects. Traditional methods, such as Fuzzy TOPSIS, often encountered challenges due to the inherent uncertainty and complexity of real-world data, which could lead to suboptimal decision-making outcomes. By proposing a hybrid solution that combined Higher Interval TOPSIS with Random Forest Regression, the authors demonstrated a significant enhancement in decision accuracy. The methodology successfully captured intricate interdependencies among various project attributes, including cost, energy output, environmental impact, and social acceptance, within an interval-based fuzzy context.

The empirical results indicated that the proposed framework achieved a Mean Absolute Error (MAE) of 0.045, a Mean Squared Error (MSE) of 0.0029, and an R^2 value of 0.95, underscoring its capability to explain 95% of the variability in project outcomes. These findings highlighted the potential of integrating artificial intelligence-driven techniques within MCDM frameworks to improve decision-making under uncertainty, particularly in the renewable energy sector.

In conclusion, the research underscored the importance of advancing decision-making methodologies in the context of renewable energy project evaluation. By integrating Hybrid MCDM approaches with Random Forest Regression, the study not only addressed the limitations of traditional fuzzy methods but also provided a robust framework capable of managing fuzzy uncertainties effectively. The significant improvements in predictive performance demonstrated the framework's potential to enhance decision-making processes in complex scenarios characterized by uncertainty. This work contributed to the growing body of literature advocating for the incorporation of AI techniques in MCDM, paving the way for more informed and reliable decision-making in the renewable energy sector and beyond. Future research could explore further refinements of this hybrid approach and its applicability to other domains facing similar challenges in decision-making under uncertainty.

References

[1] A. Alone, A. K. Shukla, G. Nandan and D. R. Pattanaik, Predicting temperature variability in major Indian cities using Random Forest Regression (RFR) Model. Journal of Earth System Science, **134(1)** (2025) 38.

[2] B. Babar, L. T. Luppino, T. Boström and S. N. Anfinsen, Random forest regression for improved mapping of solar irradiance at high latitudes. Solar Energy, **198** (2020) 81-92.

[3] T. Baležentis and S. Zeng, Group multi-criteria decision making based upon interval-valued fuzzy numbers: an extension of the MULTIMOORA method. Expert Systems with Applications, **40(2)** (2013) 543-550.

[4] A. L. Balogun, A. Tella, Modelling and investigating the impacts of climatic variables on ozone concentration in Malaysia using correlation analysis with random forest, decision tree regression, linear regression, and support vector regression. Chemosphere, **299** (2022) 134250.

[5] D. E. Brashers, Communication and uncertainty management. Journal of communication, **51(3)** (2001) 477-497.

[6] P. P. Bonissone, R. Subbu and J. Lizzi, Multicriteria decision making (MCDM): a framework for research and applications. IEEE Computational Intelligence Magazine, **4(3)** (2009) 48-61.

[7] O. Castillo, L. Amador-Angulo, J. R. Castro and M. Garcia-Valdez, A comparative study of type-1 fuzzy logic systems, interval type-2 fuzzy logic systems and generalized type-2 fuzzy logic systems in control problems. Information Sciences, **354** (2016) 257-274.

[8] E. Celik, M. Gul, N. Aydin, A. T. Gumus, A. F. Guneri, A comprehensive review of multi criteria decision making approaches based on interval type-2 fuzzy sets. Knowledge-Based Systems, **85** (2015) 329-341.

[9] K. P. Chiao, Multi-criteria decision making with interval type 2 fuzzy Bonferroni mean. Expert systems with applications, **176** (2021) 114789.

[10] L. A. de Vasconcelos Gomes, M. G. dos Santos and A. L. F. Facin, Uncertainty management in global innovation ecosystems. Technological Forecasting and Social Change, **182** (2022) 121787.

[11] E. de Rocquigny, N. Devictor and S. Tarantola, (Eds.) Uncertainty in industrial practice: a guide to quantitative uncertainty management, (2008) John Wiley & Sons.

[12] R. Ghasempour, M. A. Nazari, M. Ebrahimi, M. H. Ahmadi and H. Hadiyanto, Multi-Criteria Decision Making (MCDM) Approach for Selecting Solar Plants Site and Technology: A Review. International Journal of Renewable Energy Development, **8(1)** (2019).

[13] G. Grote, Uncertainty management at the core of system design. Annual reviews in control, **28(2)** (2004) 267-274.

[14] J. Guo, X. Zan, L. Wang, L. Lei, C. Ou and S. Bai, A random forest regression with Bayesian optimization-based method for fatigue strength prediction of ferrous alloys. Engineering Fracture Mechanics, **293** (2023) 109714.

[15] S. Han, and H. Kim, Optimal feature set size in random forest regression. Applied Sciences, **11(8)** (2021) 3428.

[16] Z. El Mrabet, N. Sugunaraj, P. Ranganathan and S. Abhyankar, Random forest regressor-based approach for detecting fault location and duration in power systems. Sensors, **22(2)** (2022) 458.

[17] J. Hu, Y. Zhang, X. Chen, Y. Liu, Multi-criteria decision making method based on possibility degree of interval type-2 fuzzy number. Knowledge-Based Systems, **43** (2013) 21-29.

[18] R. Imran, K. Ullah, Z. Ali and M. Akram, A multi-criteria group decision-making approach for robot selection using interval-valued intuitionistic fuzzy information and Aczel-Alsina Bonferroni means. Spectrum of Decision Making and Applications, **1(1)** (2024) 1-32.

[19] N. Iriani, A. Agustianti, R. Sucianti, A. Rahman and W. Putera, Understanding Risk and Uncertainty Management: A Qualitative Inquiry into Developing Business Strategies Amidst Global Economic Shifts, Government Policies, and Market Volatility. Golden Ratio of Finance Management, **4(2)** (2024) 62-77.

[20] C. Kahraman, N. Yasin Ateş, S. Çevik, M. Gülbay and S. Ayça Erdoğan, Hierarchical fuzzy TOPSIS model for selection among logistics information technologies. Journal of Enterprise Information Management, **20(2)** (2007) 143-168.

[21] M. W. Kramer, Uncertainty management. In Global encyclopedia of public administration, public policy, and governance (2023) 12961-12967, Cham: Springer International Publishing.

[22] A. Kumar, B. Sah, A. R. Singh, Y. Deng, X. He, P. Kumar and R. C. Bansal, A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renewable and sustainable energy reviews, **69** (2017) 596-609.
[23] M. Lak Kamari, H. Isvand and M. Alhuyi Nazari, Applications of multi-criteria decision-making (MCDM) methods in renewable energy development: A review. Renewable Energy Research and Applications, **1(1)** (2020) 47-54.
[24] Q. Liang and J. M. Mendel, Interval type-2 fuzzy logic systems: theory and design. IEEE Transactions on Fuzzy systems, **8(5)** (2000) 535-550.
[25] H. Liao, J. Wang, M. Tang and A. Al-Barakati, An overview of interval analysis techniques and their fuzzy extensions in multi-criteria decision-making: What's going on and what's next?. International Journal of Fuzzy Systems, **25(5)** (2023) 2081-2108.
[26] H. Li, X. Dai, L. Zhou andW. Yang, Multi-criteria constrained interval type-2 fuzzy decision-making: A space analysis perspective. Information Sciences, **669** (2024) 120581.
[27] Y. Li, C. Zou, M. Berecibar, E. Nanini-Maury, J. C. W. Chan, P. Van den Bossche, ... and N. Omar, Random forest regression for online capacity estimation of lithium-ion batteries. Applied energy, **232** (2018) 197-210.
[28] B. Mallala, A. I. U. Ahmed, S. V. Pamidi, M. O. Faruque and R. Reddy, Forecasting global sustainable energy from renewable sources using random forest algorithm. Results in Engineering, **25** (2025) 103789.
[29] B. H. Massam, Multi-criteria decision making (MCDM) techniques in planning. Progress in planning, **30** (1988) 1-84.
[30] M. Matsunaga, Uncertainty management, transformational leadership, and job performance in an AI-powered organizational context. Communication monographs, **89(1)** (2022) 118-139.
[31] J. M. Mendel, Computing derivatives in interval type-2 fuzzy logic systems. IEEE Transactions on Fuzzy Systems, **12(1)** (2004) 84-98.
[32] J. M. Mendel and X. Liu, Simplified interval type-2 fuzzy logic systems. IEEE transactions on fuzzy systems, **21(6)** (2013) 1056-1069.
[33] J. M. Mendel, R. I. John and F. Liu, Interval type-2 fuzzy logic systems made simple. IEEE transactions on fuzzy systems, **14(6)** (2006) 808-821.
[34] A. S. Muneeza, M. Qiyas and M. A. Khan, Multi-criteria decision making based on intuitionistic cubic fuzzy numbers. Granular Computing, (2022) 1-11.
[35] M. Nie and W. W. Tan, Towards an efficient type-reduction method for interval type-2 fuzzy logic systems. In 2008 IEEE International Conference on Fuzzy Systems (IEEE World Congress on Computational Intelligence) (2008) 1425-1432, IEEE.
[36] V. L. G. Nayagam, S. Muralikrishnan and G. Sivaraman, Multi-criteria decision-making method based on interval-valued intuitionistic fuzzy sets. Expert Systems with Applications, **38(3)** (2011) 1464-1467.
[37] K. C. Ng and B. Abramson, Uncertainty management in expert systems. Ieee Expert, **5(2)** (1990) 29-48.
[38] F. Özen, Random forest regression for prediction of Covid-19 daily cases and deaths in Turkey. Heliyon, **10(4)** (2024).
[39] I. Riccioni, A. Bertolazzi, A. Tereszkiewicz, M. Szczyrbak and R. Bongelli, Uncertainty management during and about the COVID-19 pandemic. Frontiers in Communication, **9** (2024) 1357832.
[40] V. Rodriguez-Galiano, M. Sanchez-Castillo, M. Chica-Olmo and M. J. O. G. R. Chica-Rivas, Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. Ore Geology Reviews, **71** (2015) 804-818.
[41] A. Jog, A. Carass, S. Roy, D. L. Pham and J. L. Prince, Random forest regression for magnetic resonance image synthesis. Medical image analysis, **35** (2017) 475-488.
[42] M. Rahim, S. A. Bajri, S. Khan, H. Alqahtani and H. A. E. W. Khalifa, Innovative Multi-Criteria Group Decision Making with Interval-Valued p, q, r-Spherical Fuzzy Sets: A Case Study on Optimal Solar Energy Investment Location. International Journal of Fuzzy Systems, (2025) 1-28.
[43] C. Ruan, S. Gong and X. Chen, Multi-criteria group decision-making with extended ELECTRE III method and regret theory based on probabilistic interval-valued intuitionistic hesitant fuzzy information. Complex & Intelligent Systems, **11(1)** (2025) 92.
[44] S. Salimian and S. M. Mousavi, A multi-criteria decision-making model with interval-valued intuitionistic fuzzy sets for evaluating digital technology strategies in COVID-19 pandemic under uncertainty. Arabian Journal for Science and Engineering, **48(5)** (2023) 7005-7017.
[45] M. R. Segal, Machine learning benchmarks and random forest regression (2004).
[46] I. Siksnelyte-Butkiene, E. K. Zavadskas and D. Streimikiene, Multi-criteria decision-making (MCDM) for the assessment of renewable energy technologies in a household: A review. Energies, **13(5)** (2020) 1164.
[47] P. F. Smith, S. Ganesh and P. Liu, A comparison of random forest regression and multiple linear regression for prediction in neuroscience. Journal of neuroscience methods, **220(1)** (2013) 85-91.
[48] L. M. Soegianto, A. T. Hinandra, P. A. Suri and M. Fajar, Comparison of model performance on housing business using linear regression, random forest regressor, svr, and neural network. Procedia Computer Science, **245** (2024) 1139-1145.
[49] H. Taherdoost and M. Madanchian, Multi-criteria decision making (MCDM) methods and concepts. Encyclopedia, 3(1) (2023) 77-87.
[50] G. Varathan, A review of uncertainty management approaches for active distribution system planning. Renewable and Sustainable Energy Reviews, **205**(2024) 114808.
[51] J. Q. Wang, K. J. Li and H. Y. Zhang, Interval-valued intuitionistic fuzzy multi-criteria decision-making approach based on prospect score function. Knowledge-Based Systems, **27** (2012) 119-125.
[52] J. Q. Wang, Z. Q. Han and H. Y. Zhang, Multi-criteria group decision-making method based on intuitionistic interval fuzzy information. Group Decision and Negotiation, **23** (2014) 715-733.

[53] Y. J. Wang, L. J. Liu and T. C. Han, Interval-valued fuzzy multi-criteria decision-making with dependent evaluation criteria for evaluating service performance of international container ports. Journal of Marine Science and Engineering, **10(7)** (2022) 991.

[54] S. Ward, C. Chapman, Stakeholders and uncertainty management in projects. Construction management and economics, **26(6)** (2008) 563-577.

[55] D. Wu, J. M. Mendel, On the continuity of type-1 and interval type-2 fuzzy logic systems. IEEE Transactions on Fuzzy Systems, **19(1)** (2010) 179-192.

[56] L. Xue, Y. Liu, Y. Xiong, Y. Liu, X. Cui and G. Lei, A data-driven shale gas production forecasting method based on the multi-objective random forest regression. Journal of Petroleum Science and Engineering, **196** (2021) 107801.

[57] E. K. Zavadskas and Z. Turskis, Multiple criteria decision making (MCDM) methods in economics: an overview. Technological and economic development of economy, **17(2)** (2011) 397-427.

[58] Z. Zhou, C. Qiu and Y. Zhang, A comparative analysis of linear regression, neural networks and random forest regression for predicting air ozone employing soft sensor models. Scientific Reports, **13(1)** (2023) 22420.

[59] L. Zhong, L. Yao, An ELECTRE I-based multi-criteria group decision making method with interval type-2 fuzzy numbers and its application to supplier selection. Applied Soft Computing, **57** (2017) 556-576.