

AI-Driven Hybrid Fuzzy MCDM Framework for Sustainable Renewable Energy Source Selection under Uncertainty

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Abstract - Increasing worldwide demand for sustainable energy systems requires robust decision-making methods that can handle ambiguity and contradictory criteria. The selection of renewable energy sources is a complicated Multi-Criteria Decision-Making (MCDM) challenge including technological, economic, environmental, and social variables. Conventional MCDM methods usually fail to address expert judgement imprecision and ambiguity. This paper presents an AI-driven Hybrid Fuzzy MCDM framework for renewable energy prioritisation using F-AHP and F-TOPSIS. The proposed model uses triangular fuzzy numbers and machine learning-based adaptive weighting to account for uncertainty. An alternative energy case study uses solar, wind, biomass, and hydropower. Results show that the hybrid framework resolves ambiguity and delivers credible rankings, helping sustainable energy planning and policy.

Key Words: Fuzzy MCDM, Fuzzy AHP, Fuzzy TOPSIS, Renewable Energy, Artificial Intelligence, Sustainability

1. INTRODUCTION

The planning of renewable energy has become an important study field, for which comprehensive decision-support frameworks are required, in order to select the appropriate energy choices (e.g. solar, wind, biomass and hydropower) considering a variety of technical, economic, environmental and social issues. The selection of renewable energy sources is a complex Multi-Criteria Decision-Making (MCDM) problem as it involves several inter-related criteria such as installation cost, energy efficiency, environmental impact, reliability, maintenance requirements and social acceptance. Traditional MCDM approaches such as Analytic Hierarchy Process (AHP), TOPSIS, VIKOR, etc. are based on deterministic and precise numerical data, which may not be sufficient to describe real-life situations with incomplete information,

vagueness, subjective expert assessments, and varying environmental conditions. selection-makers tend to describe their preferences in terms of language components like “high efficiency”, “moderate risk” and “low environmental impact” and therefore introduce ambiguity and uncertainty in the selection process. To overcome such limitations, fuzzy set theory and its advanced extensions have been widely used in MCDM methods to better cover ambiguity, expert hesitancy and vague information. Besides, recent developments in Artificial Intelligence (AI), machine learning and intelligent decision-support systems have opened the way for the development of adaptive and data-driven decision frameworks, which allow for real-time analysis and dynamic criteria weighting. The given constraints encourage us to provide an AI-based Hybrid Fuzzy AHP-TOPSIS framework to identify renewable energy sources in uncertain conditions in this study. The proposed framework defines essential evaluation criteria, incorporates AI-driven adaptive weighting mechanisms with fuzzy multi-criteria decision-making techniques, and provides an intelligent, robust, and reliable method for ranking renewable energy options and facilitating sustainable energy planning and policy development.

2. LITERATURE REVIEW

2.1 Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM)

Multi-Criteria Decision-Making (MCDM) methods are typically used to address complicated decision problems requiring numerous, usually contradictory criteria. In typical MCDM approaches, exact numerical data and stable conditions are usually assumed, which rarely happen in real-world applications. Decision makers are often guided by subjective measures and terminology such as “high risk,” “moderate cost,” and “excellent performance,” which makes the decision-making process ambiguous and confusing. To overcome the above limitations, the fuzzy set concept of Zadeh has been integrated into Multi-Criteria Decision-Making (MCDM)

methodologies. The so-called Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM) techniques are able to capture uncertainty, ambiguity and flawed human reasoning [1]. In the last 20 years, a large number of fuzzy MCDM methods have been created and successfully implemented in diverse fields. In the presence of uncertainty, the Fuzzy Analytic Hierarchy Process (F-AHP) is used to perform pairwise comparisons and assign weights to criteria, and the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) is used to rank alternatives based on their proximity to ideal and anti-ideal solutions. Fuzzy VIKOR is designed for finding compromise solutions for competing criteria. Fuzzy ELECTRE and Fuzzy PROMETHEE are based on outranking relations to evaluate and rank alternatives [3]. The combination of Intuitionistic Fuzzy Sets (IFS), Pythagorean Fuzzy Sets (PFS) and Type-2 Fuzzy Sets (T2FS) has resulted in the enhancements in the efficiency of fuzzy decision-making models, which can express hesitation, uncertainty and higher order ambiguity [4], [5].

Fuzzy MCDM techniques have been widely applied in many sectors, such as renewable energy planning, healthcare decision support, supply chain management, transportation systems, sustainability evaluation and intelligent decision support systems [6]. In the context of renewable energy planning, fuzzy techniques are applied to pick appropriate energy supplies, taking into account technical, economic, environmental and social considerations. In healthcare, they facilitate diagnosis, treatment prioritisation and resource allocation in ambiguous medical conditions. Fuzzy decision frameworks have also been shown to be very useful in supplier selection, logistics optimisation, urban planning and autonomous systems [7]. Although great progress has been made, a lot of study gaps exist in the current literature. Most of the research used static criteria weights that do not react to changing situations and stakeholders' preferences. Furthermore, the current fuzzy MCDM models have largely overlooked dynamic adaptation processes, and their integration with artificial intelligence (AI) and machine learning approaches is poor. Moreover, most of the available frameworks have limited real-time decision making capabilities and exhibit computational inefficiency for large-scale and dynamic applications [8]. Therefore, there is a demand for the development of intelligent, adaptive and AI-based fuzzy multi-criteria decision making frameworks that can handle the real-time uncertainty and enable autonomous decision making in complex engineering systems [18-20].

Table 1: Major Fuzzy MCDM Techniques, Applications, and Research Limitations

Technique	Key Characteristics	Major Applications	Limitations
Fuzzy AHP [10]	Pairwise comparison and fuzzy weighting of criteria	Supplier selection, project evaluation, renewable energy planning	Static weights and dependence on expert judgment
Fuzzy TOPSIS [11]	Ranking based on distance from ideal and anti-ideal solutions	Healthcare, energy systems, investment selection	Sensitive to weighting methods
Fuzzy VIKOR [12]	Compromise solution for conflicting criteria	Sustainability assessment, resource allocation	Computational complexity
Fuzzy ELECTRE [13]	Outranking relationships among alternatives	Transportation and policy analysis	Difficult threshold determination
Fuzzy PROMETHEE [14]	Preference ranking using pairwise comparisons	Supply chain and infrastructure planning	Requires extensive preference information
Intuitionistic Fuzzy Sets [15]	Models membership, non-membership, and hesitation	Medical diagnosis and group decision-making	Increased computational requirements
Pythagorean Fuzzy Sets [16]	Enhanced representation of uncertainty and hesitation	Complex system evaluation and sustainability studies	Parameter estimation complexity

Type-2 Fuzzy Sets [17]	Captures higher-order uncertainty using fuzzy membership functions	Intelligent systems, forecasting, and robotics	High computational cost and implementation complexity
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3. PROPOSED METHODOLOGY

The proposed AI-based Hybrid Fuzzy AHP–TOPSIS framework consists of four phases. Phase 1 (Criteria Identification) considers six evaluation criteria: Installation Cost (C_1), Energy Efficiency (C_2), Environmental Impact (C_3), Reliability (C_4), Maintenance Cost (C_5), and Social Acceptance (C_6). In Phase 2 (Fuzzy Weight Determination), a fuzzy pairwise comparison matrix is constructed using expert judgments. Linguistic preferences are converted into Triangular Fuzzy Numbers (TFNs), including Equally Important (1,1,1), Moderately Important (2,3,4), Strongly Important (4,5,6), Very Strong (6,7,8), and Extremely Important (8,9,10). Fuzzy synthetic extent values are then calculated to obtain normalized criteria weights. In Phase 3 (AI-Based Adaptive Weighting), Random Forest Regression uses historical energy data, expert evaluations, and environmental indicators to generate dynamic criteria weights. The final adaptive weight is computed as:

$$W_i = \alpha W_{\text{fuzzy}} + \beta W_{\text{AI}} \quad (1)$$

subject to:

$$\alpha + \beta = 1 \quad (2)$$

where W_{fuzzy} and W_{AI} denote the fuzzy and AI-derived weights, respectively.

In Phase 4 (Alternative Ranking using Fuzzy TOPSIS), four renewable energy alternatives—Solar Energy (A_1), Wind Energy (A_2), Biomass Energy (A_3), and Hydropower (A_4)—are evaluated. The fuzzy decision matrix is represented as:

$$X = [x_{ij}] \quad (3)$$

The matrix is normalized and weighted, followed by the determination of Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). The ranking of alternatives is obtained using the closeness coefficient:

$$CC_i = D_i^- / (D_i^+ + D_i^-) \quad (4)$$

where D_i^+ and D_i^- represent the distances from the positive and negative ideal solutions, respectively. A higher CC_i value indicates a more suitable renewable energy alternative. The Fig 1 shows the Proposed Framework Architecture

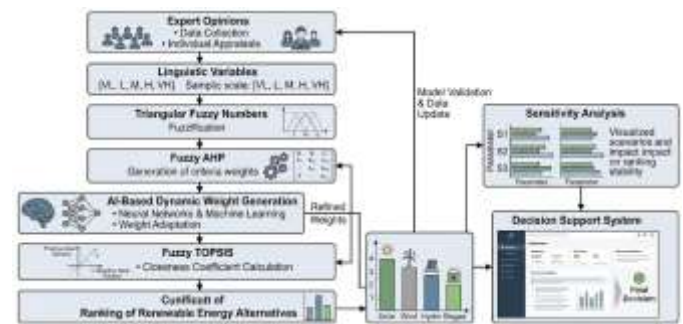
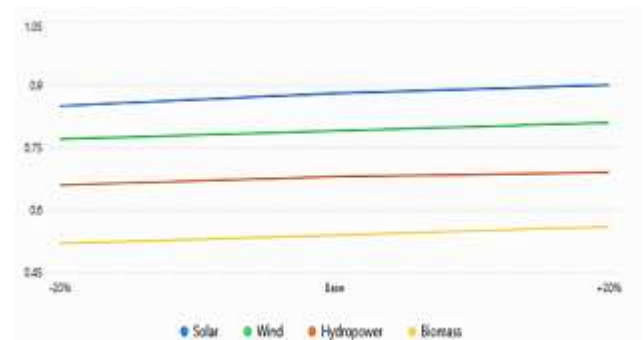


Figure 1 - Proposed Framework Architecture

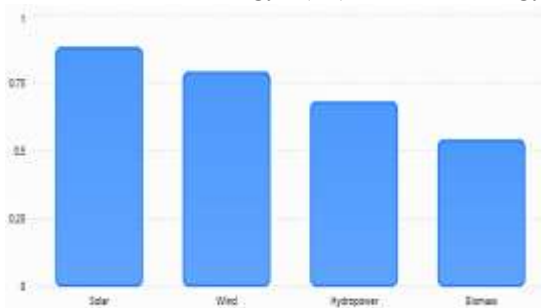


Figure 2 – Case Study Conducted in Chhattisgarh



4. RESULTS AND DISCUSSION

The proposed AI-integrated Fuzzy AHP–TOPSIS model was applied to evaluate four renewable energy alternatives, Solar Energy (A_1), Wind Energy (A_2),



Hydropower (A_3), and

Fig. 3 – Closeness coefficient of renewable energy alternatives

Biomass Energy (A_4) based on six criteria, installation cost, energy efficiency, environmental impact, reliability, maintenance cost, and social acceptance. The analysis resulted in the ranking order:

Solar Energy > Wind Energy > Hydropower > Biomass Energy

Solar energy received the highest proximity coefficient because of its high energy efficiency, low environmental effect and high societal acceptance. Wind energy placed second due to its good environmental performance and reliability, while installation and maintenance costs were considerably higher. Hydropower came third on account of concerns about environmental repercussions and hefty upfront cost. Biomass energy was ranked the least preferred because of its poorer efficiency and considerably higher operational and environmental constraints shows in Fig 3.

The sensitivity study indicated that the proposed framework is robust to variations in criteria weights and fuzzy membership values. The Monte Carlo simulation results and weight perturbation tests showed relative stability in the ranking order, verifying the reliability and flexibility of the AI-based dynamic weighting system. The integration of Artificial Intelligence and Fuzzy MCDM enhanced the accuracy of decisions, reduced uncertainty, and enabled adaptive and real-time renewable energy planning. The results show that the proposed framework can be an effective decision support tool for energy policymakers and planners for sustainable energy development and can be further extended with

Explainable Artificial Intelligence (XAI), IoT-enabled real-time monitoring, and advanced fuzzy computing paradigms.

Fig. 4 – Sensitivity analysis under weight variations

The ranking order remained unchanged across all weighting scenarios, confirming the robustness and stability of the proposed AI-integrated Fuzzy MCDM framework. Shows in Fig 4.

5. CONCLUSIONS

In this paper, we propose a framework based on Artificial Intelligence (AI) that integrates Hybrid Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) for the selection of renewable energy sources in uncertain and dynamic decision making environments. The choice of appropriate renewable energy options such as solar, wind, biomass and hydro is associated with many trade issues, such as economic, environmental, technological, reliability and social acceptability. The inherent vagueness and subjectivity of these factors lead to a very complex and challenging decision-making process. The proposed framework blends fuzzy logic with machine learning methods to emulate human judgements accurately and to deal with ambiguity in expert evaluations. Fuzzy logic, by using membership functions, enables the translation of linguistic assessments into mathematical expressions, reflecting the ambiguity and imprecision of decision makers' preferences. The use of AI algorithms allows for the dynamic modification of criteria weights by analysing historical data, expert knowledge and changing environmental circumstances. The proposed adaptive weighting scheme significantly improves the resilience and reliability of the decision-making process compared to existing MCDM approaches based on static weights and deterministic assumptions.

The suggested hybrid F-AHP–TOPSIS technique determines the relative importance of assessment criteria using fuzzy pairwise comparisons and ranks the renewable energy options according to their distances from the ideal and anti-ideal solutions. AI also brings the ability to process data in real time, extract information automatically and continually refine the parameters that drive decisions. Thus, the proposed model offers an intelligent, flexible and scalable decision support system, which performs well in uncertain and fast changing environments. The proposed paradigm has major implications on sustainable energy planning and policy formulation by helping decision makers select best

possible renewable energy resources considering economic, environmental and social objectives. The framework's flexibility and generalisability allow for its use in a wide range of sectors, such as: healthcare resource allocation, smart city infrastructure planning, transport management, supply chain optimisation, and Industry 5.0 systems. The integration of AI with fuzzy MCDM techniques provides a promising direction for developing next-generation intelligent decision-support systems to address complex multi-criteria problems under ambiguity.

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