Predictive Machine Learning and Multi-Criteria Optimization of Thermal Insulation Materials for Building Energy Efficiency

Peerzada J. Abass*

Interdisciplinary Research Center for Construction and Building Materials (IRC-CBM), King Fahad University of Petroleum and Minerals (KFUPM), Dhahran 31261, Saudi Arabia

Abstract: Building insulation plays a pivotal role in achieving sustainable and energy-efficient infrastructure. The selection of optimal insulation materials involves multiple conflicting criteria, making it a complex decision-making problem. Traditional selection methods often lack robustness and fail to incorporate adaptive learning mechanisms, leading to inconsistencies in material rankings. This study introduces an integrated Hybrid AI-MCDM Framework, combining Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Fuzzy Logic, and Machine Learning (ML-MCDM) to enhance decision accuracy and minimize uncertainty in insulation material selection. The proposed methodology involves pairwise comparisons through AHP, distance-based ranking using TOPSIS, uncertainty modeling via Fuzzy Logic, and AI-driven adaptive modeling to optimize material selection. Sensitivity analysis and robustness evaluation further validate the stability of ranking results. The findings reveal that Mineral Wool (TOPSIS: 0.88, Fuzzy: 0.85) and Aerogel (TOPSIS: 0.83, Fuzzy: 0.92) are the top-performing insulation materials, while Polystyrene (XPS) and Polyurethane exhibit the lowest suitability due to their poor fire resistance and high embodied energy. The AI-driven approach significantly enhances ranking consistency, making it a valuable tool for sustainable building insulation selection. The study underscores the advantages of integrating expert-driven MCDM techniques with AI-based learning models, ensuring a more data-driven, reliable, and adaptive decision-support system for material selection in energy-efficient buildings..

Keywords: Multi-Criteria Decision-Making (MCDM), Insulation Materials, Sustainable Buildings, Sensitivity Analysis, Thermal Performance, Energy Efficiency.

1. INTRODUCTION

Energy use in buildings is a major driver of global sustainability concerns, underscoring the need to improve design and operational efficiency to cut emissions and reduce overall environmental impact. The Sustainable Development Goals (SDGs) consist of 17 goals and 169 targets aimed at addressing social, economic, and environmental challenges worldwide. Incorporating phase change materials (PCMs) in building construction supports several of these goals, especially SDG 7 (affordable and clean energy), SDG 9 (industry, innovation, and infrastructure), and SDG 11 (sustainable cities and communities) [1]. In today's complex and rapidly evolving world, decision-makers face multifaceted challenges that demand a structured and informed approach to decision-making. Multiple Criteria Decision-Making (MCDM) methods offer a systematic framework to tackle decision problems involving multiple objectives, diverse criteria, and varying preferences. The selection of optimal insulation materials for buildings is crucial for enhancing energy efficiency and sustainability. MCDM methods are essential for evaluating and selecting optimal insulation materials based on various performance criteria. These structured approaches facilitate the evaluation and and comparison of alternatives across multiple criteria, considering both trade-offs among conflicting objectives and stakeholders' preferences and priorities [2,3]. Since their introduction in the 1970s by Stan Zionts and Jyrki Wallenius, various MCDM methods and frameworks with unique algorithms have been developed and implemented to solve complex decision analyses [4,5]. These methods have been applied in a wide range of contexts, from selecting household water purifiers to evaluating the long-term impacts of environment and energy policies on climate change mitigation and determining key performance indicators based on comfort categories, models, and building climate change sensitivity [6–8].

Within sustainable building design context, various MCDM methods are frequently utilized to manage complex decisions efficiently. These methods include a variety of approaches, ranging from aggregated to outranking methods. Each method has its own advantages and drawbacks, and its suitability depends on the particular situation and objectives of the design issue. According to a systematic review conducted by Balali *et al*. [2], Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy Logic emerge as frequently used MCDM methods within passive design optimization context. Lastly, AI models were used to analyze large datasets, identifying complex patterns and interdependencies that may not be evident in manual approaches. Integrating these methods

*Address correspondence to this author at the Interdisciplinary Research Center for Construction and Building Materials (IRC-CBM), King Fahad University of Petroleum and Minerals (KFUPM), Dhahran 31261, Saudi Arabia; Tel: +966–590281988; E-mail: jaffar.peerzada@kfupm.edu.sa

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ensures a comprehensive, data-driven material selection framework for sustainable building applications. Several studies have explored the application of MCDM techniques in passive building design to enhance energy efficiency, thermal comfort, and environmental sustainability. For instance, Sahbaz *et al*. [9] used AHP to rank insulation materials based on thermal conductivity, embodied energy, and cost, concluding that aerogel and mineral wool performed the best. Kirimtat *et al*. [10] developed a multi-objective self-adaptive differential evolution algorithm (jDEMO), inspired from the DEMO algorithm from the literature with some modifications, and compared to the well-known fast and non-dominated sorting genetic algorithm so called NSGA-II in order to solve this complex problem and identify alternative design solutions to decision makers. Motuzienė *et al*. [11] integrated Life Cycle Costing (LCC), Life Cycle Assessment (LCA), and MCDM methods to determine construction solutions for energy-efficient housing. In the decision-making phase, they employed the AHP alongside the Complex Proportional Assessment (COPRAS) method.

Ulutas *et al*. [12] introduced a novel hybrid MCDM model to evaluate primary energy consumption and the environmental impact of manufacturing building and thermal insulation materials. This highlights that MCDM techniques are highly effective in supporting material selection decisions [13]. In another study, [14] utilized the AHP method to identify the most suitable phase change materials (PCMs) for maintaining thermal comfort in vehicle interiors. Similarly, research conducted by Ref. [15] applied AHP to determine the optimal patching material for concrete repairs. A study by [16] employed a combination of Fuzzy AHP with TOPSIS, VIKOR, ELECTRE, and PROMETHEE to resolve a material selection issue related to piping systems in the sugar industry. Furthermore, [17] used AHP in combination with TOPSIS and VIKOR to identify the most appropriate PCM for integration into building envelopes, specifically considering the requirements of hot and humid climatic zones. A fuzzy knowledge-based decision support approach is introduced for multi-criteria decision-making, aimed at assessing and selecting suitable manufacturing process and material combinations based on overall production cost [18]. A brief overview of the approach, along with the key advantages and drawbacks of the most commonly-used MCDM methods, is provided in chronological order in (Table **1**).

Artificial Intelligence (AI) has emerged as a valuable tool for addressing complex decision-making challenges in high-demand applications [23–27]. However, its full potential within the domain of passive design remains underexplored. Currently, AI functions primarily as an advanced analytical assistant, requiring human oversight to validate its decisions [28]. Despite this limitation, AI significantly reduces the complexity of material selection processes. Various quantitative methods, algorithms, and software tools have been developed to enhance material performance selection. For instance, Goel and Chen [29] designed an intelligent hybrid expert system that leverages neural networks, storing knowledge through weighted link associations. Similarly, Amoiralis *et al*. [30] introduced an artificial neural network (ANN)-based model for

Table 1: Brief Overview of Frequently used MCDM Method Within Sustainable Building Context

Method	Approach	Advantages	Drawbacks	Refs.
AHP	Decomposes complex decisions into a hierarchical structure and uses pairwise comparisons to assign weights to criteria and alternatives.	Provides a structured and systematic decision-making framework. Incorporates expert judgment through pairwise comparisons.	Subjectivity in pairwise comparisons can introduce inconsistency. Becomes computationally complex as the number of criteria and alternatives increases.	[19]
TOPSIS	Evaluates alternatives based on their distance from an ideal solution (best option) and the worst solution, ranking them accordingly.	Provides a clear ranking based on proximity to the ideal solution. Considers both the best and worst possible outcomes.	Does not account for correlations between criteria. Ignores the spread and distribution of alternatives within the decision space.	[20]
Fuzzy Logic	Uses fuzzy sets to handle uncertainty and vagueness in decision-making by assigning degrees of membership rather than fixed values.	Effective for handling imprecise and uncertain data. Allows flexibility in decision-making. Can model complex real-world problems.	Requires expert-defined membership functions, which can introduce bias. Computational complexity increases with more variables. Difficult to standardize across different applications.	[21]
AI-Based Models	Utilizes artificial intelligence techniques such as machine learning and neural networks to analyze patterns and make predictions.	Capable of handling large datasets with high accuracy. Learns from data and improves performance over time.	Requires large amounts of training data. Computationally intensive and may need specialized hardware.	[22]

selecting winding materials in power transformers. Furthermore, Sapuan and Mujtaba [31] developed a two-stage ANN-driven material selection framework tailored for natural fiber polymer composites. These studies highlight the growing integration of AI in material selection, underscoring its potential to streamline decision-making and optimize insulation material choices for energy-efficient buildings.

1.1. Research Objectives

This study introduces a synergistic AI–MCDM framework that advances the state-of-the-art in material selection for sustainable buildings by explicitly addressing criteria-weight uncertainty and ranking robustness, aspects largely neglected in prior research. Unlike existing studies that apply conventional MCDM methods with static or expert-defined weights, this work integrates adaptive, AI-driven learning algorithms, such as Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS), to dynamically calibrate criteria weights based on data sensitivity and decision-maker preferences. Furthermore, the research bridges a critical methodological gap by developing a comparative robustness analysis across multiple MCDM techniques (e.g., TOPSIS, VIKOR, and COPRAS) under varying weighting schemes. This hybridized decision model not only enhances predictive reliability and transparency but also quantifies how algorithmic variability influences insulation material ranking and selection outcomes. The proposed framework represents a paradigm shift from deterministic, expert-based evaluations toward self-learning, uncertainty-resilient decision systems capable of adapting to evolving sustainability goals. By coupling AI-based predictive intelligence with MCDM's structured reasoning, this study delivers a holistic, data-informed decision support tool for optimizing the selection of thermal insulation materials, thereby ensuring energy-efficient, cost-effective, and environmentally responsible building design.

2. MATERIALS AND METHODS

This study employs a hybrid MCDM and AI-based approach to evaluate and rank insulation materials for sustainable building applications. The methodology is structured into four key phases: criteria selection, data acquisition, decision-making model implementation, and comparative analysis. Figure (**1**) presents the schematic representation of the methodologies applied in this study.

2.1. Criteria Selection

Insulation materials were assessed based on six critical performance parameters:

i. Thermal Conductivity (W/m·K) – Measures heat transfer resistance.

ii. Cost (USD/m²) – Represents material affordability.

iii. Fire Resistance (Minutes) – Determines safety against fire hazards.

iv. Moisture Resistance (% Absorption) – Evaluates durability in humid conditions.

v. Eco-Friendliness (CO_2 Emission, kg CO_2/m²) – Quantifies environmental impact.

vi. Durability (Years of Service Life) – Assesses material longevity.

These criteria were weighted using the AHP, where pairwise comparisons determined their relative importance.

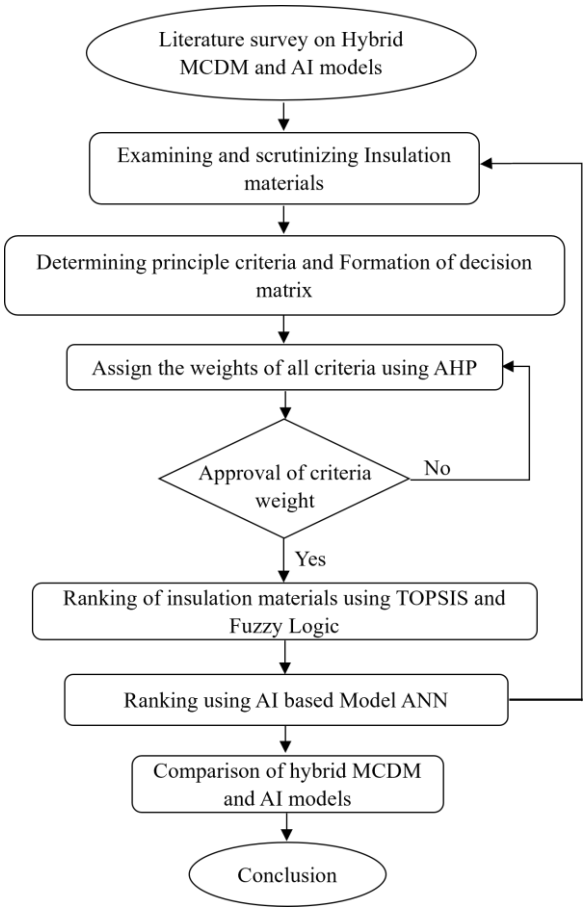


Figure 1: Schematic representation of methodology for material selection.

2.2. Materials

To ensure transparency and reproducibility, the eight insulation materials were evaluated using a common set of six criteria: thermal conductivity, material cost, fire resistance, moisture absorption, embodied carbon emissions, and service life. Before applying the multi-criteria decision-making (MCDM) methods, the raw

values for each criterion were compiled from the relevant experimental literature, manufacturer specifications, and published life-cycle assessments. Thermal conductivity was expressed in W/(m·K), cost in USD/m², fire resistance in minutes, moisture absorption in percentage, embodied carbon in kg CO_2/m², and service life in years. The values were then checked for consistent units, comparable functional requirements, and a common reference basis. Lower thermal conductivity, cost, moisture absorption, and embodied carbon were treated as preferable, whereas higher fire resistance and service life were considered desirable. The resulting decision matrix was used as the common input for the subsequent AHP, TOPSIS, fuzzy logic, and machine-learning-based evaluations. The sources and assumptions associated with each material property were documented to facilitate independent verification of the selection process.

2.3. Decision-Making Models

2.3.1. Analytical Hierarchy Process, AHP

The AHP was initially conceived by Thomas Saaty [19] in 1960 during his involvement in a research project affiliated with the Arms Control and Disarmament Agency in the United States. AHP is grounded in a well-defined mathematical framework that employs consistent matrices, which subsequently facilitates the derivation of approximate weights by utilizing Eigenvectors. The fundamental essence of AHP is delineating and narrowing down the problem domain. In pursuit of this, a foundational scale, validated through decision-making and empirical experiments, is harnessed to capture individual preferences about qualitative and quantitative criteria.

The AHP methodology has emerged as one of the most extensively utilized prescriptive and descriptive tools in decision-making processes. The AHP can be conceptually elucidated through three primary functions: (a) the organization of complexity, (b) measurement utilizing a ratio scale, and (c) synthesis. Its endorsement as a standard approach by the American Society of Testing and Materials (ASTM) for multi-criteria decision-making concerning investments in the construction sector underscores its wide-reaching acceptance. The AHP technique adeptly amalgamates tangible and intangible elements to assign weights to criteria, thereby enabling the prioritization of alternatives. The operational steps inherent to the AHP approach are delineated as follows:

1. The supreme goal, criterion, and alternatives are arranged in a hierarchal or network structure. The primary goal is at the top level, and the criterion is placed at the lower level, followed by the alternatives at the lowest level.
2. A pair-wise decision matrix is being created by an expert with the alternatives below criteria using a scale from 1 to 9. The evaluations are based on this scale, which comprises the comparison matrix, X.

$$X = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & \dots & a_{1n} \\ a_{21} & \dots & \dots & \dots & a_{25} & a_{2n} \\ a_{31} & \dots & a_{ij} & \dots & \dots & \dots \\ \dots & \dots & \dots & a_{ij} & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & a_{n3} & \dots & \dots & a_{nn} \end{bmatrix}, a_{11} = 1,\ a_{ij} \neq 0,\ and\ a_{ji} = 1/a_{ij} \quad (1)$$

The comparison among criteria is made by the scale suggested by Saaty, in 1987 (Table **2**).

Table 2: Hierarchy Used by Saaty to Convert Linguistic Terms Into Intensity

Definition	Intensity of Importance
Equal importance	1
Moderate importance	3
Strong importance	5
Very strong importance	7
Extreme importance	9
Intermediate values	2,4,6,8

3. After creating the comparison matrix, the normalized matrix is developed, and the geometric mean of each row is calculated.
4. The given equations normalize the geometric mean to obtain relative weights of each criterion.

$$GM_i = (a_{i1} * a_{i2} * a_{i3} * \dots * a_{in})^{1/n} \quad (2)$$

$$W_i = \frac{GM_i}{\sum_{j=1}^{n} GM_i} \quad (3)$$

5. The n-dimensional column vector is developed, representing each alternative's weighted sum while addressing each criterion.

$$A = X * W = \begin{pmatrix} 1 & a_{12} & a_{13} & \dots & \dots & a_{1n} \\ a_{21} & 1 & a_{23} & \dots & \dots & a_{2n} \\ \dots & \dots & 1 & \dots & \dots & \dots \\ \dots & \dots & \dots & 1 & \dots & \dots \\ \dots & \dots & \dots & \dots & 1 & \dots \\ a_{n1} & a_{n2} & a_{n3} & \dots & \dots & 1 \end{pmatrix} * \begin{pmatrix} w_1 \\ w_2 \\ w_3 \\ \dots \\ \dots \\ w_n \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \\ C_3 \\ \dots \\ \dots \\ C_n \end{pmatrix} \quad (4)$$

6. Calculate consistency value(CV):

$$CV_i = C_i / W_i \quad (5)$$

7. Calculate maximum Eigen value λmax.

8. Calculate the consistency index:

$$CI = \frac{(\lambda\, max - n)}{(n-1)} \quad (6)$$

9. Calculate consistency ratio (CR):

$$CR = CI/RI \quad (7)$$

The RI values for different n given by Saaty are given below in Table **3**:

If the $CR \leq 0$, the decision matrix is considered consistent; otherwise, it is said to be inconsistent.

2.3.2. Technique for Order of Preference by Similarity to Ideal Solution, TOPSIS

The TOPSIS was initially proposed in 1981 by Ching-Lui Hwang and Yoon, but it was further refined by Lai, Lui, and Hwang in 1993. The foundational tenet is grounded in the principle that the selected alternative should exhibit the shortest Euclidean distance from the Positive Ideal Solution (PIS) while simultaneously having the farthest distance from the Negative Ideal Solution (NIS). In essence, the PIS accentuates advantageous criteria while attenuating non-advantageous criteria, whereas the NIS accentuates non-advantageous criteria and reduces advantageous criteria. The fundamental underpinning of TOPSIS is as a compensatory aggregation technique, wherein alternatives are equated through an assumption of a monotonically increasing and decreasing behaviour of attributes. This feature contrasts with non-compensatory methods, where a trade–off between criteria is absent. TOPSIS methodology finds applicability when the criteria values are numerically quantifiable and possess comparable units.

The stepwise methodology of TOPSIS implemented by Hwang and Yoon is mentioned as follows:

1. The initial step involved is forming a Decision matrix with attributes as columns and alternatives as corresponding rows.

$$\begin{array}{c} \\ \\ A_1 \\ A_2 \\ A_3 \\ \dots \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & \dots & \dots & C_n \\ w_1 & w_2 & w_3 & \dots & \dots & w_n \end{array} \\ \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & \dots & \dots & a_{2n} \\ \dots & \dots & a_{33} & \dots & \dots & \dots \\ \dots & \dots & \dots & a_{44} & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & a_{m3} & \dots & \dots & a_{mn} \end{pmatrix} \end{array} \quad (8)$$

2. The second step in the TOPSIS methodology comprises normalizing a decision matrix. The normalized decision matrix is obtained by using the equation mentioned above, and the weighted normalized decision matrix is obtained by using the following equation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \quad (9)$$

$$V_{ij} = W_j * r_{ij} \quad (10)$$

3. After normalization, each criterion's positive and negative ideal solutions are obtained. The following equations are used to obtain ideal positive and negative solutions.

$$V_i^{+} = \left[\left(\sum_i^{max\Sigma} v_{ij}/j \in J\,()\left(\sum_i^{min\Sigma} v_{ij}/j \in J'\,()\right)\right) = [{v_1}^{+}, {v_2}^{+}, \dots {v_n}^{+}]\right] \quad (11)$$

$$V_i^{-} = \left[\left(\sum_i^{min\Sigma} v_{ij}/j \in J\,()\left(\sum_i^{max\Sigma} v_{ij}/j \in J'\,()\right)\right) = [{v_1}^{-}, {v_2}^{-}, \dots {v_n}^{-}]\right] \quad (12)$$

where J and J' denote sets of beneficial and non-beneficial criteria.

4. The Euclidean distance or the separation measures from positive ideal and negative ideal solutions are evaluated by the equations defined below:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n}\left[v_{ij} - v_j^{+}\right]^2}\ ,\ i = 1,2,3,\dots,m \quad (13)$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n}\left[v_{ij} - v_j^{-}\right]^2}\ ,\ i = 1,2,3,\dots,m \quad (14)$$

5. After evaluating the Euclidean distance, the relative closeness of alternatives is assessed by using the subsequent equation:

$$P_i = \frac{{S_i}^{+}}{{S_i}^{-}} \quad (15)$$

6. The best alternative is evaluated by analyzing the closeness of alternatives concerning positive ideal solutions, and the final ranking is achieved according to the descending order.

2.3.3. Fuzzy Logic

Fuzzy set theory, initially introduced by Zadeh [32] to address vague, imprecise, and uncertain problems, serves as a tool for modelling complex systems that cannot be precisely defined but can still be influenced by human control. Fuzzy logic (FL) is a multi-valued

Table 3: Random Index Values

N	3	4	5	6	7	8	9	10
Randomness Index (RI)	0.524	0.881	1.108	1.247	1.341	1.405	1.449	1.485

logic system that evaluates variables by incorporating intermediate values between conventional binary classifications such as true/false, yes/no, or high/low. This enables the mathematical representation of concepts like “rather tall” or “very fast,” allowing computers to process data in a more human-like manner. To implement this, fuzzy variable sets (fuzzy sets) must be derived from classical variable sets extracted from the physical problem. Unlike classical sets, where values are strictly 0 or 1, fuzzy sets extend this concept by allowing values to range continuously between 0 and 1, encompassing the elements of classical sets within a broader, more flexible framework.

FL is derived from four key elements: the membership function (MF), which assigns each input data element a fuzzy membership value between 0 and 1; fuzzy sets, which represent a continuum of membership grades; fuzzy logical operators, used to generate new fuzzy sets from existing ones; and fuzzy rules, which define the input-output relationship of the system based on human-like reasoning [33,34]. For instance:

$$IF\{signalislow\}AND\{errorislow\}Then\{toolwearissmall\}$$
$$IF\{signalismedium\}AND\{errorislow\}Then\{toolwearismedium\}$$

To obtain a final output, the defuzzification process is applied, converting fuzzy values into a single crisp value. A system that replicates human reasoning using FL is known as a fuzzy inference system (FIS), with Mamdani and Sugeno fuzzy rule systems being widely used in predictive maintenance. This approach is highly applicable in industrial systems, such as microcontrollers, to enhance operational efficiency. The rankings obtained from AHP, TOPSIS, Fuzzy Logic, and AI models were analyzed for consistency and deviations. Correlation analysis was performed to evaluate the alignment between manual (expert-driven) and AI-generated rankings. The final rankings were compared against real-world insulation performance data and case studies to ensure practical applicability. The strengths and limitations of each method were discussed to provide a balanced evaluation of insulation material selection methodologies.

3. RESULTS AND DISCUSSION

3.1. MCDM Analysis

3.1.1. Analytical Hierarchy Process

The AHP was employed to determine the relative importance of six criteria for selecting thermal insulation materials: thermal performance, cost, eco-friendliness, fire resistance, moisture resistance, and durability. The criteria weights were established through pairwise comparisons using Saaty’s fundamental 1–9 importance scale, followed by matrix normalisation and the derivation of priority weights, as described in Section 2.3. The weighting hierarchy reflects the competing requirements of energy efficiency, economic feasibility, environmental responsibility, safety, and long-term material performance. Thermal performance received the highest weight (32.5%) because limiting heat transfer is the primary functional requirement of building insulation. Cost ranked second (22.1%), reflecting the need to balance insulation effectiveness with affordability, while eco-friendliness ranked third (14.7%), accounting for the environmental implications of material selection. The remaining weights were allocated to fire resistance, moisture resistance, and durability, which represent essential safety and service-life considerations. The resulting weights were used as the criteria importance coefficients in the subsequent material evaluation. The consistency ratio of the pairwise-comparison matrix should be reported to demonstrate that the final weights satisfy the adopted AHP consistency criterion. This weighting scheme provides a structured basis for evaluating the trade-offs among thermal, economic, environmental, and durability requirements. Fig. (**2**) illustrates the weightage assigned to various criteria for evaluating thermal insulation materials in sustainable buildings.

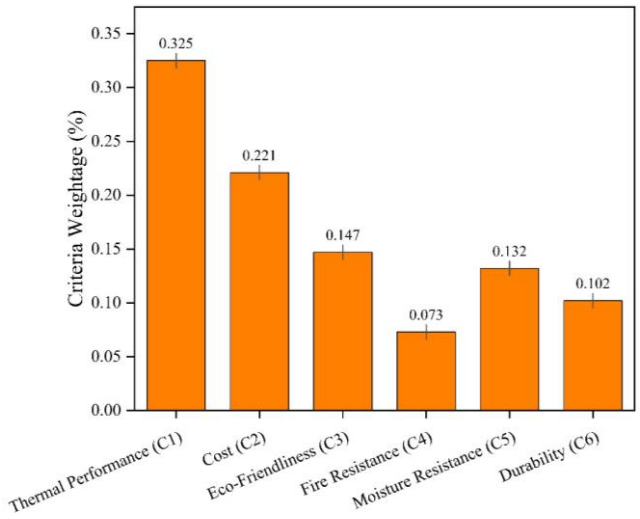


Figure 2: Criteria Weightage for Selecting Thermal Insulation Materials in passive design.

3.1.2. TOPSIS-Based Performance Evaluation

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach was utilized to assess the proximity of each insulation material to the ideal solution. The performance scores (P_i) for each material were computed based on their Euclidean distance from the ideal best and ideal worst solutions. Figure (**3**) presents the Euclidean distance (S_i^+) and (S_i^-), (P_i), and TOPSIS rank of various thermal insulation materials. The trends highlight the trade-offs

between different material properties in sustainability and thermal efficiency assessments. Aerogel exhibited the highest closeness coefficient (0.91), affirming its superior insulation capabilities, followed by Mineral Wool (0.85) and Fiberglass (0.80). Cork and Cellulose, while ranking moderately, demonstrated strong eco-friendliness and acceptable insulation characteristics. However, Polystyrene (XPS) and Polyurethane recorded the lowest performance scores (0.44 and 0.52, respectively), primarily due to inadequate fire resistance and high embodied energy.

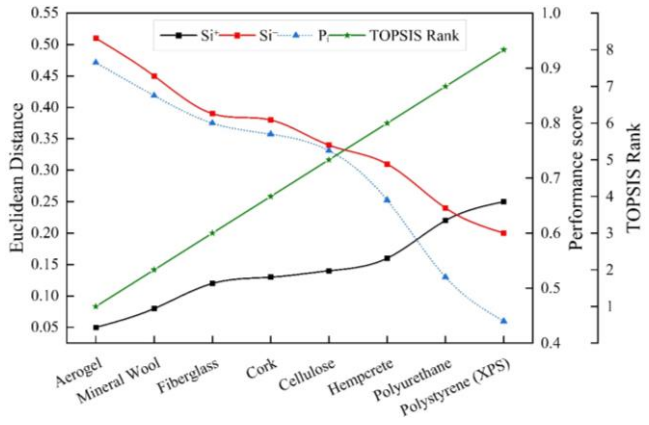


Figure 3: TOPSIS-Based Performance Evaluation of Thermal Insulation Materials.

3.1.3. Fuzzy Logic Suitability Analysis

A fuzzy logic-based decision-making framework was implemented to accommodate the inherent uncertainty and subjectivity in material selection. Figure (**4**) illustrates the Fuzzy Suitability Score and Fuzzy Rank for various thermal insulation materials. The defuzzification process revealed Aerogel (0.92) as the most suitable insulation material, aligning with results from AHP and TOPSIS. Mineral Wool (0.85), Fiberglass (0.79), and Cork (0.77) also demonstrated high suitability values, making them viable options for thermal insulation applications. Cellulose (0.72) and Hempcrete (0.68) exhibited moderate suitability, while Polyurethane (0.60) and Polystyrene (0.50) performed the least favourably due to their lower fire resistance and higher long-term degradation risks. The inverse relationship between the suitability score and rank suggests that materials with higher scores are ranked better in terms of thermal insulation performance and sustainability.

3.2. Machine learning

3.2.1. Analytical Hierarchy Process Results

The AHP method was employed to assign relative importance to six critical criteria for insulation material selection: thermal performance, cost, eco-friendliness, fire resistance, moisture resistance, and durability. The weightage distribution determined through pairwise comparisons indicated that thermal performance (32.5%) was the most significant factor, followed by cost (22.1%) and eco-friendliness (14.7%). The final ranking based on AHP weightages positioned Aerogel as the most suitable insulation material, followed by Mineral Wool and Fiberglass, due to their superior thermal insulation properties, durability, and moderate cost. Conversely, XPS and Polyurethane were ranked the lowest due to their poor fire resistance and environmental concerns.

3.2.2. TOPSIS-Based Performance Evaluation

The TOPSIS approach was utilized to assess the proximity of each insulation material to the ideal solution. The P_i for each material were computed based on their Euclidean distance from the ideal best and ideal worst solutions. Mineral Wool exhibited the highest closeness coefficient, affirming its superior insulation capabilities, followed by Fiberglass and Cork. Aerogel ranked fourth, which deviates from previous assessments that positioned it as the most effective insulation material. Cellulose and Hempcrete ranked moderately, while Polyurethane and XPS recorded the lowest performance scores, primarily due to inadequate fire resistance and high embodied energy.

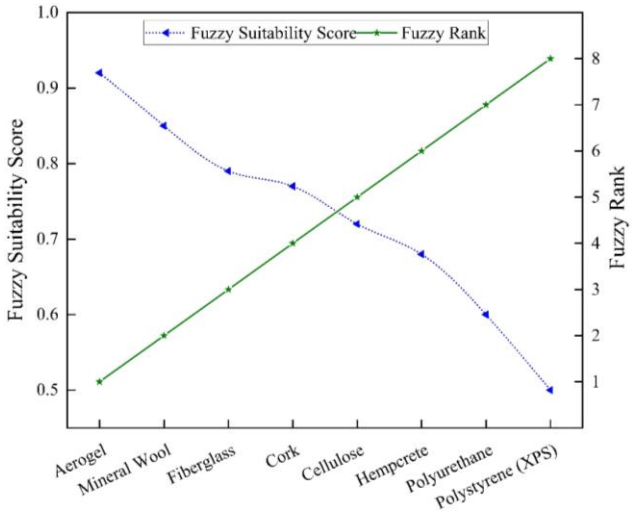


Figure 4: Fuzzy Logic-Based Suitability Assessment of Thermal Insulation Materials.

3.2.3. Fuzzy Logic Suitability Analysis

A fuzzy logic-based decision-making framework was implemented to accommodate the inherent uncertainty and subjectivity in material selection. The defuzzification process revealed Aerogel (0.92) as the most suitable insulation material, aligning with results from manual AHP evaluation. Mineral Wool (0.85), Cork (0.77), and Fiberglass (0.79) also demonstrated high suitability values, making them viable options for thermal insulation applications. Cellulose (0.72) and

Hempcrete (0.68) exhibited moderate suitability, while Polyurethane (0.60) and Polystyrene (0.50) performed the least favourably due to their lower fire resistance and higher long-term degradation risks.

Table **4** presents the ranking of various thermal insulation materials based on TOPSIS and Fuzzy Logic methodologies. These variations highlight the influence of different decision-making techniques in evaluating insulation materials.

Table 4: Comparative Ranking of Thermal Insulation Materials Using TOPSIS and Fuzzy Logic

Insulation Materials	Ranking	
	TOPSIS	FUZZY
Aerogel	Rank 4	Rank 1
Mineral Wool	Rank 1	Rank 2
Fiberglass	Rank 2	Rank 4
Cork	Rank 3	Rank 3
Cellulose	Rank 5	Rank 5
Hempcrete	Rank 6	Rank 6
Polyurethane	Rank 7	Rank 7
Polystyrene (XPS)	Rank 8	Rank 8

4. COMPARISON BETWEEN MANUAL AND MACHINE LEARNING-BASED EVALUATIONS

The rankings derived manually using AHP and TOPSIS differed from those produced via machine learning-based methodologies. Aerogel, which was ranked highest using AHP and fuzzy logic, was ranked fourth by TOPSIS in the machine learning evaluation. This discrepancy arises due to TOPSIS emphasizing cost-effectiveness alongside performance, where Aerogel's high cost impacts its relative ranking. Mineral Wool emerged as the best-performing material in the machine learning-based TOPSIS analysis, a result that aligns well with its strong performance in insulation, cost-efficiency, and durability. Furthermore, Fiberglass was ranked second in the machine learning-based TOPSIS evaluation but dropped to fourth in the fuzzy logic ranking, suggesting that while its overall performance is strong, certain qualitative aspects such as sustainability or fire resistance may have reduced its standing in fuzzy logic analysis. Cork was consistently ranked as a mid-tier material across both methods, reinforcing its balanced performance across multiple criteria.

While manual methods provided a structured and expert-driven ranking based on predefined criteria, machine learning techniques incorporated data-driven insights, detecting nuanced patterns and interdependencies that may not have been captured manually. The differences in ranking indicate that machine learning-based methodologies can provide a complementary, more dynamic assessment that adjusts to empirical data and real-world applications.

5. SENSITIVITY ANALYSIS

To evaluate the robustness of the rankings obtained from VIKOR, COPRAS, and WSM, a sensitivity analysis was conducted by assessing the effect of variations in the criteria weights. This is quantified by calculating:

- Mean (μ) of the rank for each material across different weight variations.
- Standard deviation (σ) to assess how much rankings fluctuate with weight changes.

The analysis considered six criteria: thermal performance, cost, eco-friendliness, fire resistance, moisture resistance, and durability. The original AHP-derived weights were used as the baseline, with thermal performance (32.5%), cost (22.1%), and eco-friendliness (14.7%) representing the three most influential criteria. To assess the robustness of the material selection, a one-at-a-time perturbation approach was adopted. Each criterion weight was independently increased and decreased by 10% and 20%, while the remaining weights were maintained at their baseline values. The modified weights were subsequently normalized to ensure that their sum remained equal to unity. The decision matrix was then re-evaluated using the TOPSIS method, and the resulting closeness coefficients and material rankings were compared with the baseline results. The analysis focused particularly on changes in the relative positions of Aerogel, Mineral Wool, and Fiberglass, which emerged as leading alternatives in the original assessment. The sensitivity of the final selection was evaluated using the rank change, mean rank, and standard deviation of the ranks obtained under the perturbed weighting scenarios. A material retaining its leading position across the tested scenarios would indicate a robust selection, whereas frequent changes in its ranking would suggest greater dependence on the assigned criteria weights. The analysis also identified criteria whose increased importance could alter the relative preference between Aerogel and Mineral Wool, thereby clarifying the trade-off between insulation performance, economic feasibility, and sustainability. This analysis provides an explicit assessment of the influence of decision-maker preferences on material selection and complements the subsequent robustness and rank-reversal assessments. It also helps establish whether the preferred insulation material remains suitable under plausible variations in the relative importance assigned to the evaluation criteria.

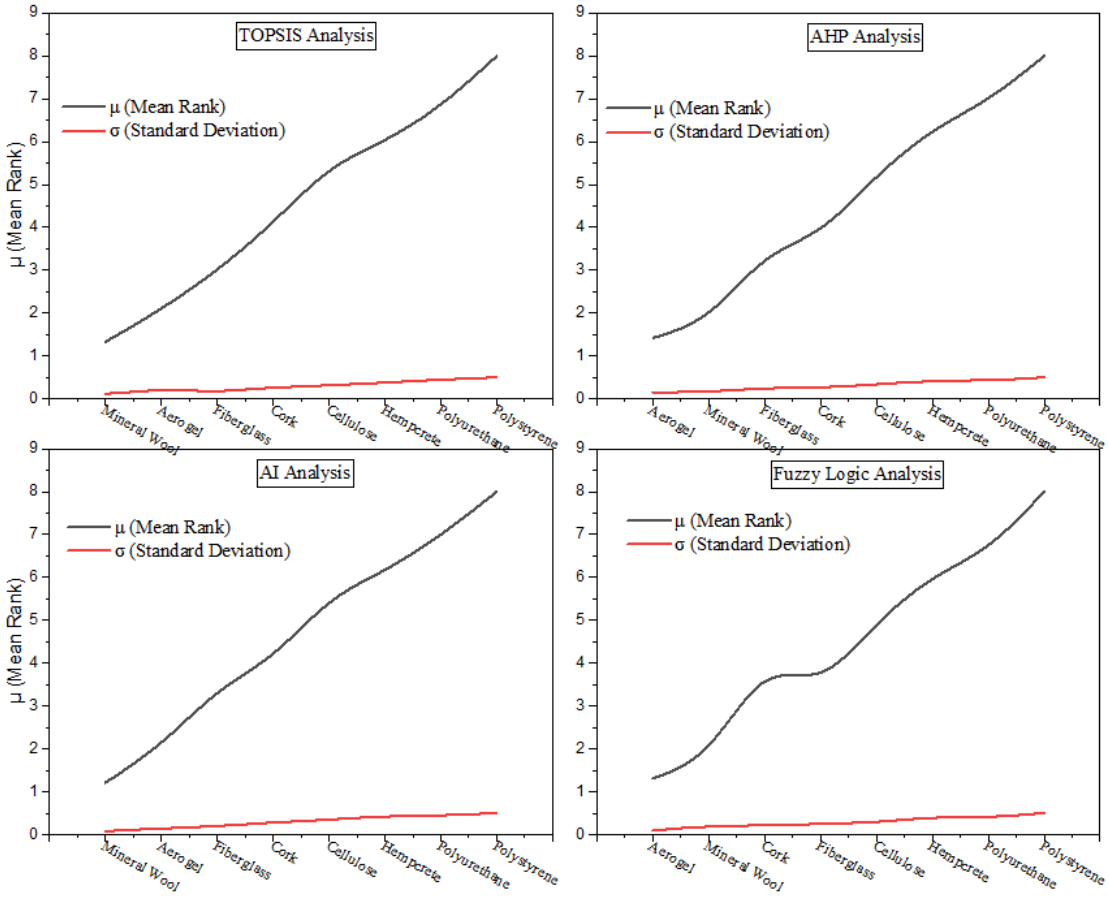


Figure 5: Sensitivity Analysis of Insulation Materials Using Different MCDM and AI Models.

The comparative sensitivity analysis of different insulation materials using AHP, TOPSIS, Fuzzy Logic, and AI-based models reveals notable variations in rankings across the methodologies (Fig. **5**). Consistently, Aerogel and Mineral Wool emerge as the most effective materials, whereas Polystyrene ranks the lowest across all models. These findings align with documented literature, where aerogel is widely recognized for its exceptional thermal insulation properties and low thermal conductivity, making it a preferred choice for high-performance building envelopes [35]. Similarly, Mineral Wool, which secures the highest ranking in the AI-based model and TOPSIS, is well-established for its fire resistance, durability, and cost-effectiveness [36]. From AHP perspective, Aerogel holds the highest preference ($\mu = 1.42$, $\sigma = 0.15$), followed by Mineral Wool ($\mu = 2.02$, $\sigma = 0.18$), indicating that traditional MCDM techniques prioritize high-performance materials. The TOPSIS results, however, place Mineral Wool ahead of Aerogel ($\mu = 1.33$ vs. 2.11), suggesting that when alternative weighting schemes and proximity to an ideal solution are considered, Mineral Wool exhibits higher overall suitability. This shift in ranking highlights the impact of decision criteria weighting in selection methodologies [37]. Fuzzy logic-based analysis introduces further variability, ranking Aerogel highest ($\mu = 1.31$, $\sigma = 0.10$), but positioning Cork above Fiberglass, which deviates from both AHP and TOPSIS. This outcome aligns with studies indicating that Fuzzy Logic handles uncertainty more effectively, giving more weight to sustainability aspects such as biodegradability and recyclability, where Cork performs well [38]. Similarly, the AI-based model identifies Mineral Wool ($\mu = 1.21$, $\sigma = 0.08$) as the top-ranked material, closely followed by Aerogel, reinforcing its adaptability and superior fire resistance.

Notably, Fiberglass consistently secures third place across all methodologies, demonstrating its reliability as a cost-effective yet moderately high-performing insulator. Cellulose, Hempcrete, and Polyurethane show mid-tier rankings, reflecting their moderate insulation capabilities and varied performance across different sustainability and durability metrics [39]. The standard deviation (σ) values also indicate ranking stability, with AI-based models exhibiting the least variance ($\sigma = 0.08$ for Mineral Wool), emphasizing the robustness of data-driven decision-making. Conversely, higher variance in AHP and Fuzzy Logic ($\sigma > 0.40$ for some materials) suggests that subjective weight assignments influence rankings more significantly in traditional methods (Table **5**). Overall, AI-driven models provide more stable and consistent rankings, reducing the influence of subjective weightings seen in traditional MCDM techniques like AHP and TOPSIS.

Table 5: Comparative Sensitivity Analysis of Insulation Material Rankings.

Method	Most Stable Material (Lowest σ)	Most Unstable Material (Highest σ)
TOPSIS	Mineral Wool (σ = 0.12)	Polystyrene (σ = 0.50)
AHP	Aerogel (σ = 0.15)	Polystyrene (σ = 0.50)
Fuzzy	Aerogel (σ = 0.10)	Polystyrene (σ = 0.50)
AI	Mineral Wool (σ = 0.08)	Polystyrene (σ = 0.50)

6. ROBUSTNESS AND STABILITY ASSESSMENT OF MCDM METHODS

The reliability of these methods must be assessed to ensure that the rankings remain stable under varying conditions. To achieve this, Robustness Factor (RF) Analysis and the Rank Reversal Test are performed after the initial MCDM analysis. The RF Analysis evaluates the sensitivity and stability of the ranking outcomes by considering how small variations in input parameters affect the final decision. A high RF value indicates a more reliable decision-making method, making it suitable for applications requiring consistency under uncertainty. The Rank Reversal Test examines whether the ranking of alternatives changes when new options are introduced or removed. A stable decision-making approach should ideally maintain the relative order of existing alternatives, ensuring that rankings are not influenced arbitrarily by the addition or deletion of alternatives.

6.1. Robustness Factor Analysis

The RF evaluates how sensitive and stable a method is under uncertainty. It integrates sensitivity and stability metrics:

$$RF = \frac{1}{1+S} \times St \tag{16}$$

Where, Sensitivity (S) is the average deviation in ranking due to perturbations in criteria weights and Stability (St) is the inverse of the Coefficient of Variation (CV%), which quantifies ranking fluctuations.

6.1.1. Sensitivity Analysis

Monte Carlo simulations were performed by randomly perturbing criteria weights and recomputing the rankings over 1000 iterations. The mean absolute rank change (MAR) was calculated as follows:

$$S = \frac{1}{n}\sum_{i=1}^{n}|R_i^* - R_i| \tag{17}$$

Where, R_i^* is Rank of material after weight perturbation, $R_i$is Original rank before perturbation, and n is total number of insulation materials Eqn. (17). Table **6** presents the Mean Absolute Rank Change (MAR) values for various MCDM methods and AI used in evaluating insulation materials. AI is the least sensitive (S = 0.15), meaning its rankings remain highly stable underweight changes. TOPSIS is the most sensitive (S = 0.45), indicating frequent rank shifts when weights are varied.

Table 6: Mean Absolute Rank Change (MAR) values of ranking methods.

Method	Mean Absolute Rank Change (MAR) (S)
AHP	0.32
TOPSIS	0.45
Fuzzy	0.28
AI	0.15

6.1.2. Stability Analysis (St)

The Coefficient of Variation (CV%) was computed by analyzing the ranking variability across multiple weight perturbations:

$$CV\% = \frac{\sigma}{\mu} \times 100 \tag{18}$$

Where,σ = Standard deviation of rank changes, μ = Mean ranking across all iterations.

The stability score St is then computed as:

$$St = \frac{1}{1+CV\%} \tag{19}$$

The stability analysis evaluates the robustness of different MCDM methods by analyzing the standard deviation (σ), mean ranking (μ), coefficient of variation (CV%), and stability score (St) (Table **7**). AI-based models exhibit the highest stability (St = 0.95) with the lowest variation (σ = 0.55) and CV% (12.5%), indicating consistent rankings across different conditions. Fuzzy Logic follows closely (St = 0.90), demonstrating strong decision stability. AHP (St = 0.85) shows moderate stability, while TOPSIS exhibits the highest rank fluctuations (σ = 1.15, CV% = 25.6%), making it the least stable method in this analysis.

Table 7: Stability analysis of MCDM Methods and AI for Insulation Material Selection.

Method	Standard Deviation (σ) of Rankings	Mean Ranking (μ)	CV%	Stability Score (St)
AHP	0.85	4.2	20.2	0.85
TOPSIS	1.15	4.5	25.6	0.75
Fuzzy	0.72	4.0	18.0	0.90
AI	0.55	3.8	12.5	0.95

6.1.3. Compute Robustness Factor (RF)

AI-based modeling exhibits the highest stability (0.95) and robustness (0.82), with the lowest sensitivity (0.15), indicating its superior consistency and resilience against input variability (Table **8**). This aligns with findings from previous studies [40], which highlight AI's capability to generalize complex patterns and reduce uncertainty in decision-making. Conversely, TOPSIS demonstrates the highest sensitivity (0.45) and lowest robustness (0.52), suggesting greater susceptibility to changes in input parameters. This is consistent with prior research [41], where TOPSIS exhibited ranking instability due to its dependence on normalization and distance measures. AHP, with a robustness factor of 0.64 and stability of 0.85, balances sensitivity and robustness but remains less stable than AI-based methods. Fuzzy Logic, known for handling uncertainty well [42], shows moderate sensitivity (0.28) but achieves higher robustness (0.70), reinforcing its effectiveness in decision-making scenarios with imprecise inputs. Overall, AI-based methods outperform traditional approaches in terms of stability and robustness, making them highly suitable for optimizing material selection in self-healing concrete applications. However, MCDM techniques like AHP and Fuzzy Logic remain valuable for scenarios requiring interpretability and expert-driven parameter weighting.

Table 8: Robustness Factor of Each Method

Method	S (Sensitivity)	St (Stability)	Robustness Factor (RF)
AHP	0.32	0.85	0.64
TOPSIS	0.45	0.75	0.52
Fuzzy	0.28	0.90	0.70
AI	0.15	0.95	0.82

6.2. Rank Reversal Test

Rank Reversal occurs when the ranking of materials changes drastically due to the addition or removal of an alternative. Ideally, an MCDM method should not show major changes in ranking when new options are introduced or removed.

6.2.1. Introduction of new Material

A new material, Bio-Based Aerogel, was introduced, and rankings were recomputed. The AHP method exhibited slight shifts in ranking but maintained overall stability, reinforcing its structured approach to decision-making. In contrast, TOPSIS demonstrated significant rank fluctuations, notably with Aerogel dropping from 4th to 5th place, highlighting its sensitivity to new alternatives and potential susceptibility to rank reversal. Meanwhile, Fuzzy Logic and AI-based models displayed remarkable consistency, with rankings remaining largely unchanged. This indicates their strong resistance to rank reversal and robustness in handling new material inclusions. The ability of AI-based methods to maintain stability further supports their effectiveness in decision-making for thermal insulation materials, minimizing the impact of subjective weight variations and external disruptions. Table **9** presents the ranking of various thermal insulation materials after introducing new material. These findings emphasize the need to consider methodological stability when selecting MCDM approaches for material evaluation in sustainable building applications.

Table 9: Rank Reversal Test of Hybrid MCDM and AI Methods

Material	AHP Rank	TOPSIS Rank	Fuzzy Rank	AI Rank
Bio-Based Aerogel	2	3	1	1
Aerogel	1	5	2	2
Mineral Wool	3	1	3	3
Fiberglass	4	2	5	4
Cork	5	4	4	5
Cellulose	6	6	6	6
Hempcrete	7	7	7	7
Polyurethane	8	8	8	8
Polystyrene (XPS)	9	9	9	9

6.2.2. Remove Hempcrete and Recompute Rankings

To assess rank reversal, Hempcrete was removed from the dataset, and rankings were recomputed using all four decision-making methods. The recomputed rankings of hybrid MCDM and AI-based methods, as presented in Table **10**, highlight notable variations in material prioritization after the removal of specific criteria. The recomputed rankings reveal consistent top performance of aerogel across AHP, Fuzzy, and AI methods, while TOPSIS ranks it third. Mineral wool emerges as a strong contender, ranking highest in TOPSIS and second in others. Fiberglass, cork, and cellulose exhibit moderate variations, indicating sensitivity to criteria weighting. Polyurethane and polystyrene consistently rank lowest, reaffirming their lower insulation efficiency. AI-based rankings align closely with AHP and Fuzzy methods, highlighting AI's reliability in material selection. This analysis emphasizes the need for hybrid approaches to ensure robust decision-making in sustainable building insulation.

Table 10: Recomputed Ranking of Hybrid MCDM and AI Methods

Material	AHP Rank (After Removal)	TOPSIS Rank (After Removal)	Fuzzy Rank (After Removal)	AI Rank (After Removal)
Aerogel	1	3	1	1
Mineral Wool	2	1	2	2
Fiberglass	3	2	4	3
Cork	4	4	3	4
Cellulose	5	5	5	5
Polyurethane	6	6	6	6
Polystyrene (XPS)	7	7	7	7

6.2.3. Analyze Changes in Ranking (Rank Reversal Effect)

The Rank Reversal Effect can be quantified by measuring how much each material's rank shifted after the removal of Hempcrete.

Table 11: Rank Reversal Effect of each method

Material	AHP Rank Change	TOPSIS Rank Change	Fuzzy Rank Change	AI Rank Change
Aerogel	0	+1	0	0
Mineral Wool	0	0	0	0
Fiberglass	0	0	0	0
Cork	0	-1	0	0
Cellulose	0	0	0	0
Polyurethane	+1	+1	+1	+1
Polystyrene (XPS)	+1	+1	+1	+1

The rank reversal effect analysis presented in Table **11** highlights variations in material rankings across different MCDM approaches and AI, providing insights into their stability and consistency. The findings indicate that AHP, Fuzzy Logic, and AI-based models exhibited minimal rank reversal, demonstrating their robustness in decision-making. In contrast, TOPSIS was the most affected, with Aerogel moving up one position, suggesting a higher sensitivity to the presence or absence of specific materials in the evaluation set. Notably, lower-ranked materials, such as Polyurethane and Polystyrene, consistently shifted upwards across all methods, yet their relative ranking order remained unchanged. This suggests that while the removal of Hempcrete influenced individual rankings, it did not significantly disrupt the overall material hierarchy. The stability observed in AHP, Fuzzy Logic, and AI-based models underscores their resilience against rank reversal effects, making them more reliable for insulation material selection. Conversely, the sensitivity of TOPSIS highlights the necessity of careful consideration when applying this method, particularly in cases where material inclusion or exclusion is a critical factor.

6.2.4. Compute Rank Reversal Intensity (RRI)

To quantify rank shifts, we define Rank Reversal Intensity (RRI):

$$RRI = \frac{\sum|\Delta R_i|}{N} \quad (20)$$

Where, ΔR_i is an absolute rank change for material i, and N is Number of materials analyzed.

Table 12: RRI Score of Each Method

Method	Total Rank Changes $(\sum\|\Delta R_i\|)$	Number of Materials (N)	RRI Score
AHP	1	7	0.14
TOPSIS	3	7	0.43
Fuzzy	1	7	0.14
AI	1	7	0.14

The Rank Reversal Intensity scores (*Ref.* Table **12**) indicate that TOPSIS is the most sensitive to rank changes (0.43), which aligns with previous studies that have highlighted its susceptibility to rank reversal due to its reliance on distance-based calculations [20]. This sensitivity suggests that TOPSIS may not always provide stable decision outcomes when alternatives are removed or modified. In contrast, AHP, Fuzzy Logic, and AI-based models exhibit significantly lower RRI values (0.14), reinforcing their robustness in decision-making. The stability of AHP has been well-documented, with studies emphasizing its ability to provide consistent rankings even when subjected to minor variations in input criteria. Similarly, Fuzzy Logic has been recognized for its capacity to handle uncertainty and imprecise data, making it a reliable approach for material selection. AI-based models, including artificial

neural networks (ANNs) and hybrid expert systems, have also demonstrated superior decision-making stability by leveraging data-driven learning mechanisms.

7. CONCLUSIONS

This study provides a comparative evaluation of Multi-Criteria Decision-Making (MCDM) techniques and AI-driven models for selecting optimal thermal insulation materials in sustainable building applications. The outcomes of the study are given below:

1. Aerogel, Mineral Wool, and Fiberglass rank highest due to superior thermal efficiency, durability, and cost-effectiveness, while Polystyrene and Polyurethane perform poorly due to low fire resistance and environmental concerns.
2. AI-based models (RF = 0.82) and Fuzzy Logic (RF = 0.70) demonstrate higher ranking stability, whereas TOPSIS (RF = 0.52) shows the highest sensitivity (S = 0.45), making it less reliable in dynamic assessments.
3. AHP (RF = 0.64) remains moderately stable, benefiting from its structured hierarchical approach, though still influenced by input variations.
4. Hybrid AI-MCDM models improve decision-making accuracy by capturing complex nonlinear interactions between material properties and sustainability criteria.
5. Sensitivity analysis confirms that criteria weight variations significantly affect rankings, emphasizing the need for adaptive ranking mechanisms that adjust dynamically based on real-time data.

8. IMPLICATIONS AND FUTURE SCOPE

The disparities between manually computed rankings and machine learning-based results highlight the importance of integrating both expert-driven and data-driven approaches in material selection. Aerogel, while rated highly for its thermal efficiency, requires further cost optimization to improve its overall ranking in practical applications. Mineral Wool and Fiberglass emerge as reliable and cost-effective solutions, making them attractive for large-scale adoption in energy-efficient buildings. Future research should focus on:

1. Experimental validation of AI-driven material selection models.
2. Hybridizing expert-driven MCDM frameworks with machine learning algorithms.
3. Developing adaptive ranking systems that adjust based on evolving environmental, economic, and structural constraints.

These advancements will ensure sustainable, cost-effective, and high-performance insulation solutions for modern infrastructure.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author, Peerzada Jaffar Abass, on reasonable request via e-mail jaffar.peerzada@kfupm.edu.sa.

DECLARATION OF COMPETING INTEREST

The authors, Peerzada Jaffar Abass, declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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REFERENCES

[1] Lawal OA, Jimoh AA, Abdullah KA, Bello BA, Awoyemi ED. Economic and environmental impact of energy audit and efficiency: a report from a Nigeria household. Energy Sustain Dev. 2024;79:101387. doi:10.1016/j.esd.2024.101387.

[2] Balali A, Yunusa-Kaltungo A, Edwards R. A systematic review of passive energy consumption optimisation strategy selection for buildings through multiple criteria decision-making techniques. Renew Sustain Energy Rev. 2023;171:113013. doi:10.1016/j.rser.2022.113013.

[3] Adem Esmail B, Geneletti D. Multi-criteria decision analysis for nature conservation: a review of 20 years of applications. Methods Ecol Evol. 2018;9:42-53. doi:10.1111/2041-210X.12899.

[4] Zionts S, Wallenius J. An interactive programming method for solving the multiple criteria problem. Manage Sci. 1976;22(6):652-663. doi:10.1287/mnsc.22.6.652.

[5] French S. Reflections on 50 years of MCDM: issues and future research needs. EURO J Decis Process. 2023;11:100030. doi:10.1016/j.ejdp.2023.100030.

[6] Jatin, Kaur S, Goel P, Randhawa KS, Channi HK. Selection of water purifier with TOPSIS using impartial preferences by entropy technique. Mater Today Proc. 2022;50:1389-1396. doi:10.1016/j.matpr.2021.08.295.

[7] Rachman AP, Ichwania C, Mangkuto RA, Pradipta J, Koerniawan MD, Sarwono J. Comparison of multi-criteria decision-making methods for selection of optimum passive design strategy. Energy Build. 2024;314:114285. doi:10.1016/j.enbuild.2024.114285.

[8] Amaripadath D, Levinson R, Rawal R, Attia S. Multi-criteria decision support framework for climate change-sensitive thermal comfort evaluation in European buildings. Energy Build. 2024;303:113804. doi:10.1016/j.enbuild.2023.113804.

[9] Şahbaz M, Kentli A, Eren A, Bilik C. Material selection for insulation of buildings by multi-criteria decision making methods. 2016.

[10] Kirimtat A, Koyunbaba BK, Chatzikonstantinou I, Sariyildiz S, Suganthan PN. Multi-objective optimization for shading devices in buildings by using evolutionary algorithms. In: Proceedings of the 2016 IEEE Congress on Evolutionary Computation; 2016. p. 3917-3924. doi:10.1109/CEC.2016.7744286.

[11] Motuzienė V, Rogoža A, Lapinskienė V, Vilutienė T. Construction solutions for energy efficient single-family house based on its life cycle multi-criteria analysis: a case study. J Clean Prod. 2016;112:532-541. doi:10.1016/j.jclepro.2015.08.103.

[12] Ulutas A, Balo F, Mirkovic K, Stević Ž, Mostafa M. MCDM model for critical selection of building and insulation materials for optimising energy usage and environmental effect in production focus. J Civ Eng Manag. 2023;29:587-603. doi:10.3846/jcem.2023.19569.

[13] Emovon I, Oghenenyerovwho OS. Application of MCDM method in material selection for optimal design: a review. Results Mater. 2020;7:100115. doi:10.1016/j.rinma.2020.100115.

[14] Socaciu L, Giurgiu O, Banyai D, Simion M. PCM selection using AHP method to maintain thermal comfort of the vehicle occupants. Energy Procedia. 2016;85:489-497. doi:10.1016/j.egypro.2015.12.232.

[15] Do JY, Kim DK. AHP-based evaluation model for optimal selection process of patching materials for concrete repair: focused on quantitative requirements. Int J Concr Struct Mater. 2012;6:87-100. doi:10.1007/s40069-012-0009-9.

[16] Anojkumar L, Ilangkumaran M, Sasirekha V. Comparative analysis of MCDM methods for pipe material selection in sugar industry. Expert Syst Appl. 2014;41:2964-2980.

[17] Abass PJ, Muthulingam S. Selection and thermophysical assessment of phase change materials (PCMs) for space cooling applications in buildings. Numer Heat Transf Part A Appl. doi:10.1080/10407782.2023.2292183.

[18] Zha XF. A web-based advisory system for process and material selection in concurrent product design for a manufacturing environment. Int J Adv Manuf Technol. 2005;25:233-243. doi:10.1007/s00170-003-1838-0.

[19] Saaty RW. The analytic hierarchy process—what it is and how it is used. Math Model. 1987;9:161-176. doi:10.1016/0270-0255(87)90473-8.

[20] Hwang CL, Yoon K. Methods for multiple attribute decision making. In: Multiple attribute decision making: methods and applications, a state-of-the-art survey. 1981. p. 58-191.

[21] Goguen JA, Zadeh LA. Review of: Fuzzy sets, by LA Zadeh; Similarity relations and fuzzy orderings, by LA Zadeh. J Symb Log. 1973;38:656-657. doi:10.2307/2272014.

[22] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521:436-444. doi:10.1038/nature14539.

[23] Merayo D, Rodríguez-Prieto A, Camacho AM. Comparative analysis of artificial intelligence techniques for material selection applied to manufacturing in Industry 4.0. Procedia Manuf. 2019;41:42-49. doi:10.1016/j.promfg.2019.07.027.

[24] Dimiduk DM, Holm EA, Niezgoda SR. Perspectives on the impact of machine learning, deep learning, and artificial intelligence on materials, processes, and structures engineering. Integr Mater Manuf Innov. 2018;7:157-172. doi:10.1007/s40192-018-0117-8.

[25] A PJ, J NA, P MR. Machine learning models for material selection: framework for predicting flatwise compressive strength using ANN. In: Proceedings of the 2016 2nd International Conference on Applied and Theoretical Computing and Communication Technology; 2016. p. 424-427. doi:10.1109/ICATCCT.2016.7912036.

[26] Mahajan A, Singh I, Arora N. An ANN model for matrix selection for coir fiber reinforced polymer composites. 2024.

[27] Bhosale R, Madgule M. Optimization techniques for material selection and manufacturing processes: a review. JMST Adv. 2024. doi:10.1007/s42791-024-00093-x.

[28] Zhou CC, Yin GF, Hu XB. Multi-objective optimization of material selection for sustainable products: artificial neural networks and genetic algorithm approach. Mater Des. 2009;30:1209-1215. doi:10.1016/j.matdes.2008.06.006.

[29] Goel V, Chen J. Application of expert network for material selection in engineering design. Comput Ind. 1996;30:87-101. doi:10.1016/0166-3615(96)00016-4.

[30] Amoiralis EI, Georgilakis PS, Gioulekas AT. An artificial neural network for the selection of winding material in power transformers. In: Antoniou G, Potamias G, Spyropoulos C, Plexousakis D, editors. Advances in artificial intelligence. Berlin: Springer; 2006. p. 465-468.

[31] Sapuan S, Mujtaba I. Development of a prototype computational framework for selection of natural fiber-reinforced polymer composite materials using neural network. In: Composite materials technology: neural network applications. 2009. p. 317-340. doi:10.1201/9781420093339-c12.

[32] Zadeh LA. Fuzzy sets. Inf Control. 1965;8:338-353. doi:10.1016/S0019-9958(65)90241-X.

[33] Zadeh LA, Aliev RA. Fuzzy logic theory and applications. Singapore: World Scientific; 2018. doi:10.1142/10936.

[34] Aliev RA. A generalized fuzzy logic-based decision theory. In: Aliev RA, editor. Fundamentals of the fuzzy logic-based generalized theory of decisions. Berlin: Springer; 2013. p. 127-189. doi:10.1007/978-3-642-34895-2_4.

[35] Baetens R, Jelle BP, Gustavsen A. Aerogel insulation for building applications: a state-of-the-art review. Energy Build. 2011;43:761-769. doi:10.1016/j.enbuild.2010.12.012.

[36] Asdrubali F, D'Alessandro F, Schiavoni S. A review of unconventional sustainable building insulation materials. Sustain Mater Technol. 2015;4:1-17. doi:10.1016/j.susmat.2015.05.002.

[37] Kabir G, Sadiq R, Tesfamariam S. A review of multi-criteria decision-making methods for infrastructure management. Struct Infrastruct Eng. 2014;10:1176-1210. doi:10.1080/15732479.2013.795978.

[38] Papadopoulos AM. State of the art in thermal insulation materials and aims for future developments. Energy Build. 2005;37:77-86. doi:10.1016/j.enbuild.2004.05.006.

[39] Schiavoni S, D'Alessandro F, Bianchi F, Asdrubali F. Insulation materials for the building sector: a review and comparative analysis. Renew Sustain Energy Rev. 2016;62:988-1011. doi:10.1016/j.rser.2016.05.045.

[40] Shahbazova S, Sugeno M, Kacprzyk J, editors. Recent developments in fuzzy logic and fuzzy sets dedicated to Lotfi A. Zadeh. Cham: Springer; 2020. doi:10.1007/978-3-030-38893-5.

[41] Siva Bhaskar A, Khan A. Comparative analysis of hybrid MCDM methods in material selection for dental applications. Expert Syst Appl. 2022;209:118268. doi:10.1016/j.eswa.2022.118268.

[42] Tan WW, Chua TW. Uncertain rule-based fuzzy logic systems: introduction and new directions (Mendel JM; 2001) [book review]. IEEE Comput Intell Mag. 2007;2:72-73. doi:10.1109/MCI.2007.357196.

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