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PAPER

Plithogenic Machine Learning Solutions to Material Selection in Renewable Energy Systems

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ABSTRACT

Plithogenic-based decision models are more effective in designing optimal solutions to intricate problems. This study work proposes an integrated decisioning model conjoining plithogeny and machine learning algorithms. This study considers the decision-making problem of selecting smart and sustainable materials for the effective functioning of renewable energy systems. The decisioning model has ten evaluation criteria and considers alternatives for materials subjected to five categories of photovoltaic, thermoelectric, piezoelectric, phase change, supercapacitor, and electrochromic. This work employs the algorithm of a random forest classifier in determining the most crucial criteria for selecting smart and sustainable materials. The plithogenic-based decision method of TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is employed in ranking materials of each kind. The proposed decisioning approach is the combination of a machine learning algorithm and a plithogenic decision approach, which is further facilitated by the intervention of Python programming. The criteria selection accuracy is compared with a support vector machine algorithm to demonstrate the efficacy of this integrated decision approach in ranking the materials used in formulating robust renewable energy systems. Sensitivity analysis is also performed to exhibit the efficacy of this proposed model. This model has few limitations, as it considers a few selected materials under each of the categories.

KEYWORDS

machine learning algorithms, plithogeny, sustainable materials, renewable energy system

1 INTRODUCTION

The increasing demand for cleaner energy primarily contributes to the transition towards renewable energy systems (RES) to handle the challenges of environmental sustainability. The materials, such as photovoltaic, thermoelectric, piezoelectric, phase change, supercapacitor, and electrochromic, are primarily applied in renewable technologies. However, the effective functioning of these renewable systems is highly dependent on the material selection. The robustness and sustainability of

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RES are reliant on the attributes of the materials, such as Energy Efficiency (EE), Cost Efficiency (CE), Durability (D), Environmental Impact (EI), Thermal Stability (TS), Electrical Conductivity (EC), Scalability (S), Ease of Integration (EAI), Maintenance (M), and Life Cycle (LC). The traditional decisioning models of multi-criteria decisioning are applied in general to make optimal choices of these materials based on the ten criteria or attributes. However, the increasing intricacy of decision-making with subjective data representations demands contemporary decisioning techniques.

This study work develops an integrated decisioning framework combining the theory of plithogenic logic with machine learning algorithms.

Presently, machine learning-based decision models are gaining more momentum, as these modelling approaches are more competent and potent at handling complex data sets. The development of fuzzy-based machine models is also employed in problem-solving to treat ambiguous data sets. However, the increasing levels of difficulty in handling imprecise, uncertain, indeterminate data representations considering more attributes with several attribute values have unveiled the necessity of Plithogenic logic in machine learning. Smarandache is the founding father of plithogenic theory, which is characterized as attribute theory and termed as the generalization of fuzzy, neutrosophic sets and other representations. Plithogenic-based decision models are applied in multi-criteria decisioning to rank the alternatives based on attributes and attribute values. These methods are also used in computing the criteria weights to determine the criteria significance. This study work explores the potential of plithogenic integrated machine learning models in material selection for smart and sustainable renewable energy systems. The proposed model in this work works in two phases. In the first phase, the machine learning algorithm of Random Forest is applied in examining the significance of the attributes considered for this study, and in the second phase, Plithogenic TOPSIS is applied in ranking the alternatives based on chosen attributes and attribute values.

The remaining contents of the paper are structured into the following sections. The state of the art of related works is presented in section 2. The methodology is described in section 3. The application of the proposed model is discoursed in section 4 using Python programming. The results are discussed in section 5, and the last section concludes the work.

2 STATE OF ART OF WORK

This section presents the state of related works pertinent to the decisioning of renewable energy systems using multi-criteria approaches and machine learning algorithms. The research gaps and noteworthy contributions are also presented in this section. Researchers have explored various aspects of renewable energy systems (RES), such as materials employed in building a resilient system, renewable energy generation, and site selection of renewable energy plants. Different approaches are utilized to make forecasts and predictions of energy generation, and researchers have applied machine learning algorithms in recent times. Houssein et al. [1] presented a systematic review of machine learning algorithms for optimizing renewable energy systems. Abualigah et al. [2] reviewed the implications of machine learning approaches with special reference to wind and solar energy systems. Sharma et al. [3] discoursed on nanofluid-based heat transfer in energy systems. Benti et al. [4], Ajibade et al. [5], and Kishore et al. [6], analyzes the machine learning trends in renewable energy. A few significant works are as follows, Perera et al. [7] discussed the applications of various machine learning techniques in renewable energy generation and integration. Khan et al. [8] demonstrated the efficacy of neural networks in forecasting wind power.

Lu et al. [9] enhanced renewable energy forecasting through error correction using multi-model blending. Sogabe et al. [10] applied deep learning optimization techniques for decentralizing the systems using weather forecasts. Tayal [11] employed data digitization for achieving high renewable energy generation. Del Ser, J., et al. [12] critically reviewed the applications of randomization-based machine learning algorithms in predicting renewable energy systems. The machine learning algorithms are widely applied with special reference to predicting the generation of renewable energy. The specific contributions of diverse machine learning algorithms are presented in Table 1.

Table 1. Various types of machine learning algorithm

Author(s) and Year	Type of Machine Learning Algorithm	Significance of the Work
Khan, G. M. et al. (2014) [8]	Neural Networks	Forecasting of wind power
Lu, S. et al. (2015) [9]	Multi-Model Blending	Forecasting of renewable energy
Sogabe, T. et al. (2016) [10]	Deep Learning	Optimization of renewable energy
Tayal, D. (2017) [11]	Data Digitization and ML	Prediction of renewable energy
Salcedo-Sanz, S. et al. (2018) [13]	Feature Selection Techniques	Prediction of renewable energy
Gu, G. H. et al. (2019) [14]	Various ML Algorithms	Predicting the efficacy of renewable energy systems
Grève, Z. D. et al. (2020) [15]	Supervised Learning	Improves self-consumption in renewable energy communities.
Ahmed, W. et al. (2020) [16]	Reinforcement Learning	Optimization through the energy management model
Ma, T. et al. (2021) [17]	ML in Heat Transfer	Heat transfer in renewable energy applications.
Tomar, A. et al. (2021) [18]	Various ML Techniques	Advances in renewable energy applications.
Izanloo, M. et al. (2022) [19]	ML-based Decision-Making	Renewable energy investment decisions.
Tirth, V. et al. (2023) [20]	ML for Nanomaterials	Sustainable energy production and storage
Fernandez, M. et al. (2024) [21]	Optimization Techniques	Optimizes renewable energy utilization in waste recycling using ML.
Matos, M. et al. (2024) [22]	Forecasting ML Models	Forecasting for renewable energy communities.

On the other hand, the multi-criteria decision-making methods are also applied in the context of renewable energy systems, especially in renewable energy source selection and site selection of renewable energy plants. The MCDM methods applied are presented in Table 2.

Table 2. Application of MCDM methods

Author(s) and Year	MCDM Method	Area of Application
Raza, S. S., Janajreh, I., and Ghenai, C. (2014) [23]	Sustainability Index	Energy storage systems for intermittent renewable sources
Das, A. (2016) [24]	Analytical Hierarchy Process (AHP)	Renewable energy source selection in case study analysis
Ishfaq, S., Ali, S., and Ali, Y. (2018) [25]	Multi-Criteria Decision Making (MCDM)	Renewable energy source optimization for Pakistan
Büyüközkan, G., Karabulut, Y., and Güler, M. (2018) [26]	Hesitant Fuzzy MCDM	Strategic renewable energy source selection in Turkey
Khan, M. J., et al. (2020) [27]	Remoteness Index-based VIKOR	Renewable energy source selection using fuzzy sets
Tarigan, A. P. M., et al. (2021) [28]	Analytical Hierarchy Process (AHP)	Renewable energy source selection for green ports

(Continued)

Table 2. Application of MCDM methods *(Continued)*

Author(s) and Year	MCDM Method	Area of Application
Goswami, S. S., et al. (2022) [29]	MEREC Integrated PIV MCDM	Green renewable energy source selection in India
Joshi, B. P., Joshi, N., and Gegov, A. (2023) [30]	TOPSIS with Moderator Intuitionistic Fuzzy Sets	Renewable energy source selection
Amiri, A. A., et al. (2024) [31]	AHP-TOPSIS	Renewable energy source selection in Saudi Arabia
Yiarayong, P. (2024) [32]	q-rung Linear Diophantine Fuzzy Hypersoft Operators	Renewable energy decision-making
Sasirekha, D., and Senthilkumar, P. (2024) [33]	Pythagorean Neutrosophic Fuzzy Sets	Renewable energy source selection analysis

From both Tables 1 and 2, a few research gaps can be identified.

- Either machine learning algorithms or multi-criteria decision methods are applied in combination with special reference to renewable energy systems.
- The decisioning problem of material selection in renewable energy systems is not much explored in the literature.
- The notion of a sustainable and smart renewable energy system with a suitable material selection problem is not discussed to the best of our knowledge.
- The theory of plithogeny is not discoursed in the decisioning framework of RES with the intersection of machine learning and MCDM.

The above research gaps have motivated the authors to develop an integrated decisioning approach combining both the machine learning algorithm of Random Forest and the multi-criteria decision method of TOPSIS with plithogenic representations. The methods of RFA and TOPSIS are chosen in modelling, as these methods are proved to be efficient and competent in handling intricate decision problems.

3 METHODOLOGY

This section describes the procedure followed in the proposed integrated modeling framework. The two-fold procedure is explained as follows.

3.1 Phase i: Random forest in criteria reduction

Random Forest Algorithm (RFA) is a robust kind of ensemble learning method comprising a multitude of decision trees and sums the output to determine optimal predictions. This kind of algorithm facilitates identifying the most substantial criteria or features by assessing their influence on the predictive model. This algorithm works with the generation of T decision trees by training each on a randomized data subset and features. The output is computed using aggregated values from each of the trees either by classification or regression techniques. The significance of the features is computed based on either of the impurity metrics of Gini impurity and Mean Squared Error.

Step 1: Defining decisioning problem: The alternatives, criteria, and the decision matrix with linguistic variable representations and their equivalent fuzzy quantifications are initially determined.

Step 2: Construction of trees: A random sample is drawn from the training data set, and it is trained to select the features at each spilt. Impurity-based spilt is performed to construct the trees using Gini or mean squared error metrics.

Gini Impurity (Classification)

Gini impurity is defined for a node m in a decision tree as

$$G_m = 1 - \sum_{i=1}^{C} p_i^2 \tag{1}$$

Here, C is the count of classes and p_i refers to the proportion of samples subjected to class i at node m

The Gini impurity reduction at times of the spilt of the data at a node m by a feature f is given by

$$\Delta G_m(f) = G_m - \left(\frac{n_L}{n} G_L + \frac{n_R}{n} G_R\right) \tag{2}$$

Were

- G_L, G_R: Gini impurities for left and right child nodes
- n, n_L, n_R: The count of the samples at node m, left child, and right child, respectively

Mean Square Error (Regression)

The impurity reduction for each node m is defined at times of regression tasks as

$$MSE_m = \frac{1}{n_m} \sum_{i=1}^{n_m} (y_i - \bar{y}_m)^2 \tag{3}$$

Were

- n_m: Count of samples at node m
- y_i: Actual value of sample i
- $\bar{y}_m$: Mean of target values at node m

The impurity reduction in MSE at times of data splitting by feature f is

$$\Delta MSE_m(f) = MSE_m - \left(\frac{n_L}{n} MSE_L + \frac{n_R}{n} MSE_R\right) \tag{4}$$

Step 3: Computation of feature significance: The impurity reduction for each of the features in each of the trees is calculated, and it is aggregated to compute all the reductions I(f).

$$I(f) = \frac{1}{T} \sum_{t=1}^{T} \sum_{m \in nodesj} \Delta Impurity_m(f) \tag{5}$$

Were

- T: Count of trees in the forest
- $nodes_f$: Set of nodes where a feature f is used for splitting
- $\Delta Impurity_m(f)$: Reduction in impurity for feature f at node m

The scores of the features are determined on normalizing, and the features with least scores are eliminated for further study.

The scores I(f) are the normalized to sum to 1

$$\text{Normalized Importance}(f) = \frac{I(f)}{\sum_{j=1}^{F} I(j)}, \tag{6}$$

F is the total count of features.

3.2 Phase ii: Ranking using plithogenic topsis

A plithogenic set is basically a quintuple of the form (P, a, V, d, c) with P as a PS, a is the attribute and V is the set of attribute values, d is the degree of appurtenance of the attribute values with respect to the dominant attribute value, and c is the degree of contradiction.

The significant criteria obtained in phase I are considered for ranking the alternatives considered under the broad classification of materials such as photovoltaic, thermoelectric, piezoelectric, phase change, supercapacitor, and electrochromic. Plithogenic sets are of the form (P, a, V, d, c), where P is the set, a is the attribute, V is the set of attribute values subjected to the attribute 'a', d is the degree of appurtenance, and c is the degree of contradiction. Plithogenic sets are developed primarily to handle attributes. The degree of appurtenance and contradiction is determined by subjecting it to dominant attribute values.

Step 4: Determination of dominant attribute values: The criteria, or the attributes refined from phase I, are explored further to find the attribute values subjected to each of the attributes. The contradiction degrees of the attribute values presented in the decision matrix with respect to the dominant attribute values are computed. The contradiction matrix $[C_D]$ with linguistic variables is thus framed to find the ranking of the alternatives. It is later quantified using fuzzy representations.

Step 5: Normalization of the contradiction matrix: The modified contradiction matrix is normalized using vector normalization irrespective of benefit and cost criteria.

$$r_{Dij} = \frac{C_{Dij}}{\sqrt{\sum_{i=1}^{m} \left(C_{Dij}\right)^2}} \tag{7}$$

Step 6: Weighted normalization of the contradiction matrix: The weighted normalized contradiction matrix is computed using $v_{Dij} = w_j r_{Dij}$

Step 7: Determination of positive and negative ideal solutions: For benefit criteria, the positive ideal solution $v_j^+ = (v_1^+, v_2^+, \ldots\ldots v_n^+) = \max(v_{im})$ is determined. Similarly for cost criteria, the negative ideal solution $v_j^- = (v_1^-, v_2^-, \ldots\ldots v_n^-) = \min(v_{im})$ is obtained.

Step 8: Computation of Relative Closeness Measure: The positive and negative separation measures for each of the alternatives are computed

Positive ideal separation

$$S_{Di}^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{8}$$

Negative ideal separation

$$S_{Di}^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{9}$$

The relative closeness to the ideal solution

$$RC_{Di} = \frac{S^-_{Di}}{S^+_{Di} + S^-_{Di}} \tag{10}$$

Step 9: Ranking of the alternatives: The alternatives are ranked based on the score values RC_{Di}. The alternatives with high scores are given priority.

4 PROBLEM DESCRIPTION

Let us consider the decisioning environment of choosing the materials for building a sustainable renewable energy system. The materials used in general are broadly classified as presented in Table 3. The criteria chosen for ranking are presented with the criteria sub-values as in Table 4. The decisioning problem is to rank these materials under each of the classifications to facilitate sustainable renewable energy systems. Both the terms attribute and criteria are used invariably to describe the decisioning environment.

4.1 Phase i: Random forest in criteria reduction

Table 3. Broader classification of materials

Photovoltaic	Thermoelectric	Piezoelectric	Phase Change	Supercapacitor	Electrochromic
P1: Silicon	T1: Bismuth Telluride	P11: Lead Zirconate Titanate	PC1: Paraffin Wax	S1: Activated Carbon	E1: Tungsten
P2: Cadmium Telluride	T2: Lead Telluride	P12: Barium Titanate	PC2: Eutectic Salts	S2: Graphene	E2: Nickel Oxide
P3: Copper Indium Gallium Selenide	T3: Silicon Germanium	P13: Quartz	PC3: Hydrate Salts	S3: Carbon Nanotubes	E3: Prussian Blue
P4: Perovskite	T4: Skutterudite	P14: Polyvinylidene Fluoride	PC4: Fatty Acids	S4: Metal Oxides	E4: Viologen Compounds
P5: Organic Photovoltaics	T5: Magnesium Silicide	P15: Zinc Oxide	PC5: Polyethylene Glycol	S5: Conductive Polymers	E5: Polyniline

Table 4. Criteria for ranking with criteria values

Notation	Criteria	Criteria Values	Fuzzy Triangular Representations
EE	Energy Efficiency	Excellent (EX)	(0.8, 1.0, 1.0)
		Good (G)	(0.4, 0.6, 0.8)
		Moderate (MO)	(0.2, 0.4, 0.6)
		Low (L)	(0.0, 0.2, 0.2)
CE	Cost Efficiency	Affordable (A)	(0.8, 1.0, 1.0)
		Moderate (MO)	(0.4, 0.6, 0.8)
		Costly (C)	(0.0, 0.2, 0.4)
		Expensive (E)	(0.0, 0.0, 0.2)

(Continued)

Table 4. Criteria for ranking with criteria values *(Continued)*

Notation	Criteria	Criteria Values	Fuzzy Triangular Representations
D	Durability	Very Highly Durable (VHD)	(0.8, 1.0, 1.0)
		Highly Durable (HD)	(0.6, 0.8, 1.0)
		Moderately Durable (MD)	(0.2, 0.4, 0.6)
		Low Durability (LD)	(0.0, 0.2, 0.4)
EI	Environmental Impact	Very High Impact (VHI)	(0.0, 0.0, 0.2)
		High Impact (HI)	(0.2, 0.4, 0.6)
		Moderate Impact (MI)	(0.4, 0.6, 0.8)
		Low Impact (LI)	(0.8, 1.0, 1.0)
TS	Thermal Stability	Very Stable (VS)	(0.8, 1.0, 1.0)
		Moderate Stability (MS)	(0.4, 0.6, 0.8)
		Stable (S)	(0.2, 0.4, 0.6)
		Limited Stability (LS)	(0.0, 0.2, 0.4)
EC	Electrical Conductivity	Excellent (E)	(0.8, 1.0, 1.0)
		High (H)	(0.4, 0.6, 0.8)
		Satisfactory (S)	(0.2, 0.4, 0.6)
		Minimal (M)	(0.0, 0.2, 0.4)
S	Scalability	Very Highly Scalable (VHS)	(0.8, 1.0, 1.0)
		Highly Scalable (HS)	(0.4, 0.6, 0.8)
		Moderate (MO)	(0.2, 0.4, 0.6)
		Limited (LI)	(0.0, 0.2, 0.4)
EAI	Ease of Integration	Seamless (S)	(0.8, 1.0, 1.0)
		Easy (EA)	(0.6, 0.8, 1.0)
		Moderate (MO)	(0.4, 0.6, 0.8)
		Challenging (C)	(0.0, 0.2, 0.4)
M	Maintenance	Frequent (F)	(0.8, 1.0, 1.0)
		Regular (R)	(0.4, 0.6, 0.8)
		Occasional (O)	(0.2, 0.4, 0.6)
		Low (L)	(0.0, 0.0, 0.2)
LC	Life Cycle	Extended (E)	(0.8, 1.0, 1.0)
		Prolonged (P)	(0.6, 0.8, 1.0)
		Average (A)	(0.4, 0.6, 0.8)
		Short-term (ST)	(0.0, 0.2, 0.4)

The attribute values, or the criteria values subjected to each of the attributes, are presented in the above Table 4. The decision-making matrix with linguistic representations is presented as follows in the Table 5.

Table 5. Initial decision matrix

Alternatives	EE	CE	D	EI	TS	EC	S	EAI	M	LC	Performance Score
Photovoltaic Materials											
P1	EX	MO	MD	HI	VS	E	MO	EA	O	E	High
P2	L	EXP	LD	VHI	ST	SA	LI	MO	R	E	Moderate
P3	L	CO	HD	MI	ST	SA	MO	C	R	P	Moderate
P4	G	MO	MD	VHI	LS	H	MO	EA	F	ST	Moderate
P5	MO	MO	LD	M	ST	H	HS	S	O	P	Moderate
Thermoelectric Materials											
T1	EX	CO	HD	HI	VS	H	MO	MO	R	P	High
T2	G	MO	LD	MI	MS	SA	LI	C	F	E	Moderate
T3	L	EXP	MD	MI	VS	H	MO	EA	R	E	Moderate
T4	G	MO	LD	HI	ST	SA	MO	MO	F	P	Moderate
T5	MO	EXP	MD	VHI	MS	SA	HS	EA	O	ST	Moderate
Piezoelectric Materials											
P11	G	MO	HD	MI	VS	H	LI	C	F	P	Moderate
P12	MO	MO	LD	VHI	ST	H	MO	EA	R	ST	Moderate
P13	L	EXP	MD	VHI	VS	M	LI	S	O	E	Moderate
P14	MO	CO	LD	MI	ST	SA	MO	MO	R	ST	Moderate
P15	G	EXP	MD	HI	LS	M	HS	C	F	E	Moderate
Phase Change Materials											
PC1	L	EXP	LD	VHI	ST	M	HS	MO	O	ST	Moderate
PC2	MO	MO	LD	HI	VS	M	LI	EA	R	P	Moderate
PC3	G	CO	MD	MI	ST	M	MO	C	F	P	Moderate
PC4	L		LD	HI	ST	M	HS	EA	O	ST	Moderate
PC5	MO	MO	LD	MI	MS	SA	MO	S	R	E	Moderate
Supercapacitor Materials											
S1	EX	MO	HD	MI	VS	H	HS	EA	O	E	High
S2	L	EXP	HD	MI	VS	M	MO	S	R	P	Moderate
S3	L	EXP	LD	VHI	ST	SA	LI	C	F	ST	Low
S4	G	CO	LD	MI	VS	H	LI	EA	R	P	Moderate
S5	G	MO	MD	MI	ST	SA	MO	S	O	E	Moderate
Electrochromic Materials											
E1	L	MO	HD	MI	VS	SA	MO	C	R	P	Moderate
E2	G	A	LD	HI	ST	M	LI	S	L	ST	Moderate
E3	L	MO	MD	HI	LS	SA	LI	MO	R	E	Moderate
E4	MO	CO	LD	VHI	ST	M	HS	C	F	ST	Moderate
E5	G	A	HD	MI	VS	H	LI	EA	O	P	High

By using the libraries of Random Forest in Python programming, the significant features are obtained, and the results obtained are presented in Figure 1.

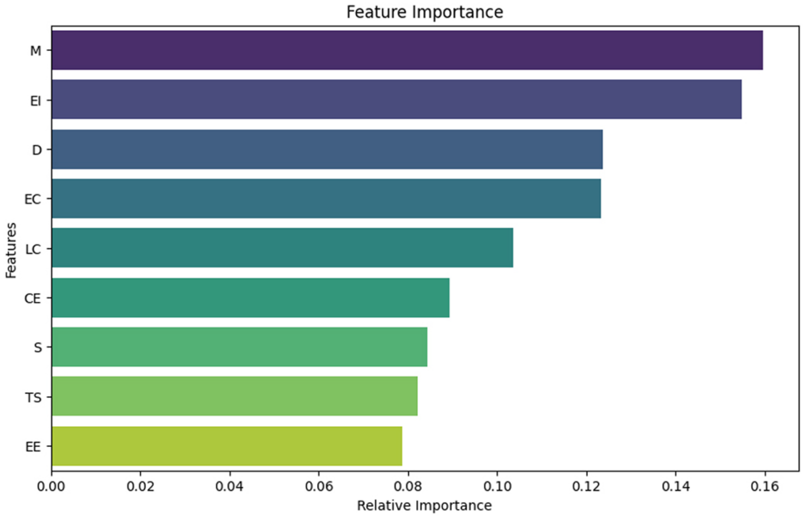

Fig. 1. Feature importance

The score values of the significant features are presented in Table 6.

Table 6. Criteria significance values

Criteria	M	EI	D	EC	LC	CE
Weights	0.22	0.2	0.17	0.16	0.13	0.12

4.2 Phase ii: Ranking by TOPSIS

In this phase the alternatives are ranked using the method of TOPSIS by considering the dominant values of each of the criteria.

The dominant attribute values of each of the attribute/criteria are presented in the Table 7.

Table 7. Dominant attribute values

Attributes	M	EI	D	EC	LC	CE
Dominant Attribute Values	Low	Low	Very Highly Durable	Excellent	Extended	Affordable

The method of TOPSIS is applied to each of the categorization of the materials and ranked accordingly. The contradiction matrix with linguistic values is presented Table 8.

Table 8. Contradiction matrix

Alternatives to Photovoltaic Materials	D	EI	EC	M	LC	CE
P1	M	M	L	L	VL	L
P2	H	H	H	M	M	M
P3	L	M	L	M	VL	H
P4	M	H	M	L	H	M
P5	H	VH	H	H	M	L

The above matrix is quantified numerically by assigning 0.1, 0.3, 0.5, 0.7 and 0.9 for VL, L, M, H, and VH, respectively. By following the steps 5–9 described in Phase II, the ranking results are obtained as in Table 9.

Table 9. Ranking of photovoltaic materials

Alternatives	P1	P2	P3	P4	P5
Rankings	2	1	5	4	3

By repeating the same procedure for other types of materials, the ranking results thus obtained are presented in Table 10.

Table 10. Final ranking of the alternate materials

Materials	Ranking Results
Thermoelectric	T2 > T1 > T5 > T4 > T3
Piezoelectric	P12 > P11 > P13 > P14 > P15
Phase Change	PC2 > PC1 > PC4 > PC5 > PC3
Supercapacitor	S2 > S1 > S3 > S5 > S4
Electrochromic	E2 > E1 > E4 > E5 > E3

For better understanding of the readers, the ranking results are presented in Figure 2.

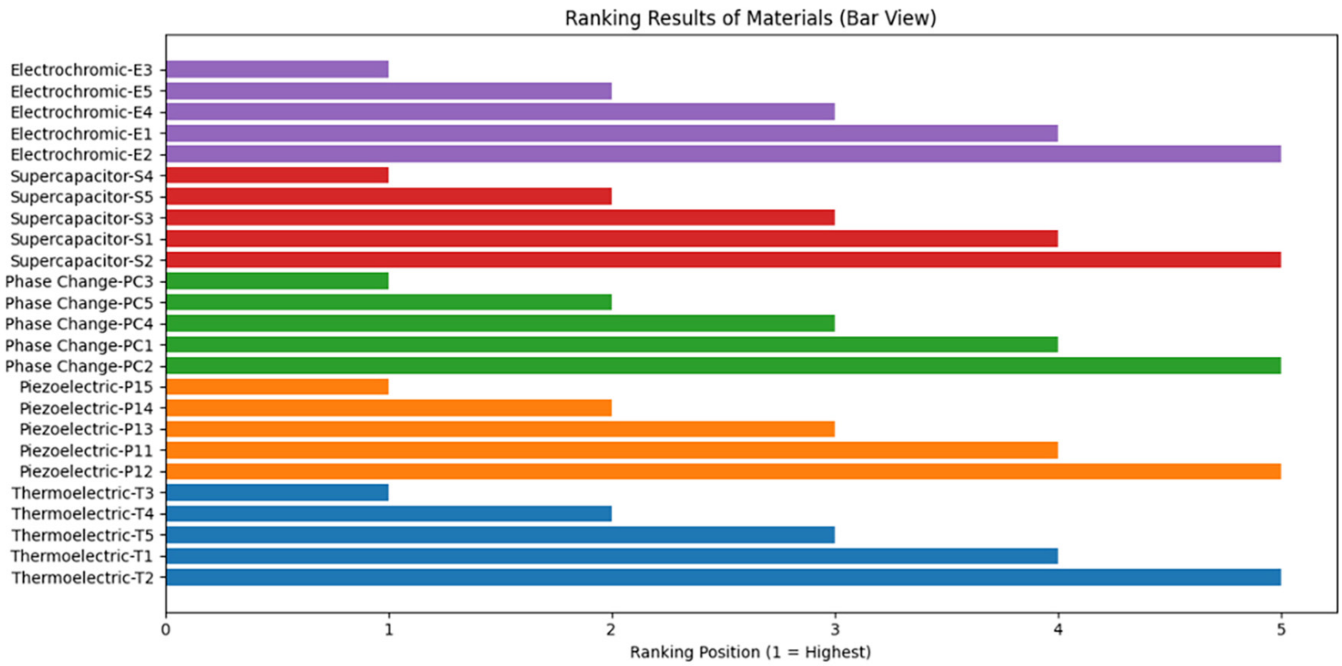

Fig. 2. Graphical representation of final ranking results

5 RESULTS AND DISCUSSION

The feature extraction signifies the criteria selection for the decisioning problem of ranking the alternatives. The method of random forest is applied, and to check the consistency of this algorithm, the support vector machine (SVM) algorithm is applied to extract the significant features. The accuracy obtained in both of the methods is presented in Table 11.

Table 11. Comparison of results

Methods	Accuracy
RFA	91.12
SVM	89.13

The accuracy results are relatively closer to one another, and this indicates the precision of the feature extraction i.e criteria reduction.

6 CONCLUSION

This study work explores the application of an integrated decisioning model based on machine learning and Plithogenic TOPSIS in determining the optimal ranking of the materials employed in a renewable energy system. The ranking results facilitate the decision makers to make ideal decisions on the materials. The manufacturing systems shall employ either of the materials or the combination of the materials under each of the broader classifications. As sustainable renewable energy systems are required for smart functioning, this decisioning model assists the decision makers to choose the materials under each of the classifications. This decisioning model shall be extended by considering other machine learning algorithms and multi-criteria approaches.

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