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Multi-Criteria Selection of Chitosan-Derived Biodegradable Polymer Composites for Sustainable Energy-Storage Applications

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Abstract: The goal of the present work is to evaluate and select the optimum chitosan-based biodegradable biopolymer composite for energy storage devices for sustainable planning. In this study, “sustainable planning” is specifically addressed at the material selection stage, focusing on the identification of biodegradable and environmentally benign polymer composites that reduce long-term ecological impact and electronic waste generation. The proposed model therefore supports early-stage sustainable design decisions without requiring a full life-cycle assessment. To assess the options—pure chitosan and chitosan modified with different weight percent (10%, 20% and 30%) of 2,6-pyridinedicarboxylic acid; the study offers an integrated multi-criteria decision-making (MCDM) approach called TOPSIS. The entropy approach is used to overcome the impreciseness of eliciting judgments in the preferences of criteria since information pertaining to material attributes is always imprecise. The best sources are then chosen using the TOPSIS approach. According to the results, alternating current (AC) conductivity (40 Hz) is the most important criterion, and chitosan–2,6-pyridinedicarboxylic acid (CPCA) 20 is the best option with the greatest score value. The robustness of the proposed methodology is further demonstrated by sensitivity analysis.

Keywords: Bio-polymer composite; Decision making; Entropy method; TOPSIS method; Sensitivity analysis

1 Introduction

Energy storage devices are in high demand for many applications, like solid-state capacitors, electric vehicles, nanogenerators, memory devices, wearable electronics, etc. A wide range of materials, including silicon- and lead-based compounds, inorganic and organic polymers, ceramics, and nanomaterials, have been utilized for energy storage applications in both large- and small-scale industries [1, 2]. However, the exorbitant use of these materials often leads to a large amount of toxic and non-biodegradable e-wastes. This in turn affects both animals and plants, resulting in severe environmental concern. The environmentally benign materials for electrical energy harvesting and storage devices thus gained utmost importance in the present scenario. Thus, natural fibers and polymers from plants and animals, like starch, cellulose, chitin, etc. have received immense research interest for the fabrication of energy storage devices.

Chitin is a naturally abundant polysaccharide with its monomer containing amine and hydroxyl groups [3]. Many creatures like crabs, prawns, insects, and arthropods have chitin in their exoskeletons. Chitin is also present in the cell walls of some fungi, gladii of molluscs and in some nematodes and diatoms. This makes chitin easily extractable from these natural resources. Chitosan is derived from chitin through the process of deacetylation. On the other hand, dipicolinic acid, or pyridine-2,6-dicarboxylic acid, is present in bacteria like *Bacillus subtilis* for the purpose of heat resistance. This work explores the dielectric behaviour of dipicolinic acid-doped chitosan composites with variation of doping concentrations.

The variation in dielectric properties with doping concentration is primarily attributed to changes in intermolecular interactions, dipolar polarization, and charge carrier mobility within the composite. At optimal doping levels, enhanced interfacial polarization and improved charge transport pathways contribute to higher dielectric constants and conductivity, whereas excessive doping may lead to aggregation effects and increased energy loss.

The dielectric constant is a key physical parameter for assessing the suitability of materials for energy applications [4]. It governs energy storage density of dielectric capacitors, while alternating current (AC) conductivity and dielectric loss determine leakage and energy dissipation, respectively. In the case of composite materials, the dielectric behaviour varies according to the extent of doping into the base material. This variation depends on several parameters, including the nature and type of interactions between dopant and base materials, type of polarizations involved, polarity of materials, etc. The optimization of the dielectric characteristics arising from different concentrations of doping will give a deeper understanding of the interaction and polarization within the composite, which can finally assist in fabricating an efficient and high-performing device. Polymer composites having a high dielectric constant and a low tangent loss are widely valued as substrates for modern high-speed electronics [5, 6]. Conventional dielectric polymers such as polyvinylidene fluoride, polyethylene terephthalate (PET), and polyimide [7–9] offer high performance but suffer from poor biodegradability and environmental persistence [10, 11]. In contrast, the chitosan–pyridine-2,6-dicarboxylic acid (PCA) composite provides a biodegradable alternative derived from renewable resources, addressing sustainability concerns associated with polymer-based electronic materials. The fully biodegradable nature of both chitosan and PCA enables environmentally benign end-of-life disposal, reducing electronic waste accumulation. Unlike conventional fluorinated polymers, the proposed system avoids long-term environmental persistence and supports the development of transient and eco-friendly electronic devices.

In the context of the present work, sustainable planning is addressed specifically from a design-stage material selection perspective. The objective is to prioritize biodegradable polymer composites that minimize environmental persistence, reduce toxicity, and limit electronic waste at the end-of-life stage of energy storage devices. Rather than performing a comprehensive life-cycle assessment, the study focuses on early-stage sustainability integration, where material choice plays a decisive role in determining the environmental footprint, recyclability, and disposal behaviour of the final product.

However, selection of optimum bio-degradable bio-polymer composite for application as polymer dielectric capacitors in biodegradable flexible energy storage devices mainly involves how well several conflicting criteria affect the final selection. Multi-criteria decision-making (MCDM) models are thus essential for the selection of optimum bio-degradable bio-polymer composites for energy storage because they allow decision makers to consider multiple factors when evaluating and selecting the alternatives. Accordingly, the sustainability dimension incorporated in this study is limited to environmental material attributes, ensuring that the selection process aligns with sustainable product development goals while maintaining analytical simplicity.

Nevertheless, many existing MCDM approaches for material selection rely on subjective weighting techniques such as AHP or SWARA, where the importance of criteria is determined based on expert judgment. While effective, such approaches may introduce bias and inconsistency, particularly in cases where reliable experimental data are available but expert preferences are uncertain or unavailable. In addition, several studies employing TOPSIS utilize predefined or arbitrary weights, which may limit the objectivity of the ranking outcomes.

To address these limitations, the present study adopts an integrated entropy–TOPSIS framework, where the entropy method is used to derive objective, data-driven weights based on the variability of experimental data, thereby minimizing subjectivity. This is complemented by the TOPSIS method, which enables systematic ranking of alternatives based on their proximity to the ideal solution under multiple conflicting criteria.

The experimental observations reveal distinct variations in dielectric behaviour across different doping levels, indicating the presence of an optimal composition that balances energy storage capability and electrical losses. However, due to the presence of multiple conflicting performance criteria, it is challenging to identify the best material solely based on direct observation. Therefore, a systematic decision-making framework is required to quantitatively integrate these experimental trends into a unified evaluation model.

In this study, dielectric constant, AC conductivity, and tangent loss are selected as the key decision criteria due to their direct influence on the performance of dielectric energy storage devices. The dielectric constant governs the energy storage capacity, AC conductivity reflects charge transport behaviour and electrical conduction efficiency, while tangent loss represents energy dissipation within the material. Together, these parameters provide a comprehensive evaluation of the material's electrical performance under varying frequency conditions. Wherein, pure chitosan, and chitosan modified with different weight percentages of 2,6-pyridinedicarboxylic acid viz., 10% (chitosan–2,6-pyridinedicarboxylic acid (CPCA) 10), 20% (CPCA 20), and 30% (CPCA 30), are the four alternatives considered to make the decision matrix from experimental data (data has been gathered for every alternative while varying the frequency level from 40 Hz to 20000000 Hz). Different stakeholders may have varying priorities and preferences, and these criteria may be incompatible. Such complexities are addressed by MCDM techniques, which aid in decision-making when more conventional analytical tools are insufficient.

2 Literature

Researchers have been investigating a wide array of bio-degradable bio-polymer composites for a variety of applications. Literature also witnessed various studies on bio-material selection for sustainability planning that concentrated on different MCDM techniques, but no study or least amount of study is available to the scientific community where optimum selection of chitosan-based bio-degradable biopolymer composite as polymer dielectric capacitors for energy storage is evaluated using MCDM methods. A quick discussion of some of the most driven research in the aforesaid field is highlighted in this section.

İpek et al. [12] assessed important characteristics such as impact resistance, strength, corrosion resistance, formability, biocompatibility, and cost. This study used an expert system technique to tackle the problem of material selection for automobile components. The technique determined stainless steel with polymers (polyvinyl chloride, polyethylene) for implants, glass fiber reinforced plastics (GFRP)/carbon fiber reinforced plastics (CFRP) and cast iron/steel for flywheels based on speed, and polymeric materials (polypropylene, high-density polyethylene (HDPE), and polymethyl methacrylate) for bumpers. The outcomes closely matched previous research, confirming the efficacy of the expert system in industrial material selection optimization.

AL-Oqla et al. [13] suggested a new approach for choosing the best polymer matrix for composites reinforced with natural fibers in automotive applications. To rank polymers according to their overall performance, the model simultaneously evaluates 20 physical, mechanical, chemical, environmental, and technological factors. The result gives a roadmap for more extensive engineering applications as well as a dependable framework for choosing sustainable polymers.

To maximize the selection of natural fiber-reinforced composites for automotive applications, this study used expert choice software to implement the AHP. The study determined that hemp–polypropylene composites were the most highly regarded material by using sensitivity analysis to evaluate the major and sub-criteria with an emphasis on environmental sustainability. The findings encourage the use of green technology in vehicle manufacturing by being in line with industrial design specifications [14].

Al-Oqla et al. [15] ranked natural fibers for sustainable automobile composites using an AHP-based decision-making model that was bolstered by expert input. Flax was ranked top among the fibers that were studied (coir, date palm, flax, hemp, and sisal), while date palm fiber was shown to be a competitive and affordable substitute. The model identified mechanical characteristics and particular performance as the most important factors, guaranteeing dependable selection for environmentally friendly automotive applications. It was validated by a pilot questionnaire and sensitivity analysis.

Fuzzy-TOPSIS and Fuzzy-AHP were used to assess biodegradable composite materials [16]. The process ranked the composites based on weights assigned to performance-defining characteristics like elongation, transport qualities, tensile, flexural, and impact strength. According to the data, BC-7 (fiber, matrix, and graphite at 45, 55, and 15 weight percent) was the best formulation, exceeding the others.

Three HDPE–hydroxyapatite polymer blends (HDHA)-10, 20, 30 were created by Das et al. [17] and assessed by surface characterization and mechanical testing. HDHA-30 was determined to be the mix with the best performance using the TOPSIS decision-making technique. It is advised to use HDHA-30 for acetabular liners in hip implants because of its roughness (296 nm) in comparison to ultra-high molecular weight polyethylene (UHMWPE) (1100 nm).

Zindani et al. [18] used a novel prospect theory-based decision-making framework in a hesitant fuzzy environment with normal wiggly hesitant fuzzy sets to optimize the processing parameters of bio-epoxy composite particleboards made from Punica granatum agro-waste treated with sodium bicarbonate. According to the framework, the ideal combination for attaining the best technical, environmental, and financial results was 30% agro-waste loading followed by five days of chemical treatment. The robustness of the model was confirmed by sensitivity analysis and compared with fuzzy TODIM (*Tomada de Decisão Interativa Multicritério*, Interactive Multicriteria Decision Making) techniques, offering a dependable tool for creating sustainable green composites from agro-waste.

Ranking of sustainable polymeric composites based on compressive strength, flexural strength, density, abrasive wear, and water absorption, Soni et al. [19] used the weighted aggregated sum product assessment (WASPAS) technique in conjunction with AHP-based weighting. Correlation checks against other MCDM techniques and comparative and sensitivity analysis validated the approach's consistency and robustness. The results confirmed the efficacy of MCDM in material selection for industrial applications by identifying the ideal composition for floor tiles as 70 weight percent polypropylene, 15 weight percent rice husk ash, and 15 weight percent sand.

Mahajan et al. [20] used a hybrid MCDM framework that included the Entropy and CRITIC methods for criterion weighting with TOPSIS, VIKOR, and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) II to rank natural fibers for sustainable composites. The most reliable results were obtained by comparing TOPSIS and PROMETHEE II with entropy weights using Spearman's rank correlation. Across all sensitivity scenarios, basalt fiber was the most popular option, demonstrating its applicability in automotive, medical, and transportation equipment.

Ramesh et al. [21] employed a hybrid MCDM strategy to choose sustainable lignocellulosic biomass for second-generation ethanol production in India. The Python-based Evaluation Based on Distance from Average Solution algorithm was used to assess five biomass sources: vetiver, rice straw, wheat straw, moringa, and sugarcane bagasse. The outcomes were compared with COPRAS, TOPSIS, and PROMETHEE rankings. The best substitute was vetiver grass, whereas sugarcane bagasse came in last, indicating effective biomass priority to produce bioethanol.

Bioplastics derived from rice and maize starch were investigated by Kang et al. [22] as environmentally friendly substitutes for synthetic plastics in packaging applications. Finding the optimal formulation among different starch-based composites was the MCDM challenge that the study tackled using the Probabilistic Hesitant Fuzzy Set (PHFS)-based COPRAS approach with CRITIC-derived weights. The outcomes validated the viability of using rice and maize thermoplastic starches to create flexible, recyclable, and environmentally friendly packaging materials.

Gupta and Bellare [23] investigate how additive manufacturing can help biomimicry progress by making it possible to fabricate intricate, nature-inspired structures that are not possible with conventional techniques. It draws attention to manufacturing strengths and weaknesses in terms of processing methods and material selection. It also covers the use of MCDM techniques to determine the best materials and procedures for certain biomimetic uses.

In order to pick 3D printed composites in difficult environments, Xie et al. [24] developed a hybrid multi-stage MCDM framework that uses probabilistic interval-valued hesitant fuzzy sets (PIVHFS) to overcome expert hesitation and uncertainty. Interdependencies between criteria were taken into consideration by integrating the Choquet fuzzy integral with the Shapley value, and the best material was found using the PIVHFS-based TODIM-TOPSIS methodology. The robustness of the model was confirmed by an automotive chassis case study, comparison analysis, and sensitivity analysis, providing a trustworthy tool for choosing composite materials in challenging situations.

For sustainable polymer composites, Soni et al. [25] suggested an AO-based integrated SWARA–MABAC architecture with q-rung orthopair fuzzy numbers (q-ROPFNs) to solve the material selection problem. The robustness of the model was confirmed by sensitivity and comparative analyses, demonstrating its dependability in the face of uncertainty. The technique showed its application for sustainable material selection in the circular economy by identifying an ideal floor tile combination of 80 weight percent HDPE, 10 weight percent rice husk ash, and 10 weight percent sand. This composite achieved exceptional mechanical qualities with minimum abrasive wear.

The difficulty of choosing materials and processes for creating toys that promote sensory integration in kids with autism was tackled by Canete et al. [26]. Important technological, design, social, economic, and environmental attributes were given priority across hypersensitive and hyposensitive sensory profiles using MCDM with the Ansys Granta Edu pack. The framework's efficacy in discovering sustainable, lightweight, safe, and long-lasting materials to improve user comfort and engagement was illustrated through a case study on a smart toy.

Poly (vinylidene fluoride-trifluoro ethylene) [P(VDF-TrFE)], titanium di-oxide (TiO_2), and polydimethylsiloxane-based hybrid nanogenerators were created by Kumar et al. [27] by combining triboelectric and piezoelectric phenomena to enhance energy harvesting efficiency. For the first time, the impact of TiO_2 variation was examined, and the device produced an output voltage of 52 V and a current of 5.36 μA. Outperforming other current nanogenerators with easier design and fabrication, the SA-4 nanocomposite was determined to be the ideal material using the TODIM-MCDM technique with sensitivity analysis.

A new hybrid multi-criteria group decision-making (MCGDM) framework (PF-SD-RS-OCRA) is presented by Liu et al. [28] for evaluating and choosing sustainable green building materials in the face of uncertainty. To balance objective data and expert opinions, the model uses an expanded OCRA approach, rank sum weighting, and a new fuzzy symmetric divergence measure. A case study illustrated its adaptability and resilience, outperforming current models and offering a trustworthy resource for choosing sustainable building materials.

Using a twin-screw extruder and PBI loadings of 1, 3, and 5 weight percent, Ramesh et al. [29] created HDPE/PBI composites via melt intercalation to improve wear resistance in industrial applications. ANOVA and CODAS ranking in conjunction with two-body abrasive wear tests showed that 5 weight percent polybenzimidazole provided the optimum performance, although sliding distance and greater load increased the specific wear rate. The association between wear and process factors was confirmed by Scanning Electron Microscope (SEM) analysis and machine learning models, especially multilayer perceptrons, which showed dependable predicting capacity for composite performance.

Mardina et al. [30] present Circular Materials MCDM for Medical Devices (CM3D), an MCDM tool that addresses environmental consequences throughout the whole product life cycle when choosing circular materials for medical devices. Material choices are objectively ranked by the framework using the VIKOR algorithm and stakeholder-informed criteria. The application of CM3D for sustainable medical device design was demonstrated by a case study on laparoscopic scissors, which found that stainless steel for handles and tungsten carbide for blades were the best circular materials.

Mohit et al. [31] combined eggshell waste with inorganic fillers (alumina, titania, and aluminum trihydrate) to create glass fiber-reinforced epoxy hybrid composites that improved mechanical, thermal, and environmental performance. With an 8.92% higher glass transition temperature, the ideal composite (L7GEATAER) demonstrated a 25.4% decrease in water absorption, an increase in density, and improvements in flexural and tensile strengths of 2.14 and 1.57 times, respectively. Uniform filler dispersion and strong interfacial bonding were confirmed by convolutional neural network (CNN)-based SEM analysis, indicating the promise of biowaste–inorganic hybrid composites for high-performance, sustainable applications in the construction, automotive, and aerospace industries.

A PROMETHEE II-based MCDM approach was used by Dimitrellou et al. [32] to choose the best Fused Deposition Modeling (FDM) 3D printing materials from a variety of standard, engineering, and high-performance polymers. Three industrial product scenarios were used to evaluate a variety of parameters, including mechanical, thermal, chemical, dimensional, and cost aspects. High-performance polymers were shown to be the most adaptable and durable materials, proving the usefulness of the MCDM technique for well-informed material selection in industrial additive manufacturing applications.

For the selection of optimal bio-degradable bio-polymer composites as polymer dielectric capacitors for energy storage devices, this study proposes an integrated entropy-TOPSIS method. While entropy and TOPSIS have been widely used in material selection problems, their combined application in the context of biodegradable polymer composites for energy storage - particularly using experimentally derived dielectric data - remains limited.

Unlike many existing studies that rely on subjective weighting schemes or generalized material databases, the present work emphasizes a data-driven and application-specific evaluation framework. The integration of entropy-based objective weighting with TOPSIS ranking, supported by sensitivity analysis, provides a consistent and reproducible approach for selecting sustainable materials under multiple performance criteria. Therefore, the contribution of this study lies primarily in the targeted application and validation of an established MCDM framework for a novel material system rather than the development of a new decision-making method.

3 Research Methodology

In this section, an integrated entropy-TOPSIS-based MCDM methodology is presented for the selection of chitosan-based bio-degradable bio-polymer composites for energy storage devices. Figure 1 depicts the proposed research framework. In this study there are three criteria: dielectric constant, AC conductivity, and tangent loss [1–4], and four alternatives are likely; pure chitosan, CPCA 10, CPCA 20, and CPCA 30 have been taken into consideration. Thereafter, authors have conducted various experiments (varying the frequency from 40 Hz to 20000000 Hz) to get desired data. As has been stated in literature [5, 6], the values fall within the ranges of practical applications as polymer dielectrics. Then data has been analyzed using an integrated entropy-TOPSIS methodology. Firstly, the entropy technique is used to find the criteria weight. The criterion weight of a MCDM problem can be measured using the entropy method, a decision assistance tool created by Shannon [33], particularly in situations where decision makers' trials are not feasible. The entropy method helps to determine the weight of each criterion by computing the relative importance of one parameter in relation to another [34, 35]. Secondly, the TOPSIS method is used to rank alternatives as per their merit. TOPSIS, a straightforward and well-known MCDM technique, finds an alternative solution from a finite set by maximizing the distance from the negative ideal point and minimizing the distance from the positive ideal point [36–41]. Thirdly, order of merit or the Borda method is also utilized to check the ranking by integrated methodology. Finally, a sensitivity study demonstrates the suggested methodology's resilience. The selection of the entropy–TOPSIS combination is particularly suitable in this context, as it allows objective determination of criteria weights directly from experimental data while ensuring an efficient ranking of alternatives under conflicting performance requirements. This enhances the reliability and transparency of the decision-making process compared to purely subjective or single-method approaches. Within this framework, sustainability is operationalized through the inclusion of biodegradable and environmentally compatible material characteristics, integrated alongside key electrical performance criteria in the decision model.

The following steps are used to get the result based on the proposed integrated entropy-TOPSIS methodology:

- Step 1: Create hierarchy model.
- Step 2: Create matrix of decisions.
- Step 3: Develop normalized decision matrix.
- Step 4: Compute entropy value.
- Step 5: Calculate the degree of divergence value.
- Step 6: Create a weighted normalized decision matrix by the TOPSIS method.
- Step 7: Measure the performance.
- Step 8: Calculate the distance.
- Step 9: Determine the closeness coefficient and ranking.
- Step 10: Check the order of merit.

The Euclidean distance function is utilized in the Entropy-TOPSIS methodology to tackle multi-objective decision-making problems. This function computes the proximity coefficient values based on the subjective and objective weights and estimates the distance from the ideal solution. The entropy method does not require complicated mathematics for practitioners and offers an effective way to determine the weight while maintaining consistency in assessments. Under conflicting conditions, the integrated technique serves as a repository for the ranking of the best sources according to the values of the closeness coefficient.

Thus, the proposed methodology serves as a bridge between experimentally observed material behaviour and decision-making analysis by systematically incorporating measured dielectric properties into the ranking process.

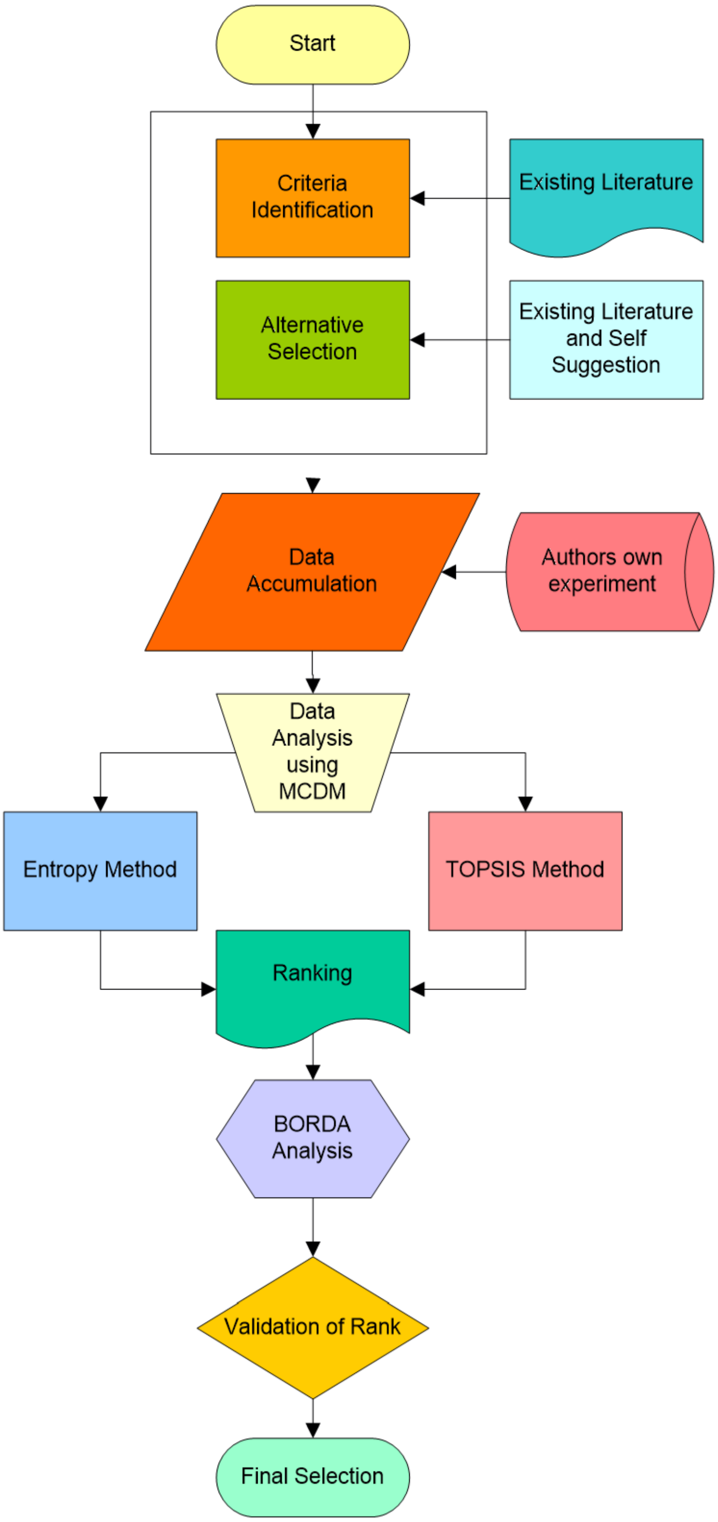


Figure 1. Proposed research flow diagram

4 Result and Discussion

In this study, an integrated entropy-TOPSIS methodology is applied to evaluate and select the optimum biodegradable bio-polymer composite for energy storage device application by considering multiple criteria into account. To show the applicability of the proposed research framework, data have been collected from the authors' own experiment. The alternatives and corresponding criteria are as follows:

- The decision alternatives are pure chitosan, CPCA 10, CPCA 20 and CPCA 30.
- Factors for the decision model are dielectric constant, AC conductivity and tangent loss (varying the frequency from 40 Hz to 20 ×10^6 Hz)

Each step of the application procedure is briefly explained in the subsection that follows.

Step 1: Creation of a hierarchy

All the choice options and the criteria that go with them are identified, and they are shown in a top-bottom hierarchy with the aim at the top, different criteria in the middle, and the numerous alternatives at the bottom. In Figure 2, the hierarchy is displayed.

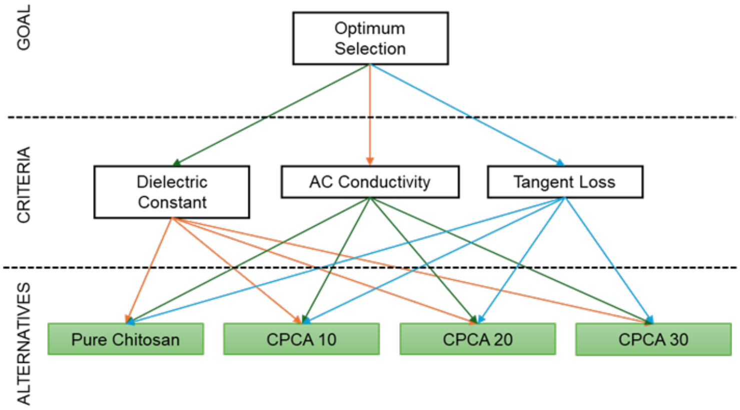


Figure 2. Hierarchy of the proposed model

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid; AC = alternating current.

Step 2: Create a matrix of decisions

In this step, three Pugh matrices, also known as decision matrices p_{ij}, are developed from the experimental data under each criterion varying the frequency level and shown in Appendix A. This study considers four primary biodegradable bio-polymer composite alternatives and their corresponding three criteria from the experiment. Firstly, bio-degradable bio-polymer composites are listed down in rows, and criteria are in column headings, respectively. Thereafter, the optimal choice is determined by assigning a score to each option for each criterion in the decision table (shown in Appendix A; Table A1) using various techniques and calculating the relative relevance of the criteria. In practically every significant decision-making situation where there isn't a clear and obvious preferred option, Pugh matrix analysis is a useful tool [35].

Step 3: Develop normalized decision matrix

In this step, a normalized decision matrix (q_{ij}) is developed (considering dielectric constant as criteria and data taken for different frequency levels for all the selected alternatives), by dividing each element of the decision matrix by its column sum. Normalization is obvious to neutralize the irregularities of different measurement units associated with the quantitative variables of the decision matrix. Normalization is done using Eq. (1) and shown in Table 1. In this study only one sample is shown for a clear understanding of the method. Similarly, for other criteria, the same analysis is carried out and reported in Appendix B and C, respectively.

Table 1. Normalized decision matrix (dielectric constant)

	40 Hz	**100 Hz**	**1000 Hz**	**10000 Hz**	**100000 Hz**	**1000000 Hz**	**20000000 Hz**
Pure chitosan	0.1212	0.1276	0.1643	0.0643	0.0308	0.0226	0.0151
CPCA 10	0.2523	0.2416	0.2396	0.0879	0.0398	0.0217	0.0235
CPCA 20	0.4869	0.4870	0.5051	0.1387	0.0670	0.0453	0.0407
CPCA 30	0.1394	0.1435	0.0907	0.0253	0.0199	0.0190	0.0178

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid.

$$q_{ij} = \frac{p_{ij}}{\sum_{i=1}^{n} p_{ij}} \tag{1}$$

where, p_{ij} represents the performance value of the i^{th} alternative under the j^{th} criteria.

The normalized decision matrix eliminates the influence of differing measurement scales across frequency levels, enabling a consistent comparison of alternatives. Higher normalized values indicate relatively better performance of a given material under the selected criterion.

Step 4: Calculation of entropy value

After the normalization of each element in decision matrix, the entropy value (b_j) is calculated using Eq. (2); by taking the log for each element of the normalized values and depicted in Table 2.

$$b_j = -c \sum_{j=1}^{n} q_{ij} \ln q_{ij} \tag{2}$$

where, c is a constant and can be expressed as $c = (\ln(e))^{-1}$.

Table 2. Entropy value

	40 Hz	**100 Hz**	**1000 Hz**	**10000 Hz**	**100000 Hz**	**1000000 Hz**	**20000000 Hz**
Pure chitosan	-2.1090	-2.0581	-1.8054	-2.7429	-3.4795	-3.7872	-4.1929
CPCA 10	-1.3770	-1.4201	-1.4284	-2.4310	-3.2216	-3.8276	-3.7479
CPCA 20	-0.7195	-0.7192	-0.6828	-1.9752	-2.7017	-3.0938	-3.1991
CPCA 30	-1.9699	-1.9412	-2.3996	-3.6736	-3.9141	-3.9613	-4.0270

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid.

The entropy values reflect the degree of dispersion in the data for each frequency level. Lower entropy indicates higher variability and thus greater discriminating power of the corresponding parameter in the decision-making process.

Step 5: Calculate the degree of divergence value

The degree of divergence values is calculated using Eq. (3), and each divergence value is divided by its row sum to assign the weight of the corresponding criterion as shown in Table 3.

$$w_j = 1 - b_j \tag{3}$$

Table 3. Weight of criteria

	40 Hz	**100 Hz**	**1000 Hz**	**10000 Hz**	**100000 Hz**	**1000000 Hz**	**20000000 Hz**
Weight	0.2530	0.2042	0.1313	0.1562	0.1022	0.0795	0.0732

The derived weights indicate the relative importance of each frequency-level dataset in distinguishing between alternatives. Criteria associated with higher weights contribute more significantly to the final ranking of materials.

Step 6: Weighted normalized decision matrix by TOPSIS method

Thereafter, the previously normalized decision matrix by the entropy method is utilized here to prepare the weighted normalized matrix. In the TOPSIS method, the very first two steps are to create the decision matrix and normalization. To maintain integrity in the calculation, this study followed the same procedure for both analysis methods mentioned above. Thereafter, the weighted normalized decision matrix is calculated as per the steps described by the TOPSIS methodology using Eq. (4). In this step, entropy weights (Table 3) are incorporated to find the weighted normalized decision matrix and shown in Table 4.

$$h_{ij} = w_j \times q_{ij} \tag{4}$$

where, h_{ij} represents the normalized decision matrix, wherein w_j stands for weight of j^{th} criteria.

The weighted normalized matrix integrates both the normalized performance values and their corresponding importance weights. This step ensures that criteria with higher relevance exert a stronger influence on the evaluation process.

Table 4. Weighted normalized decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	0.0306	0.0260	0.0335	0.0100	0.0031	0.0018	0.0011
CPCA 10	0.0638	0.0493	0.0489	0.0137	0.0040	0.0017	0.0017
CPCA 20	0.1232	0.0994	0.1031	0.0216	0.0068	0.0036	0.0029
CPCA 30	0.0352	0.0293	0.0185	0.0039	0.0020	0.0015	0.0013

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid

Step 7: Measure the performance

For every criteria alternative, the best performance (A^+) and worst performance (A^-) is calculated using Eqs. (5) and (6) respectively and shown in Table 5.

$$A^+ = \{a_1^+, a_2^+, \ldots, a_n^+\} = \{(\mathrm{Max}_j\, h_{ij} \mid j \in j'), (\mathrm{Min}_j\, h_{ij} \mid j \in j'')\} \tag{5}$$

$$A^- = \{a_1^-, a_2^-, \ldots, a_n^-\} = \{(\mathrm{Min}_j\, h_{ij} \mid j \in j'), (\mathrm{Max}_j\, h_{ij} \mid j \in j'')\} \tag{6}$$

Table 5. Best and worst performance

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
A^+	0.1232	0.0994	01031	0.0216	0.0068	0.0036	0.0029
A^-	0.0306	0.0260	0.0185	0.0039	0.0020	0.0015	0.0011

Note: A^+ = best performance, A^- = worst performance.

The best and worst performance values define the ideal and negative-ideal solutions, respectively. These serve as reference points for evaluating how close each alternative is to the optimal performance condition.

Step 8: Calculate the distance

As TOPSIS is based on the principle of Euclidean distance function, this measures the distance from the ideal solution. Therefore, the alternative is chosen by the shortest distance from the positive ideal solution (R_i^+) and the longest distance from the negative ideal solution (R_i^-) using Eqs. (7) and (8) respectively.

$$R_i^+ = \sqrt{\sum_{j=1}^{n} \left(h_{ij} - A_j^+\right)^2} \tag{7}$$

$$R_i^- = \sqrt{\sum_{j=1}^{n} \left(h_{ij} - A_j^-\right)^2} \tag{8}$$

Step 9: Determine the closeness coefficient and ranking

For every alternative, the distance to the negative solution is divided by the sum of the distance to the negative and positive solutions with the quotient, represented by C_i. C_i exhibits similarity to the positive ideal solution as shown in Eq. (9). According to the magnitude of C_i, alternatives are arranged as shown in Table 6. The alternative with the largest C_i value is selected as an optimum one. Larger values of C_i means that the alternative is closer to the ideal solution.

$$C_i = \frac{R_i^-}{R_i^- + R_i^+} \tag{9}$$

where, C_i stands for closeness index.

The ranking results obtained from the entropy-TOPSIS method are consistent with the observed experimental trends. CPCA 20 demonstrates superior dielectric performance due to its balanced combination of high dielectric constant and AC conductivity along with relatively lower tangent loss. These characteristics enhance energy storage efficiency while minimizing dissipation losses. The entropy weighting method assigns higher importance to criteria with greater variability in experimental data, thereby ensuring that significant performance differences are appropriately reflected in the ranking. As a result, the decision model effectively translates experimental behaviour into a quantitative ranking framework.

Finally, based on Table 6, the alternative with the highest score value is said to be the optimum choice (CPCA 20, which is also in line with the experimental result), and the rest of the alternatives are ranked according to closeness to the ideal solution. At the outset, selecting the optimum bio-degradable bio-polymer composite for energy storage applications is entirely necessary using various techniques. Identifying the best techniques effectively improves the performance and behaviour of the selection process and yields decisions.

Table 6. Ranking of alternatives

Alternatives	C_i	**Rank (Dielectric Constant)**	C_i	**Rank (AC Conductivity)**	C_i	**Rank (Tangent Loss)**	C_i	**Rank (Borda Method)**
Pure chitosan	0.1056	3	0.0997	3	0.1155	3	0.0625	3
CPCA 10	0.3518	2	0.2849	2	0.3549	2	0.2986	2
CPCA 20	1	1	0.9496	1	1	1	1	1
CPCA 30	0.0381	4	0.0913	4	0.0371	4	0.0054	4

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid; AC = alternating current, C_i = closeness index.

Step 10: Order of merit checking

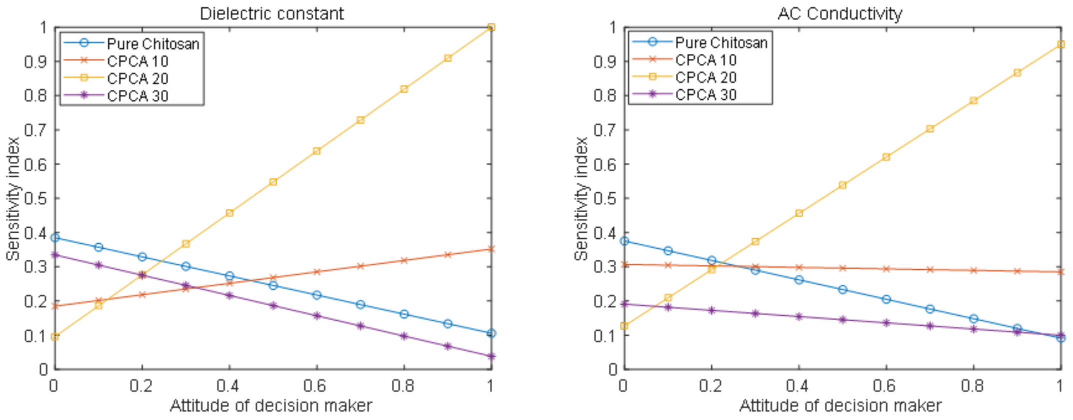
This research utilized the concept "order of merit" to check the ranking of alternatives again. And, it has been found that the ranking is similar compared to the ranking of the integrated entropy-TOPSIS methodology. The calculation process and results are highlighted in Appendix D for better understanding. The order of merit or Borda method was put forth during the French Revolution to be applied in a situation where there were several decision-makers [42, 43]. It was later modified to solve ranking problems using several criteria [42, 43]. One technique for rating a group of criteria or options is Borda. This method's main concept is to create a global ranking by combining multiple individual rankings created by a group of experts or DMs. The sum of the scores from each separate ranking serves as the basis for the combination [44]. Using a numerical scale with integer values ranging from 0 to n-1, where n is the number of criteria, the individual ranking is accomplished. A score is assigned to each criterion according to how highly it ranks in the preferences of the individual. Assigning a score of n-1 points to the criterion that is rated first, n-2 points to the criterion that is ranked second, and so on, down to 0 points for last place, is the most common method of assigning scores to criteria [44]. In the end, the criterion with the highest scores prevails. This approach merely creates an order for the criteria without determining their weights.

5 Sensitivity Analysis

Sensitivity analysis is the process of examining the degree of uncertainty in an analysis's output that can be attributed to various sources of uncertainty as inputs. This study demonstrates, using a mathematical model, the uncertainty of the best choice of a chitosan-based biodegradable biopolymer composite for energy storage device application under three segments and alternative rankings in numerous parameters [45–47].

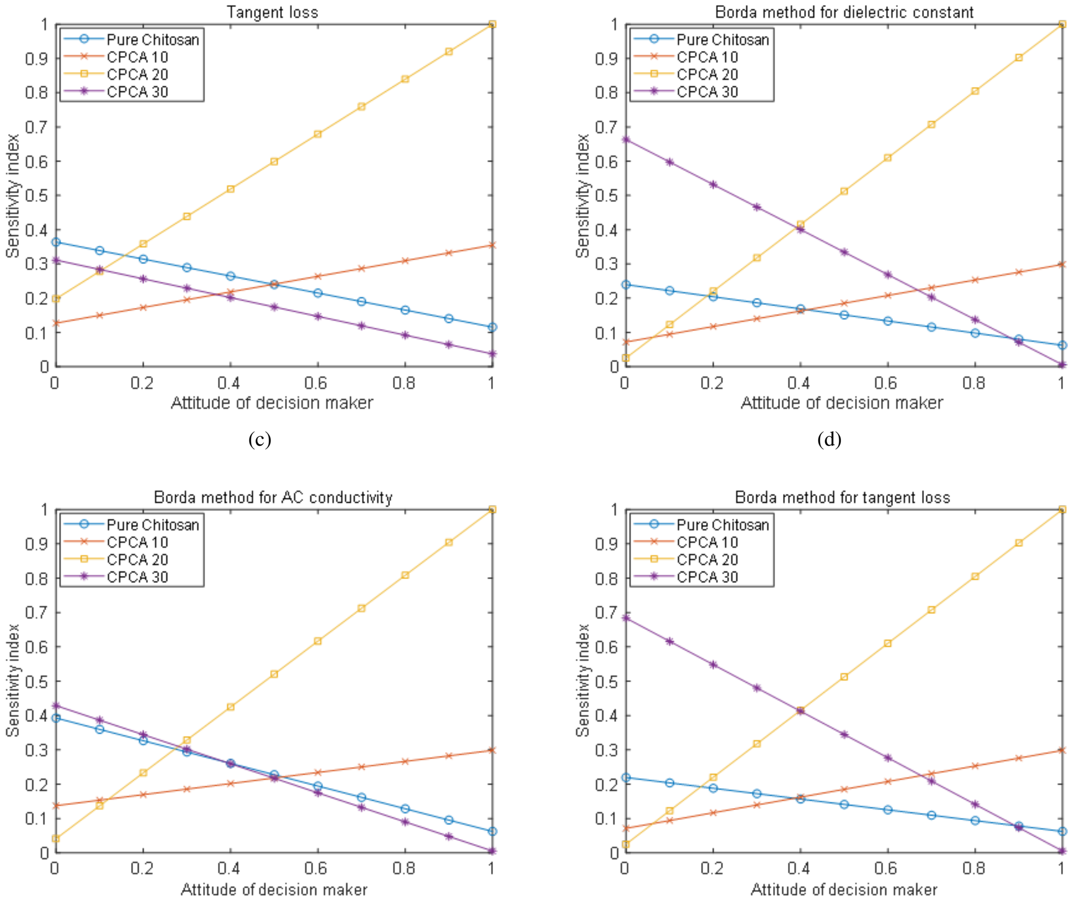
$$\mathrm{SI}_i = [(\alpha\mathrm{SFM}_i) + (1-\alpha)\mathrm{OFM}_i] \tag{10}$$

where, $\mathrm{OFM}_i = \frac{1}{\left[\mathrm{OFD}_i \sum_{i=1}^{n} \mathrm{OFD}^{-1}\right]}$.



(a)

(b)



(c) (d)

(e) (f)

Figure 3. Sensitivity analysis of integrated entropy-TOPSIS and Borda method for alternatives under various criteria: (a) dielectric constant; (b) AC conductivity; (c) tangent loss; (d) dielectric constant; (e) AC conductivity; and (f) tangent loss

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid; AC = alternating current.

Table 7. Analysis of Figures 3a–3f

Criteria	Reference Figure	Alternative's Rank	Decision Maker Attitude Value
Dielectric constant	3a	CPCA 20 > CPCA 10 > CPCA 30 > pure chitosan	$\alpha = 0.312$
		CPCA 10 > Pure chitosan > CPCA 30	$\alpha = 0.514$
		CPCA 20 > CPCA 30 > CPCA 10	$\alpha = 0.289$
		CPCA 20 > CPCA 10	$\alpha = 0.178$
	3d	CPCA 20 > CPCA 30 > CPCA 10 > pure chitosan	$\alpha = 0.437$
		CPCA 10 > CPCA 30 > pure chitosan	$\alpha = 0.711$
		CPCA 20 > pure chitosan > CPCA 10	$\alpha = 0.234$
		CPCA 20 > pure chitosan	$\alpha = 0.45$
		CPCA 20 > CPCA 10	$\alpha = 0.097$
		CPCA 30 > pure chitosan	$\alpha = 0.914$
AC conductivity	3b	CPCA 20 > CPCA 10 > CPCA 30 > pure chitosan	$\alpha = 0.210$
		CPCA 10 > pure chitosan > CPCA 20 > CPCA 30	$\alpha = 0.285$
		CPCA 20 > CPCA 10 > pure chitosan > CPCA 30	$\alpha = 0.2$
		CPCA 20 > CPCA 30	$\alpha = 0.098$
	3e	CPCA 20 > CPCA 10 > CPCA 30 > pure chitosan	$\alpha = 0.345$
		CPCA 20 > pure chitosan > CPCA 10	$\alpha = 0.323$

Continued on next page

Table 7 (continued)

Criteria	Reference Figure	Alternative's Rank	Decision Maker Attitude Value
		CPCA 10 > CPCA 30	$\alpha = 0.475$
		CPCA 10 > CPCA 30	$\alpha = 0.567$
		CPCA 10 > CPCA 30	$\alpha = 0.6$
		CPCA 20 > CPCA 10	$\alpha = 0.153$
Tangent loss	3c	CPCA 20 > pure chitosan > CPCA 30 > CPCA 10	$\alpha = 0.231$
		CPCA 10 > pure chitosan > CPCA 30	$\alpha = 0.6$
		PCA 20 > CPCA 30 > CPCA 10	$\alpha = 0.193$
		CPCA 10 > CPCA 30	$\alpha = 0.433$
	3f	CPCA 20 > CPCA 30 > pure chitosan > CPCA 10	$\alpha = 0.467$
		CPCA 10 > CPCA 30 > pure chitosan	$\alpha = 0.793$
		CPCA 30 > pure chitosan	$\alpha = 0.916$
		CPCA 20 > pure chitosan > CPCA 10	$\alpha = 0.210$
		CPCA 10 > pure chitosan	$\alpha = 0.436$
		CPCA 20 > CPCA 10	$\alpha = 0.097$

Note: CPCA = chitosan–2,6-pyridinedicarboxylic acid; AC = alternating current.

The sensitivity index is represented by SI, the objective factor weight by α, the global priorities of each biodiesel option by SFM positions [46] and the objective factor measure by OFM. There are n alternatives (in this case, n = 4), and the objective factor dimension is OFD. The final scores from Table 6 are the normalized SFM values used in Eq. (10) in this investigation. The experimental results are the source of the OFM values. The selection of the α value is an important factor. Based on personal choice, it is the decision maker's perception of the significance of both objective and subjective factor measures. However, the alternative assessment may specify several sets of results for various values of α for the same alternatives with different criteria. Therefore, to analyze the impact of the best choice of chitosan-based bio-degradable bio-polymer composite for energy storage device application in accordance with the study purpose, the sensitivity plots shown in Figures 3a–3f are highly recommended. The sensitivity plot results are summarized in Table 7, which further demonstrates the importance of carefully choosing the appropriate objective component weight value. This leads to the conclusion that the sensitivity analysis and the ranking determined in each case utilizing integrated methods are consistent.

6 Conclusions

When choosing the best option, a range of options must be considered, demonstrating the participation of several decision-making groups. In this work, an integrated entropy-TOPSIS technique is used to analyze the selection problem for a biodegradable biopolymer composite based on chitosan. Literature provides the standards required to gauge the bio-polymer composite's performance. This paper uses an actual set of experimental data to demonstrate the applicability of the suggested integrated methodology. In one decision-making scenario, which aims to identify the best material, four bio-polymer composite alternatives were ranked using three criteria with seven distinct frequency levels. It is important to note that the novelty of this work lies in the application of an established entropy–TOPSIS framework to a new class of biodegradable materials, rather than in the development of a new MCDM technique. Since linguistic variables are frequently used in MCDM methods, performance values cannot be adequately addressed by numerical values. Optimal selection issues are typically ambiguous and unpredictable. This kind of problem cannot be solved with the conventional single criterion-based method. This study employs an integrated entropy-based TOPSIS methodology to find the best answer. The weight of each criterion is first established using Shannon's entropy approach. The findings show that AC conductivity has the highest preference at the 40 Hz frequency level, followed by tangent loss and dielectric constant.

The TOPSIS approach, on the other hand, assists decision-makers in obtaining assessments of each bio-polymer composite alternative's performance in relation to each criterion by means of linguistic values. According to the results, the best option produced by the integrated entropy-TOPSIS methodology is CPCA 20. A sensitivity study is conducted to verify the suggested methodology's capacity. The relative performances of the options in relation to their respective criteria constitute the basis of Figures 3a–3f graphical portrayal. The outcomes of the sensitivity analysis are compatible with the ranking of alternatives using an integrated entropy-TOPSIS. The suggested approach is the first analysis in this field of study and can be used as a standard for any situation involving uncertainty. From a sustainable planning perspective, the proposed model contributes by enabling informed material selection decisions at the early design stage, where the adoption of biodegradable and non-persistent materials can significantly reduce environmental impact. The approach emphasizes environmentally responsible material choice without the need for full life-cycle modelling, thereby providing a practical and scalable pathway for sustainable product development.

It is anticipated that the integrated framework will play a key role in developing an eco-friendly selection method that would increase an organization's competitiveness while promoting sustainable development. Additionally, this study shows that the single criteria-based strategy is insufficiently robust and helpful for today's selection problems. Furthermore, choosing a bio-polymer composite without considering several competing factors is not always the best option. As a result, other decision-making issues can also be effectively resolved by the suggested integrated methodology. Using quantitative methods, this research might be expanded by adding and identifying additional important decision matrix parameters that could help achieve the necessary resilience and long-term technological development levels. Additionally, in some particularly unpredictable situations, various MCDM techniques could be applied to assess and choose the best options.

The selected alternative, CPCA 20, demonstrates significant potential for practical applications in biodegradable electronic materials, particularly in dielectric components and triboelectric nanogenerators, where high dielectric permittivity and ionic conductivity are desirable. This makes it suitable for applications such as wearable energy-harvesting devices and eco-friendly electronic systems. Future work may focus on validating the selected material (CPCA 20) through device-level performance testing, particularly in triboelectric nanogenerators and flexible electronic systems. Additionally, the decision-making framework can be extended by incorporating additional criteria such as mechanical stability, biodegradability rate, and long-term durability to enhance the robustness of material selection.

Author Contributions

Conceptualization, C.M. and K.C.; methodology, C.M. and C.B.; software, C.B.; formal analysis, C.B.; investigation, C.M.; data curation, C.M.; writing—original draft preparation, C.M., A.K., A.R.D., K.C., and C.B.; writing—review and editing, A.K., A.R.D., K.C., and C.B.; visualization, C.B.; supervision, A.K. and K.C. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

During the preparation of this work the authors used GPT-4 & Google Gemini 3.0 to improve readability, rectify grammatical errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix

Appendix A (Dielectric Constant)

Table A1. Decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	100.12	84.6	71.88	53.16	25.45	18.71	12.47
CPCA 10	208.36	160.12	104.8	72.62	32.94	17.97	19.46
CPCA 20	402.12	322.71	220.88	114.55	55.4	37.43	33.69
CPCA 30	115.16	95.09	39.68	20.96	16.48	15.72	14.72

Appendix B (AC Conductivity)

Table B1. Decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	1.423	1.53	1.74	8.44	70	240	360
CPCA 10	1.74	1.74	1.94	21	97	320	450
CPCA 20	4.2	4.5	10	42	140	480	720
CPCA 30	2.8	3.24	3.74	4.72	12	81	140

Table B2. Normalized decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	0.1400	0.1390	0.0999	0.8305	6.8877	23.6151	35.4226
CPCA 10	0.1712	0.1580	0.1114	2.0663	9.5444	31.4868	44.2783
CPCA 20	0.4133	0.4087	0.5741	4.1326	13.7755	47.2301	70.8452
CPCA 30	0.2755	0.2943	0.2147	0.4644	1.1808	7.9701	13.7755

Table B3. Entropy value (AC conductivity)

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	-1.9660	-1.9735	-2.3037	-0.1858	1.9297	3.1619	3.5674
CPCA 10	-1.7649	-1.8449	-2.1949	0.7258	2.2560	3.4496	3.7905
CPCA 20	-0.8837	-0.8947	-0.5550	1.4189	2.6229	3.8550	4.2605
CPCA 30	-1.2891	-1.2232	-1.5385	-0.7669	0.1662	2.0757	2.6229

Table B4. Weight of criteria

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Weight	-0.0014	-0.0015	-0.0019	0.0061	0.0653	0.3514	0.5819

Table B5. Weighted normalized decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	-0.0002	-0.0002	-0.0002	0.0004	0.0020	0.0080	0.0088
CPCA 10	-0.0003	-0.0004	-0.0004	0.0005	0.0026	0.0076	0.0137
CPCA 20	-0.0007	-0.0007	-0.0007	0.0009	0.0044	0.0159	0.0237
CPCA 30	-0.0002	-0.0002	-0.0001	0.0002	0.0013	0.0067	0.0104

Table B6. Best and worst performance

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
A^+	-0.0002	-0.0002	-0.0001	0.0009	0.0044	0.0159	0.0237
A^-	-0.0007	-0.0007	-0.0007	0.0002	0.0013	0.0067	0.0088

Appendix C (Tangent Loss)

Table C1. Decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	0.3424	0.2442	0.1755	0.2979	0.4533	0.2925	0.2394
CPCA 10	0.9798	0.6617	0.3107	0.3893	0.5174	0.2961	0.2376
CPCA 20	0.6288	0.4515	0.3418	0.5612	0.4588	0.2522	0.212
CPCA 30	0.4003	0.4497	0.6215	0.3345	0.1681	0.1115	0.095

Table C2. Normalized decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	0.1456	0.1351	0.1211	0.1267	0.1928	0.1244	0.1018
CPCA 10	0.4167	0.3662	0.2143	0.1656	0.2200	0.1259	0.1011
CPCA 20	0.2674	0.2498	0.2358	0.2387	0.1951	0.1073	0.0902
CPCA 30	0.1702	0.2489	0.4288	0.1423	0.0715	0.0474	0.0404

Table C3. Entropy value

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	-1.9267	-2.0015	-2.1113	-2.0660	-1.6462	-2.0843	-2.2846
CPCA 10	-0.8754	-1.0047	-1.5401	-1.7984	-1.5139	-2.0720	-2.2921
CPCA 20	-1.3189	-1.3869	-1.4447	-1.4326	-1.6341	-2.2325	-2.4061
CPCA 30	-1.7705	-1.3909	-0.8468	-1.9501	-2.6382	-3.0487	-3.2088

Table C4. Weight of criteria

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Weight	0.1641	0.1428	0.1252	0.1548	0.1532	0.1336	0.1264

Table C5. Weighted normalized decision matrix

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
Pure chitosan	0.0199	0.0182	0.0235	0.0100	0.0047	0.0030	0.0019
CPCA 10	0.0414	0.0345	0.0342	0.0136	0.0061	0.0029	0.0030
CPCA 20	0.0799	0.0695	0.0721	0.0215	0.0103	0.0061	0.0052
CPCA 30	0.0229	0.0205	0.0130	0.0039	0.0031	0.0025	0.0023

Table C6. Best and worst performance

	40 Hz	100 Hz	1000 Hz	10000 Hz	100000 Hz	1000000 Hz	20000000 Hz
A^+	0.0799	0.0695	0.0721	0.0215	0.0103	0.0061	0.0052
A^-	0.0199	0.0182	0.0130	0.0039	0.0031	0.0025	0.0019

Appendix D (BORDA Method or Order of Merit)

Table D1. Decision matrix

	Dielectric Constant	AC Conductivity	Tangent Loss
Pure chitosan	0.1057	0.0913	0.1156
CPCA 10	0.3518	0.2850	0.3549
CPCA 20	1.0000	0.9496	1.0000
CPCA 30	0.0382	0.0997	0.0371

Table D2. Normalized decision matrix

	Dielectric Constant	AC Conductivity	Tangent Loss
Pure chitosan	0.0707	0.0641	0.0767
CPCA 10	0.2352	0.1999	0.2354
CPCA 20	0.6686	0.6661	0.6633
CPCA 30	0.0255	0.0699	0.0246

Table D3. Entropy value

	Dielectric Constant	AC Conductivity	Tangent Loss
Pure chitosan	-2.6499	-2.7481	-2.5685
CPCA 10	-1.4472	-1.6099	-1.4463
CPCA 20	-0.4026	-0.4063	-0.4105
CPCA 30	-3.6685	-2.6600	-3.7046

Table D4. Weight of criteria

	Dielectric Constant	AC Conductivity	Tangent Loss
Weight	0.3308	0.3348	0.3344

Table D5. Weighted normalized decision matrix

	Dielectric Constant	AC Conductivity	Tangent Loss
Pure chitosan	0.0234	0.0214	0.0256
CPCA 10	0.0778	0.0669	0.0787
CPCA 20	0.2212	0.2230	0.2218
CPCA 30	0.0084	0.0234	0.0082

Table D6. Best and worst performance

	Dielectric Constant	AC Conductivity	Tangent Loss
A^+	0.2212	0.2230	0.2218
A^-	0.0084	0.0214	0.0082