An Integrated Intuitionistic Fuzzy MCDM Approach to Rank Alternatives of Polycarbonate Thermoplastic Resins

Ilknur Karacan, Ismet Karacan, and Inanc Erdogan
AN-EL Anahtar ve Elektrikli Ev Aletleri San. A.S.
Pendik, 34896, Turkey
anelprs145@an-el.com.tr, anelprs142@an-el.com.tr, anel@an-el.com.tr

Ozlem Senvar, Serol Bulkan
Department of Industrial Engineering
Marmara University
Maltepe, 34854, Turkey
ozlem.senvar@marmara.edu.tr, sbulkan@marmara.edu.tr

Abstract

Polycarbonate (PC) resins are widely preferred by manufacturers to produce a large portfolio of products. It is in the group of thermoplastic polymers. PCs are durable, flame-retardant, and have efficient electricity insulation performance. They can be used to produce many different types of products like capacitors, dome lights, roofing sheets, compact disks, water bottles, decorative bezels, etc. It is a crucial issue to select rational PC resin specific to the application area. The manufacturers can optimize their processes, as well as finances by selecting the most appropriate resin. Many methods may be applied to optimize the selection process. In this paper, a Multi-Criteria Decision-Making (MCDM) Model is proposed that considers both technical criteria and operational criteria. The Intuitionistic Fuzzy Analytical Hierarchy Process (IF-AHP) method is integrated into the Intuitionistic Fuzzy Goal Programming (IF-GP) method to weight criteria, assess the alternatives, and suggest ranking of the alternatives. A sensitivity analysis completes the methodology to determine the boundaries of the solution. The results reveal that they are very sensitive to weighting preferences since PC resin alternatives show very similar properties considering defined criteria.

Keywords
Intuitionistic Fuzzy Set, Analytical Hierarchy Process, Goal Programming, Polycarbonate

1. Introduction
Being a part of developments in polyester chemistry, the first variants of PC for the production industry were derived at the end of the 19th Century and the beginning of the 20th century. A derivation of PC from resorcinol and hydroquinone by Einhorn (1898) was followed by Bischoff and Hedenstroem (1902) using diphenyl carbonate. The inadequate solubility of these resins caused difficulties for processing resulting repulsion of manufacturers (Bendler, 1999). However, promising advances after mid of 20th century tantalized the market for an alternative raw material. It was strange that these advances were achieved as technical results of lab experiments rather than requirements by the market (Clagett and Shafer, 1985). The simultaneous lab studies by Schnell (1964) at Bayer AG and Fox (Christopher and Fox, 1962) at General Electric Company were significant milestones for mass production. Being mostly announced as an engineering plastic today, the most common production process is polycondensation by reaction of Bisphenol A (BPA) with phosgene (Kyriacos, 2017).

Today, PC thermoplastic resins have a wide range of application areas in the industry, i.e., household appliances, automotive parts, glass/lighting, medical components, due to their lower costs compared to alternatives. The total consumption of PC resins exceeded 5 million tonnes in 2021 and is expected to grow linearly (Statistica, 2021). Although the naive form presents advantages like utmost toughness, electrical insulation, high heat distortion temperature, it has also some disadvantages. The resins should be dried before injection, the resistance to UV light and chemicals is limited, and it has a low performing notch sensitivity. (Kyriacos, 2017). These disadvantages may be overcome by including additives during the production of the resins. As a result, the resins may be encountered in the form of tinted, pigmented, filled, or glass-reinforced pellets apart from its mostly used colorless or transparent form in injection machines. Having this variety of alternatives, manufacturers have the flexibility to select from alternative resins to optimize their costs and production processes. Many technical and operational properties of types should be evaluated during this selection. Such a complex decision-making process may be optimized with Multi-Criteria Decision-Making (MCDM). Methodologies. This study integrates an Intuitionistic Fuzzy Analytical Hierarchy Process (IF-AHP) and Intuitionistic Fuzzy Goal Programming (IF-GP) method, and sensitivity analysis for this selection process. The studies in the literature compare the suppliers or different alternative materials for an application. Applying the proposed methodology considering both technical and operational properties of the same raw material presents a comprehensive approach to evaluate it in all dimensions and introduces the novelty of this study. Besides, this is the first study that integrates IF-AHP into IF-GP and completes the methodology with sensitivity analysis to the best of the authors' knowledge. Thus, the criteria that may be expressed with only linguistic terms, as well as the mutual importance of any criterion can be easily managed.

Many alternatives of PC resins are commercially available for the injection molding process on components. These resins have different properties that affect the quality of the injection process. In addition to technical parameters, operational parameters, i.e., cost, availability, should be also considered for a robust selection. This study aims to integrate a comprehensive methodology to evaluate and rank alternatives of PC resins considering the injection process.

2. Literature Review

Many studies considering material selection exist in the literature. The common approach is to handle the problem with criteria in the same category. The alternatives are considered in one aspect, i.e technical, operational. According to the review by Jahan et al. (2010), the most popular MCDM algorithms in the literature since 2005 are Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Elimination and Choice Translating Reality (ELECTRE), and Analytic Hierarchy Process (AHP). The review emphasizes the increasing complexity of AHP pairwise comparisons for the higher number of alternatives and output limitations of ELECTRE while it highlights the advantages of TOPSIS. Based on the comparison by Mulliner et al. (2016), Mousavi-Nasab and Sotoudeh-Anvari (2017) declared that due to vector normalization, TOPSIS presents more realistic results compared to VIKOR that implies linear normalization. As a result, they compare TOPSIS, COPRAS and Data Envelopment Analysis (DEA) and conclude that TOPSIS and COPRAS are highly suitable for material selection process. Wang et al. (2019) considered supplier selection for the plastic industry. The study identifies the criteria via Supply Chain Operations Reference (SCOR) metrics and integrates the Fuzzy Analytic Network Process (FANP) to VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) to rank customers. However, the study ignores the properties of materials themselves assuming they have the same performance. Petković et al. (2015) applied a novel MCDM method for coating material selection. The study includes a comparison of three technical criteria with naive forms of Complex Proportional Assessment (COPRAS), Weighted Aggregated Sum Product Assessment (WASPAS), and TOPSIS. Raju et al. 2020 preferred to integrate AHP to TOPSIS and Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) to compare composite materials. Emovon and Oghenenyerovwho surveyed the literature of MCDM methodologies on material selection from 1994 to 2019. The survey reveals that the most common approach is to apply hybrid methodologies that consist of over half of the studies. Another finding of the study is that the MCDM methods are deployed to material selection mostly for the automotive industry and manufacturing which in total form 70 percent of the studies. The common sense for hybrid versions is to input the criteria weights obtained by AHP algorithm to a successive algorithm that sorts alternatives according to their performances.

This study integrates two methods, namely AHP and Goal Programming with their IF versions to improve the capability of the decision-making process by eliminating individual shortcomings of the methods. IF integration ensures an analytic approach even if the alternatives should be evaluated with linguistic terms even considering a criterion. IF transforms any linguistic term into numerical form keeping the hesitancy that is covered in the term.

3. Methods

An MCDM approach is embraced to present a ranking considering the alternatives of PC resins. The approach is developed by integrating IF-AHP and IF-GP and followed by a sensitivity analysis.

3.1. Intuitionistic Fuzzy Sets

Fuzzy Sets Theory was proposed by Zadeh (1965) to convert uncertainties into numerical values by defining the degree of memberships. Since then, many improved versions were proposed to overcome the shortcomings of the naive fuzzy sets. Intuitionistic Fuzzy Set (IFS) was proposed by Atanassov (1986) as an extension of the original theory. In addition to indicating the degree of membership, IFS enables to express the degree of non-membership and hesitancy. An IFS number, N can be formalized as in Equation 1.

$$N = \{[x; \mu_N(x), v_N(x), \pi_N(x)] \mid x \in C\} \tag{1}$$

where x stands for a crisp number in the set of C crisp numbers, the function $\mu_N(x): C \rightarrow [0,1]$ presents the degree of membership, $v_N(x): C \rightarrow [0,1]$ defines the degree of nonmembership, and $\pi_N(x): C \rightarrow [0,1]$ declares the hesitancy. For this definition, the sum of these three functions is equal to 1. Hence, an IFS number can comprise and express degrees of membership, nonmembership, and as well as hesitancy.

3.2. Intuitionistic Fuzzy-Analytical Hierarchy Process

Proposed by Saaty (1980), AHP is a widely known and applied MCDM method. It can be easily applied to determine the weights of categories and criteria via pairwise comparisons by decision-makers (DM) or experts. Classical AHP allows comparing the criteria by precise considerations. Nevertheless, a DM may need to express her/his uncertainty aside from her/his concrete opinion (Abdullah and Najib, 2014). IF theory is integrated into Classical AHP to overcome this incompetence. The flow of IF-AHP is defined in the following steps considering the methodology by Ilknur et al. (2020).

Step-1: Construct the model by defining alternatives, categories, and criteria.

Step-2: Determine the linguistic terms scale and corresponding triangular IFS numbers for pairwise comparison. DMs should consider these terms during comparing the mutual importance of categories and criteria.

Step-3: Determine the linguistic terms and corresponding triangular IFS numbers to rate the importance of DMs.

Step-4: Select the appropriate linguistic term defined in Step 3 to determine the importance of DM and calculate the crisp weight λ_l of DM by Equation-2 (Al-Qudaimi and Kumar, 2018).

$$\lambda_l = \frac{\left[\mu_l + \pi_l\left(\frac{\mu_l}{\mu_l + v_l}\right)\right]}{\Sigma_{l=1}^{d}\left[\mu_l + \pi_l\left(\frac{\mu_l}{\mu_l + v_l}\right)\right]} \tag{2}$$

Step-5: Make the DMs mutually compare the categories and criteria within each category using the linguistic terms that are defined in Step 3. Record the comparison matrices for each DM separately.

Step-6: Convert the linguistic terms in the matrices to the corresponding triangular IFS number.

Step-7: Aggregate each row of decision matrices into a single triangular IFS number so that each triangular IFS number presents the evaluation of DM for the corresponding category or criterion. Let $w_j^{(l)} = \left[\mu_j^{(l)}, v_j^{(l)}, \pi_j^{(l)}\right]$ be triangular IFS representing the preference of l^{th} DM for the j^{th} category or criterion. Then, the aggregated triangular IFS number may be calculated by Intuitionistic Fuzzy Weighted Average (IFWA) operator (Xu, 2007) in Equation 3.

$$\begin{aligned} w_j &= IFWA_\lambda(w_j^{(1)}, \dots, w_j^{(n)}) \\ &= \lambda_1 w_j^{(1)} \oplus \lambda_2 w_j^{(2)} \oplus \dots \oplus \lambda_d w_j^{(n)} \\ &= \left[1 - \Pi_{l=1}^{d}\left(1 - \mu_j^{(l)}\right)^{\lambda_l}, \Pi_{l=1}^{d}\left(v_j^{(l)}\right)^{\lambda_l}, \Pi_{l=1}^{d}\left(1 - \mu_j^{(l)}\right)^{\lambda_l} - \Pi_{l=1}^{d}\left(v_j^{(l)}\right)^{\lambda_l}\right] \end{aligned} \tag{3}$$

The resulting $w_j = \left(\mu_j, v_j, \pi_j\right)$ is the aggregated triangular IFS number for the j^{th} category or criterion.

Step-8: Check the inconsistency of decision matrices using Consistency Ratio (CR) in Equation 4. The CR formula in Equation 4 is the updated version by Abdullah and Najib (2014) based on the classical version by Saaty (1980). Any CR value below 0.10 proves that the matrix is consistent. If CR is higher than 0.10, DM should be requested to review her/his comparisons for the corresponding matrix to increase consistency.

$$CR = \frac{(\lambda_{max}-k)/(k-1)}{RI} \tag{4}$$

To ease the calculation, the value of $(\lambda_{max} - k)$ should be assumed as the average of π_d.

Step-9: Calculate the final crisp weight of each category and criterion using the formula in Equation 5 (Al-Qudaimi and Kumar, 2018).

$$w_j^c = \frac{\left[\mu_j+\pi_j\left(\frac{\mu_j}{\mu_j+\nu_j}\right)\right]}{\Sigma_{j=1}^{n}\left[\mu_j+\pi_j\left(\frac{\mu_j}{\mu_j+\nu_j}\right)\right]} \tag{5}$$

3.3. Intuitionistic Fuzzy-Goal Programming

Charnes and Cooper (1961) proposed GP as a mathematical model that can minimize deviations considering defined objective values. In terms of MCDM, GP designates alternatives their ranks in terms of deviation from weighted objective values of categories and criteria. Hence, the model assigns better ranks to alternatives with smaller deviations from objectives. The method is summarized in the below steps.

Step-1: Construct the decision matrix by ordering alternatives in the rows and categories/criteria in the columns.

Step-2: Convert each a_{ij} which corresponds to the value of alternative i for criterion j into an IFS number according to defined scale if the value is a linguistic term.

Step-3: Convert the IFS numbers to crisp values considering the formula in Equation 6.

$$a_{ij}^c = \frac{\left[\mu_{ij}+\pi_{ij}\left(\frac{\mu_{ij}}{\mu_{ij}+\nu_{ij}}\right)\right]}{\Sigma_{i=1}^{m}\left[\mu_{ij}+\pi_{ij}\left(\frac{\mu_{ij}}{\mu_{ij}+\nu_{ij}}\right)\right]} \tag{6}$$

Step-4: Transform the values in each column of the decision matrix by using Min-Max normalization.

Step-5: Develop the GP mathematical model. The generic model is defined below:

- Parameters:
  w_{jk}: The weight of Criterion j under Category k.
  c_{ijk}: The deviation coefficient of alternative i for Criterion j under Category k.
  g_{jk}: The goal value for Criterion j under Category k.

- Decision Variables:
  d_{jk}^+: The positive deviation of Criterion j from its goal value.
  d_{jk}^-: The negative deviation of Criterion j from its goal value.
  x_{jk}: $\left\{\begin{matrix} 1, & if\ alternative\ i\ is\ selected \\ 0, & otherwise \end{matrix}\right\}$

- Model:

$$Min\ z = \sum_{j=1}^{n}\sum_{k=1}^{p} w_{jk}(d_{jk}^+ + d_{jk}^-) \tag{7}$$

$$\sum_{i=1}^{m} c_{ijk}x_i + d_{jk}^+ - d_{jk}^- = g_{jk}\ , \forall_j \forall_k \tag{8}$$

$$\sum_{i=1}^{m} x_i = 1 \ , \forall_j \forall_k \tag{9}$$

$$x_i \in \{0,1\} \ , \forall_i \tag{10}$$

$$d_{jk}^{+}, d_{jk}^{-} \ \geq 0, \forall_j \forall_k \tag{11}$$

where Equation 7 is the objective function that sums the weighted deviations from goal values, Equation 8 is the constraint that measures the deviation from Criterion j of Category k if the alternative i is selected, Equation 9 ensures that only one alternative is selected, Equation 10 and Equation 11 are the domain constraints.

Step-5: Solve the GP model.

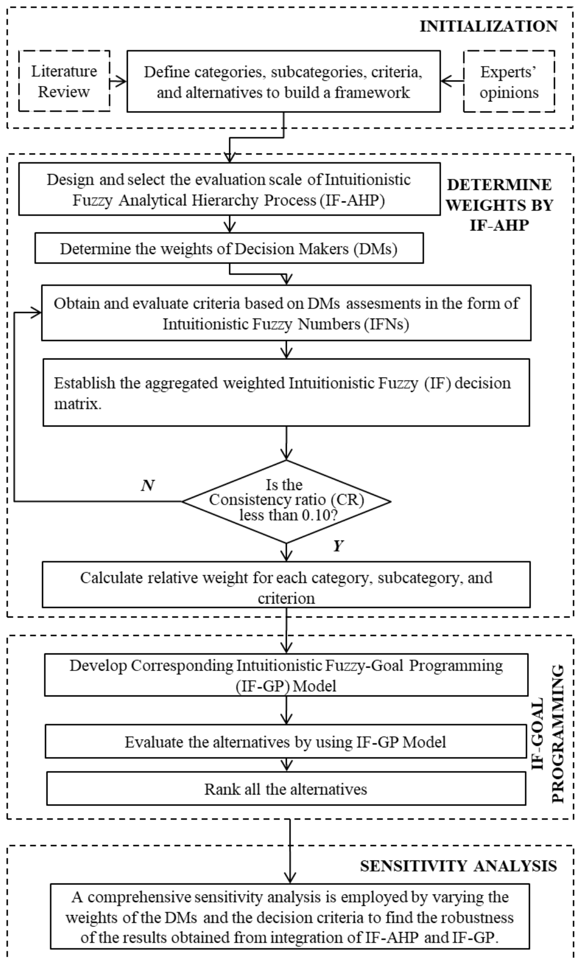

Figure 1. The Flow of the Proposed Methodology

3.4. Proposed Methodology

The flow of the proposed methodology is shown in Figure 1. The methodology is initialized defining the MCDM Model. IF-AHP is deployed to determine the weights of criteria and categories. IF-GP ranks the alternatives considering the weighted criteria and categories. A sensitivity analysis completes the flow by determining the boundaries for weights that lead to significant differences in ranking order.

Table 1. Definitions for Criteria in Operational Category

Criterion Name	Definition	Objective
Unit price	The average price in USD per unit weight (kg)	Minimization
Lead Time	Time interval from purchase order to the readiness of the order in days	Minimization
Shipment Cost	Average cost for transportation per unit weight (kg)	Minimization
Reliability	Linguistic term to express the reliability of the supplier	Maximization
Delivery Performance	The rate of the shipments by the supplier on promised/declared shipment dates compared to all shipments	Maximization
Financial Strength	Linguistic term to define the financial strength of the supplier	Maximization
Packaging	Linguistic term to define the appropriateness of the packaging of the commodity during transportation	Maximization

Table 2 shows the definitions and objectives for the criteria in the technical category.

Table 2. Definitions for Criteria in Technical Category

Criterion Name	Definition	Objective
Density	Mass (g) per unit volume (cm^3) at 23°C temperature.	Minimization
Mold Shrinkage	Percentage of shrinkage of the plastic during the cooling and solidifying parts of the injection process.	Minimization
Water Absorption	Humidity absorption of the plastic in its environment in percentage at 23°C temperature.	Minimization
Melt Volume Rate	Measure for easiness in respect to melted plastic measured with cm^3/10 minutes at 300 C° with 12 kgs.	Maximization
Tensile Strength Yield	Maximum stress at that the material may preserve its form measured as MPa.	Maximization
Charpy Impact Notched	The amount of energy absorbed during the fraction.	Maximization
Tensile Modulus	The ratio of tensile stress to strain during deformation measured with MPa.	Maximization
Flexural Modulus	The ratio of stress to strain in flexural deformation measured with MPa.	Maximization
Flexural Strength	The stress before yielding in flexural test measured with MPa.	Maximization
Refractive Index	The ratio of light speed in vacuum to in the medium	Minimization
HDT/Be	The temperature at which the polymer is deformed under 0.45 MPa.	Maximization
HDT/Ae	The temperature at which the polymer is deformed under 1.8 MPa.	Maximization
Vicat Softening Temperature	The temperature at which a flat-ended needle penetrates the plastic to a depth of 1 mm with a force of 50N under the heating rate of 50°C/h.	Maximization
Dielectric Strength	The maximum electrical potential that the material can avoid an electrical flow measured as Volts per millimeter.	Maximization
Melt Temperature	The temperature of the polymer leaving the nozzle and entering to mold.	Minimization
Mold Temperature	The temperature at which the mold should be maintained.	Minimization

4. Data Collection

AN-EL Anahtar ve Elektrikli Ev Aletleri Sanayi A.S. (AN-EL) is a firm located in Turkey that produces components for Household Appliance producers. Engineering thermoplastics comprises a high portion of the raw material in AN-EL to produce these components in its machinery park. Alternative PC resins may be injected having their advantages or disadvantages. The case study consists of data for these types of PC resins that are approved for production by AN-EL. The data consists of two categories, namely technical category and operational category. The technical category covers the criteria related to the injection process. The operational category contains criteria considering supply conditions. The definitions and objectives for the criteria in the operational category are shown in Table 1.

5. Results and Discussion

The case study considers ranking the alternative PC resins of the injection molding process of AN-EL. Ten alternatives are available from different suppliers. The required scales in Step-2, Step-3, and Step-9 are referred to the studies that are mostly cited in the literature since both scales fit well to the case study problem. IF-AHP is applied with the following steps.

Step-1: The model is constructed. The final MCDM hierarchy for the case study is shown in Figure 2. The brands of the alternative PC resins are not declared in the hierarchy to avoid any commercial conflict.

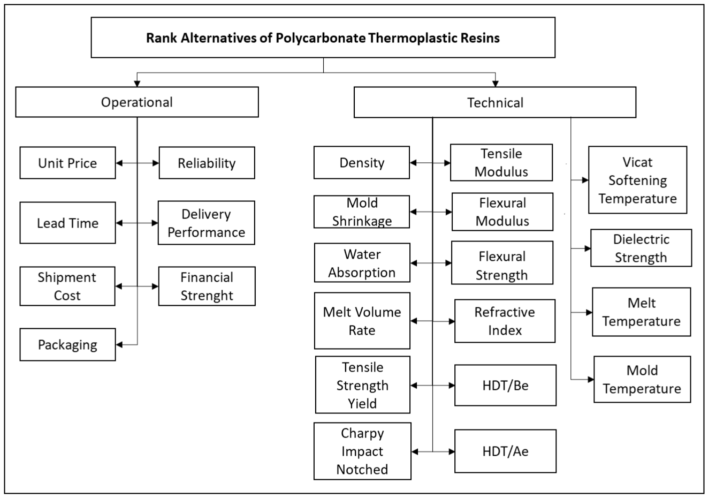

Figure 2. MCDM Hierarchy for Case Study

Step-2: The preferred scale for pairwise comparisons (Ilknur et al., 2020) is presented in Table 3.

Table 3. Scale for pairwise comparisons.

Linguistic Variables	Preference Numbers	Intuitionistic Fuzzy Numbers	Reciprocals Preference Numbers	Reciprocal Intuitionistic Fuzzy Numbers
Equally Important (EI)	1	(0.02,0.18,0.80)	1/1	(0.02,0.18,0.80)
Intermediate Value (IV1)	2	(0.06,0.23,0.70)	1/2	(0.23,0.06,0.70)
Moderately More Important (MI)	3	(0.13,0.27,0.60)	1/3	(0.27,0.13,0.60)
Intermediate Value (IV2)	4	(0.22,0.28,0.50)	1/4	(0.28,0.22,0.50)
Strongly More Important (SI)	5	(0.33,0.27,0.40)	1/5	(0.27,0.33,0.40)
Intermediate Value (IV3)	6	(0.47,0.23,0.30)	1/6	(0.23,0.47,0.30)
Very Strong More Important (VSI)	7	(0.62,0.18,0.20)	1/7	(0.18,0.62,0.20)
Intermediate Value (IV4)	8	(0.80,0.10,0.10)	1/8	(0.10,0.80,0.10)
Extremely More Important (EMI)	9	(1.00,0.00,0.00)	1/9	(0.00,1.00,0.00)

Step-3: The scale in Table 4 by Boran et al. (2009) is preferred for this study to determine the weight of DMs.

Table 4. Scale for Determining Decision Maker Importance

Linguistic Variables	Intuitionistic Fuzzy Numbers
Very Important (VI)	(0.90,0.05,0.05)
Important (I)	(0.75,0.20,0.05)
Medium (M)	(0.50,0.40,0.10)
Unimportant (UNIMP)	(0.25, 0.60, 0.15)
Very Unimportant (VUNIMP)	(0.10, 0.80,0.10)

Step-4: Three DMs are rated according to their knowledge, experience, and relevance as Important, Medium, and Very Important that leading to crisp weights 0.344, 0.242, and 0.413, respectively.

Step-5: The DMs complete their pairwise comparisons and decision matrices are built. A sample matrix is shown in Table 5.

Table 5. Pairwise Comparison Matrix by DM_1 for Criteria under Operational Category

DM_1	Unit Price	Lead Time	Shipment Cost	Packaging	Reliability	Delivery Performance	Financial Strength
Unit Price	EI	VSI	SI	EMI	IV4		
Lead Time		EI			IV3	VSI	IV3
Shipment Cost		IV3	EI	SI			
Packaging		MI		EI	MI	IV1	IV2
Reliability			MI		EI	SI	IV2
Delivery Performance	MI		IV2			EI	IV1
Financial Strength	IV1		IV1				EI

Step-6: The linguistic terms are converted to the corresponding triangular IFS numbers. A sample matrix is shown in Table 6.

Table 6. IFS Number Matrix of DM_1 for Criteria under Operational Category

DM_1	Unit Price			Lead Time			Shipment Cost			Packaging			Reliability			Delivery Performance			Financial Strength		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
Unit Price	0,02	0,18	0,80	0,62	0,18	0,20	0,33	0,27	0,40	1,00	0,00	0,00	0,80	0,10	0,10	0,27	0,13	0,60	0,23	0,07	0,70
Lead Time	0,18	0,62	0,20	0,02	0,18	0,80	0,23	0,47	0,30	0,27	0,13	0,60	0,47	0,23	0,30	0,62	0,18	0,20	0,47	0,23	0,30
Shipment Cost	0,27	0,33	0,40	0,47	0,23	0,30	0,02	0,18	0,80	0,33	0,27	0,40	0,27	0,13	0,60	0,28	0,22	0,50	0,23	0,07	0,70
Packaging	0,00	1,00	0,00	0,13	0,27	0,60	0,27	0,33	0,40	0,02	0,18	0,80	0,13	0,27	0,60	0,07	0,23	0,70	0,22	0,28	0,50
Reliability	0,10	0,80	0,10	0,23	0,47	0,30	0,13	0,27	0,60	0,27	0,13	0,60	0,02	0,18	0,80	0,33	0,27	0,40	0,22	0,28	0,50
Delivery Performance	0,13	0,27	0,60	0,18	0,62	0,20	0,22	0,28	0,50	0,23	0,07	0,70	0,27	0,33	0,40	0,02	0,18	0,80	0,07	0,23	0,70
Financial Strength	0,07	0,23	0,70	0,23	0,47	0,30	0,07	0,23	0,70	0,28	0,22	0,50	0,28	0,22	0,50	0,23	0,07	0,70	0,02	0,18	0,80

Step-7: Each row of the matrices is aggregated by the IFWA operator. A sample matrix is presented in Table 7.

Table 7. Aggregated Matrix of DM_1 for Criteria under Operational Category

DM_1	μ	ν	π
Unit Price	1,00	0,00	0,00
Lead Time	0,35	0,25	0,40
Shipment Cost	0,28	0,19	0,54
Packaging	0,13	0,31	0,56
Reliability	0,19	0,29	0,52
Delivery Performance	0,16	0,24	0,60
Financial Strength	0,18	0,21	0,62

Step-8: Consistency of each aggregated decision matrix is checked with CI formula and confirmed that all CIs are below 0.10.

Step-9: Crisp weights for all criteria are calculated.

Upon completion of IF-AHP steps, IF-GP steps are followed. The scale by Buyukozkan and Guleryuz (2015) in Table 8 is considered to evaluate alternatives considering linguistic criteria.

Table 8. Scale for Linguistic Criteria to Rate Alternatives

Linguistic Terms	Intuitionistic Fuzzy Numbers
Extremely Good (EG)	(1,0,0)
Very Good (VG)	(0.75,0.10,0.15)
Good (G)	(0.60,0.25,0.15)
Moderately Good (MG)	(0.50, 0.40, 0.10)
Medium (M)	(0.50, 0.50,0)
Moderately Bad (MD)	(0.40, 0.50, 0.10)
Bad (B)	(0.25,0.60,0.15)
Very Bad (VB)	(0.10,0.75,0.15)
Extremely Bad (EB)	(0,0.90,0.10)

Solving the IF-GP model yields the ranking in Table 9.

Table 9. Ranking of the Alternatives

Alternative	Score	Rank
A_8	0,347	1
A_3	0,374	2
A_9	0,407	3
A_2	0,433	4
A_4	0,454	5
A_6	0,471	6
A_7	0,515	7
A_1	0,558	8
A_5	0,561	9
A_{10}	0,593	10

The ranking of Alternative 8 considering all criteria is shown in Figure 3.

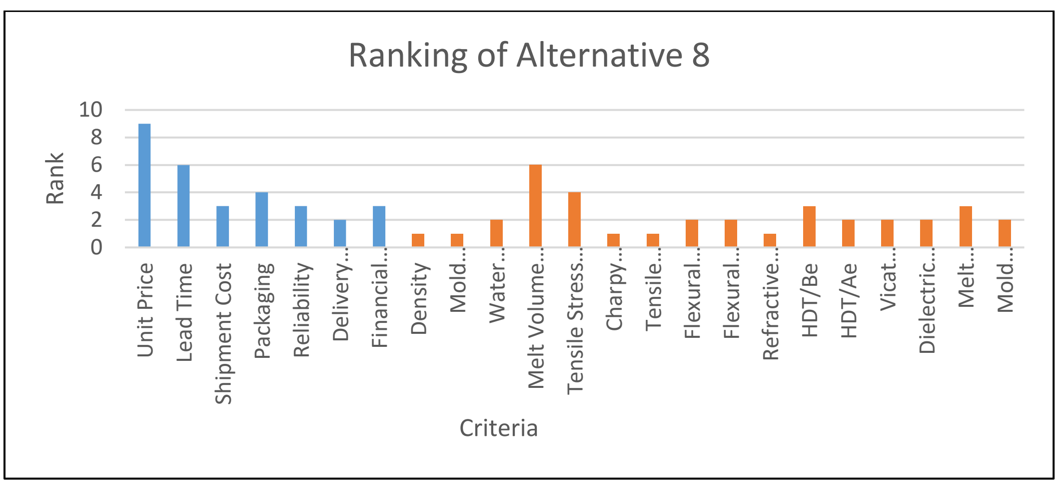

Figure 3. Ranking of Alternative 8 Considering all Criteria

The weighting of criteria may influence the results since the weights may be biased due to the subjective evaluations of DMs. Sensitivity Analysis is an important tool to reveal the boundaries that affect the ranking of the solution. Three scenarios are considered for this study to reveal the effect of o weighting scheme. In scenario S_1, both weights operational and technical categories are assumed equal. The weight of the operational category is assumed as 1.00 in scenario S_2 where the weight of the technical category is 0.00. The weighting in S_3 is vice versa weighting scheme o S_3.

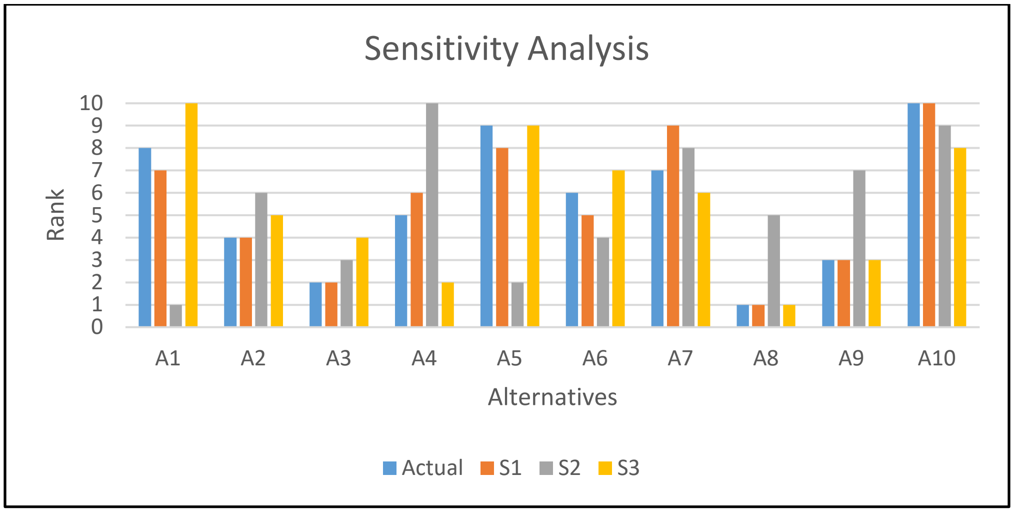

Figure 4. Ranking of Alternatives in Different Scenarios

With a comprehensive evaluation the results shown in Figure 4, it can be inferred that the weighting scheme has a great influence on the solution. The alternative A_8 has the best rank except in scenario S_2 in which the weight of the operational category is 1.00. As clearly visible in Figure 3, performing well in the criteria of technical category, A_8 has relatively low performance in criteria of operational categories. A_8 has the first rank if the weight of the technical category is greater than 0.49. Another interesting finding in sensitivity analysis is the pattern of A_1. Having the 8th rank in the sequence by weighting scheme of DMs, A_1 gains the first rank in S_2 and the last rank in S_3. As a result, it can be inferred that every single criterion has an impact that can divert the result of ranking, and being powerful in part of criteria may not be sufficient to achieve a high rank. In the case study, having the best performance with respect to operational criteria is not adequate to name an alternative as the "best" alternative. The technical category has more influence on the solution. Having the 2nd highest unit price, A_8 is ranked as the best alternative.

6. Conclusions and Future Research

By replacing alternative materials in production lines, the use and consumption of engineering plastics constantly increase. The market in 2020 was valued at USD 90 billion and projected to get bigger (Mordorintelligence, 2021). Being part of this market, PC is highly preferred to produce a variety of components. It is very important to select the most appropriate alternative resin to minimize operational and quality costs, and optimize process.

In this study, we propose an MCDM methodology to rank alternatives of PC resins for the injection molding process. To the best of the authors' knowledge, this is the first study that integrates IF-AHP into IF-GP and analysis the results with sensitivity analysis. The methodology can reflect the concrete or uncertain preferences of DMs even the alternative may be evaluated with linguistic terms instead of crisp values. The results reveal that any subjective evaluation for weighting may easily influence the results of the ranking. This outcome consolidates the importance of sensitivity analysis. Another originality is in the case study. The dataset for the case study covers both operational and technical criteria of PC resins that are mostly handled separately in studies.

As a future study, different types of MCDM algorithms may be integrated into IF-AHP to determine and compare IF-GP performance. Another point is the hesitancies in both weighting and alternative evaluations. Different types of fuzzy sets may be deployed to model these uncertainties and compared to IFS.

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Biographies

Ilknur Karacan graduated from the Naval Academy with a Bachelor's Degree in Electrical-Electronical Engineering in 2004, received a Master's Degree in Operations Research from the Naval Sciences and Engineering Institute in 2015, has her Ph.D. degree in the field of Industrial Engineering from Marmara University in 2021. She is currently Manager of Production Processes Analysis and Development Unit at AN-EL Anahtar ve Elektrikli Ev Aletleri A.S. Her research interests include decision making, scheduling, and data mining.

Ismet Karacan graduated from the Naval Academy with a Bachelor's Degree in Industrial Engineering in 2003 and received a Master's Degree in Operations Research from the Naval Sciences and Engineering Institute in 2014. He is a Ph.D. candidate at Marmara University. He is currently Manager of the R&D Center at AN-EL Anahtar ve Elektrikli Ev Aletleri A.S. His research interests include decision making, optimization, data mining, machine learning, scheduling, and simulation.

Inanc Erdogan graduated from the Istanbul Technical University with a Bachelor's Degree in Electrical Engineering in 1989. He is General Manager of AN-EL Anahtar ve Elektrikli Ev Aletleri A.S since 1996. His research interests include metallurgy on electrical components, project management, lean manufacturing, and data mining.

Ozlem Senvar is an Associate Professor at Marmara University in the Department of Industrial Engineering. Ozlem Senvar was officially granted (Ref.2013/327-350) by European Commission for her post-doctoral researches in France. She has been the author of many peer-reviewed international articles, book chapters, and conference papers. Her research interests involve Production and Operations Management, Advanced Quality Engineering, Statistics, Artificial Intelligence, Fuzzy Logic, Data Science, Machine Learning, and Decision Science.

Serol Bulkan graduated from the Management Engineering Department of Istanbul Technical University in 1986. He got his first MSc degree from the same department in 1989, a second MSc degree in Operations Research from Florida Institute of Technology in 1992, and a Ph.D. degree in Industrial Engineering from Cleveland State University in 1999. Dr. Bulkan is currently at the Industrial Engineering Department of Marmara University, Turkey. His teaching and research areas are Operations Research, Scheduling Theory, Network Theory, Production Planning.