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PROJECT SELECTION REVISITED: CUSTOMIZED TYPE-2 FUZZY ORESTE APPROACH FOR PROJECT PRIORITIZATION

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In this study, a customized version of a less-preferred methodology in decision-making processes, i.e., the interval type-2 fuzzy ORESTE (IT2F-ORESTE), is proposed, and its effectiveness for selecting the most viable projects is demonstrated. The findings are evaluated against those of fuzzy TOPSIS, which is among the most preferred methods, to provide evidence that the proposed method achieves comparable and even superior results. To this end, multicriteria decision-making studies conducted between 2016 and 2021 were examined. Subsequently, 30 automotive manufacturing projects were evaluated over seven criteria using the fuzzy TOPSIS and customized IT2F-ORESTE methods. The results revealed that IT2F-ORESTE assigned the highest ranks to projects with high earning potential, low cost, low number of operations, and high production capacity, whereas fuzzy TOPSIS failed to select the best project. To the best of the authors' knowledge, this is the first study to utilize this new IT2F-ORESTE method in project evaluation within the automotive industry and demonstrate its superiority over that of conventional methods.

Keywords: Interval Type-2 Fuzzy ORESTE, Fuzzy TOPSIS, Project Selection, Multicriteria Decision-Making, Automotive Industry

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1. INTRODUCTION

Project selection, which involves assessing each potential project and selecting the one with the highest priority (Sadi-Nezhad, 2017), is considered a key component of project portfolio management. Thus far, various approaches have been adopted to select project portfolios, including mathematical optimization modeling for portfolio planning (Salehi *et al.*, 2022) and project prioritization, in which the priority of potential projects is determined (Ghassemi and Amalnick, 2017). Multicriteria decision-making (MCDM) methods are suitable for prioritizing projects because of the diverse criteria that exist for project selection (Trijana and Ciptomulyono, 2021). The MCDM methods include a collection of techniques that can help decision-makers rank, evaluate, and select alternatives (such as suppliers or projects) based on assessments considering various criteria. Accordingly, a general MCDM problem comprises several alternatives for evaluation and several criteria for assessment (Karande *et al.*, 2016). Organizations prefer MCDM methods because they can help select "signature" alternatives or projects that have the potential to yield significant benefits (Wu *et al.*, 2017). Therefore, many existing project selection studies focused on using MCDM techniques.

Sadi-Nezhad (2017) examined 60 articles published between 1980–2017 on the use of MCDM techniques for project selection and found that TOPSIS and AHP/ANP integration were the most utilized methods for project selection, followed by the VIKOR method. In contrast, data envelopment analysis, GRA, and MOORA were the least used methods (Sadi-Nezhad, 2017). Similarly, de Souza *et al*. (2021) examined studies conducted on determining R&D project portfolios based on MCDM since the 1970s and reported AHP-ANP/fuzzy AHP/ANP, ROA/fuzzy ROA, and TOPSIS/fuzzy TOPSIS as the most used methods, with MAUT and COPRAS being the least used. To the best of the authors' knowledge, these literature reviews did not find any case where the ORESTE method was used for project selection. The literature review conducted in this study identified only one study that used the ORESTE method to prioritize sewer rehabilitation projects (Ana *et al.*, 2009). The fuzzy-ORESTE method was not been applied to project selection problems.

This study aims to prioritize project alternatives using a customized interval type-2 fuzzy ORESTE (IT2F-ORESTE) method, which is among the least utilized decision-making methods. To the best of the authors' knowledge, this was the first study to use IT2F-ORESTE for project evaluation in the automotive industry. The findings were compared with those

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of the fuzzy TOPSIS method to demonstrate that the IT2F-ORESTE method achieved better results than the frequently used traditional method. In this study, 30 project alternatives in a plant manufacturing automotive parts were evaluated over seven criteria using the fuzzy TOPSIS and proposed IT2F-ORESTE methods.

The remainder of this paper is organized as follows. First, the literature on the implementation of MCDM methods in general and specifically for project selection is introduced. Then, the fuzzy TOPSIS and customized IT2F-ORESTE methods are presented, followed by their applications in automotive industry settings. Finally, the results and conclusions are presented, along with suggestions for future research.

2. LITERATURE REVIEW

2.1 Related Literature About the Usage of MCDM Techniques

There exist comparative studies for MCDM techniques (Karande *et al.*, 2016; Baydaş and Elma, 2021), literature reviews (Stojčić *et al.*, 2019), and case studies/applications (Pourjavad and Shirouyehzad, 2011; Nipanikar *et al.*, 2018; Chivukula and Pattanaik, 2023; Ali *et al.*, 2023; Makki *et al.*, 2023). Among these, literature reviews focus on areas in which MCDM methods are applied, and the cumulative number of MCDM studies were determined based on the years. However, to the best of the authors' knowledge, no existing study directly examined the detailed number of individual MCDM methods based on the years or determined the most/least used methods. In this study, research conducted on MCDM methods between 2016 and 2021 were searched systematically using the Google Scholar and Web of Science databases and fuzzy versions of these methods were included in the literature review. The individual numbers per year and total numbers and percentages of MCDM studies are listed in Table 1.

Table 1. Number of studies that used MCDM methods with respect to years (including fuzzy versions)

Method	2016	2017	2018	2019	2020	2021	Total	%
TOPSIS	383	540	404	452	455	529	2763	18.0
Entropy	295	297	313	357	364	322	1948	12.7
AHP	294	297	301	311	334	321	1858	12.1
PROMETHEE	229	259	241	237	242	291	1499	9.7
EDAS	185	208	262	231	238	293	1417	9.2
DEMATEL	223	196	230	188	179	234	1250	8.1
MOORA	63	99	156	176	223	198	915	5.9
SAW	69	75	117	142	227	205	835	5.4
VIKOR	94	103	136	171	156	163	823	5.3
ELECTRE	142	84	73	118	124	144	685	4.5
COPRAS	52	45	51	57	69	82	356	2.3
MAUT	23	17	23	38	82	111	294	1.9
WASPAS	9	10	29	74	55	69	246	1.6
ARAS	38	31	30	42	52	52	245	1.6
MACBETH	18	17	19	22	40	56	172	1.1
Copeland	1	7	4	4	1	7	24	0.2
ORESTE	3	1	5	6	3	5	23	0.1
GRA	4	1	2	2	4	7	20	0.1
EVAMIX	4	3	1	3	4	4	19	0.1

The literature search presented in Table 1 reveals that the most utilized technique is TOPSIS, followed by Entropy and AHP (Table 1), and the least-used methods are EVAMIX, GRA, and ORESTE. This study focuses on utilizing the ORESTE method, wherein the superiority of alternatives is determined according to each criterion. Although the fuzzy ORESTE method has been used in recent years, its applications remain limited (Jin *et al.*, 2021). In fact, the IT2F-ORESTE method is rarely used (Zheng *et al.*, 2021).

2.2 Literature on the Use of MCDM Methods for Project Selection

A detailed literature review on the use of MCDM techniques in project selection is presented in Table 2. Among the MCDM methods, TOPSIS/fuzzy TOPSIS and AHP/fuzzy AHP are commonly used for project selection (Amiri, 2010; Misra and Ray, 2012; da Silva *et al.*, 2022; Dadasheva, 2022) (Table 2). Other methods, such as VIKOR/fuzzy VIKOR and DEMATEL/fuzzy DEMATEL, are also frequently used for project selection (San Cristóbal, 2011; Alinezhad and Simiari, 2013; Ghorabaee *et al.,* 2015; Vinodh and Swarnakar, 2015) (Table 2).

Table 2. Literature on the use of MCDM methods for project selection

Reference	Project type / industry	Method
AHP and TOPSIS		
Mahmoodzadeh *et al.* (2007)	Manufacturing	Fuzzy AHP and TOPSIS
Huang *et al*. (2008)	R&D	Fuzzy AHP
Dodangeh and Mojahed (2009)	Telecommunication	TOPSIS
Amiri (2010)	Oil-fields development	AHP and fuzzy TOPSIS
Tan *et al*. (2010)	Construction	Fuzzy TOPSIS
Misra and Ray (2012)	Software	AHP, TOPSIS, DEMATEL-TOPSIS and COPRAS comparison
Parvaneh and El-Sayegh (2016)	Construction	Combined approach of AHP and LP
Polat *et al*. (2016)	Urban renewal project	Integration of AHP and PROMETHEE
Çoban (2020)	Solar energy plant project	AHP-based hesitant fuzzy linguistic evaluation
da Silva *et al.* (2022)	Urban mobility projects	AHP and TOPSIS
Dadasheva (2022)	Information system	Type-2 fuzzy TOPSIS
Mahmoudi *et al.* (2021)	Project selection	TOPSIS-OPA
Aleksić *et al.* (2022)	Information technology	Criteria weights via AHP
VIKOR		
San Cristóbal (2011)	Renewable energy	VIKOR
Bakshi *et al.* (2011)	Computing	fuzzy AHP and VIKOR
Fouladgar *et al.* (2011)	Construction	VIKOR under fuzzy environment
Thipparat and Thaseepetch (2013)	Sustainable research	integrated VIKOR and fuzzy AHP
Ghorabaee *et al.* (2015)	Project selection	extended VIKOR with IT2F sets
Salehi (2015)	Project selection	hybrid fuzzy MCDM method through AHP and VIKOR combination
Brahma and Mitra (2019)	Flood control	Fuzzy AHP and fuzzy VIKOR
DEMATEL		
Wu (2008)	Information technology	Hybrid approach using DEMATEL with the ANP and ZOGP
Alinezhad and Simiari (2013)	Project selection	Hybrid method using DEMATEL/DEA
Vinodh and Swarnakar (2015)	Lean six sigma	Hybrid method using fuzzy DEMATEL-ANP-TOPSIS
Ortíz *et al*. (2015)	Six sigma	Comparison of DEMATEL-ANP and ANP
Yalcin *et al.* (2020)	R&D	IF-DEMATEL and IF-TOPSIS
PROMETHEE		
Halouani *et al.* (2009)	Project selection	PROMETHEE-MD-2T
Baynal *et al.* (2016)	Textile industry	combined AHP-PROMETHEE approach
López and Almeida (2014)	Electric utility company	PROMETHEE
Almeida *et al.* (2014)	Information systems	PROMETHEE V with C-optimal concept
Entropy		
Zamri and Abdullah (2014)	Flood control	IT2 entropy weight with IT2F-TOPSIS
Abbassi *et al.* (2014)	R&D	Cross-entropy based methodology
Haddadha *et al.* (2017)	Project selection	Combination of Shannon entropy and MCDM techniques
MOORA		
Bakshi *et al.* (2011)	Project selection	AHP and MOORA
Mohamed and Ahmed (2012)	Project selection	SDVMOORA (standard deviation - MOORA)

Reference	Project type / industry	Method
Mohagheghi and Mousavi (2019)	High-technology projects	Pythagorean fuzzy WASPAS, mathematical modeling and MOORA
ELECTRE		
Buchanan and Vanderpooten (2007)	Electric utility	ELECTRE III
Chen and Hung (2008)	R&D	Fuzzy linguistic variable and ELECTRE
Daneshvar Rouyendegh and Erol (2012)	Engineering	Fuzzy ELECTRE
Faezy Razi (2015)	Industrial engineering	Grey-based fuzzy ELECTRE
COPRAS		
Popovic *et al.* (2012)	Investment project	COPRAS
Aghdaie *et al.* (2012)	Constructing projects	AHP and COPRAS-G
Anyaeche *et al.* (2017)	Banking services	COPRAS and fuzzy TOPSIS
Cheng *et al.* (2017)	R&D	Fuzzy-based ANP model
Mohagheghi *et al.* (2019)	Sustainable infrastructure	MOORA and COPRAS named MORAS in an interval type 2 fuzzy environment
MAUT		
Wang *et al.* (2010)	R&D	MAUT
Khalafalla and Rueda-Benavides (2022)	Cost-duration-based projects	MAUT
WASPAS		
Yazdi *et al.* (2020)	Oil project	Hybrid method using best-worst method (BWM) and WASPAS
Rudnik *et al.* (2021)	Improvement projects	Fuzzy WASPAS
Sen (2023)	R&D	Gray-WASPAS
ARAS		
Bakshi and Sarkar (2011)	Project selection	Comparison among AHP and ARAS
Akbari *et al.* (2019)	Information technology	Combination of fuzzy QFD and ARAS
GRA		
Tuzkaya and Yolver (2015)	R&D	Integrated grey ANP and GRA
Faezy Razi (2015)	Industrial engineering	Grey-based fuzzy ELECTRE
Yoo and Choi (2019)	Six sigma	Fuzzy AHP and GRA
Valmohammadi *et al.* (2021)	Six sigma	Hybrid approach FAHP-FTOPSIS and GRA
ORESTE		
Ana *et al*. (2009)	Sewer rehabilitation	ORESTE

PROMETHEE, MOORA/fuzzy MOORA, ELECTRE/fuzzy ELECTRE, COPRAS/fuzzy COPRAS, Entropy, WASPAS/fuzzy WASPAS, MAUT, ARAS and GRA methods are utilized less frequently for project selection (López and Almeida, 2014; Mohagheghi and Mousavi, 2019; Faezy Razi, 2015; Popovic *et al.*, 2012; Abbassi *et al.*, 2014; Rudnik *et al.*, 2021; Khalafalla and Rueda-Benavides, 2022; Bakshi and Sarkar, 2011; Yoo and Choi, 2019) (Table 2). Only one study used the ORESTE method to prioritize sewer rehabilitation projects (Ana *et al.*, 2009), and no study utilized the SAW, MACBETH and fuzzy ORESTE methods for project selection.

The project types evaluated through MCDM methods include construction, information systems/information technology, RandD, oil-field development, solar energy plants, urban mobility, telecommunications, flood control, renewable energy, textile industry, electric utility, investment, sustainable infrastructure, engineering, and sewer rehabilitation projects (Bakshi and Sarkar, 2011; Abbassi *et al.*, 2014; Faezy Razi, 2015; Mohagheghi and Mousavi, 2019; Rudnik *et al.*, 2021) (Table 2).

A general literature search revealed that the most utilized decision-making method was TOPSIS, whereas ORESTE was among the least used methods (Table 1). A similar scheme was observed for the project-selection literature; TOPSIS and AHP were among the most utilized methods, whereas ORESTE was utilized only in a limited number of studies (only one study was found). In addition, there is no fuzzy ORESTE implementation in the project-selection literature. Therefore, in this study, 30 project alternatives in an automotive component manufacturing plant were evaluated over seven criteria using the proposed IT2F-ORESTE method, and its superiority to fuzzy TOPSIS was demonstrated.

3. METHOD

3.1 Fuzzy TOPSIS Method

In the TOPSIS method, the best alternative is selected by minimizing the distance to the ideal solution and maximizing the distance to the negative ideal solution (Nipanikar *et al.*, 2018). The fuzzy TOPSIS method has a flexible structure that can be evaluated using both quantitative and qualitative criteria. Triangular fuzzy numbers are used in the fuzzy TOPSIS application. For triangular fuzzy numbers represented as $\tilde{X} = (x_1, x_2, x_3)$, x_1, x_2, and x_3 represent the lowest possible value, most likely value, and highest possible value, respectively. Figure 1 shows the membership function of a triangular fuzzy number. The flow of the algorithm for this method is shown in Figure 2, and the steps of the method are explained below (Lee and Chen, 2008).

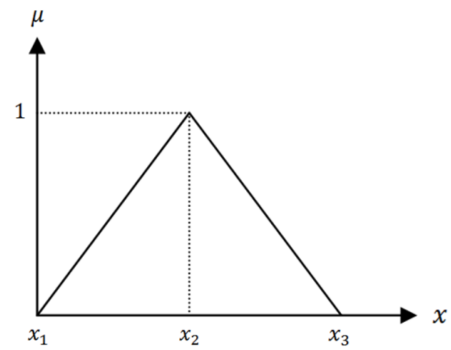

Figure 1. Triangular membership function

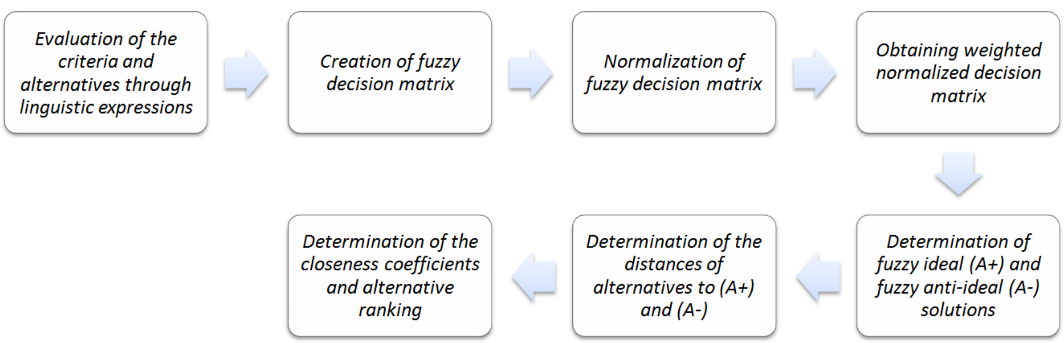

Figure 2. Algorithm flow of the fuzzy TOPSIS method

Step 1. In the first step, the decision-maker evaluates the criteria and alternatives through the linguistic expressions (variables) defined in Table 3.

Table 3. Criterion weighting and alternative rating scales (Zheng *et al.*, 2021)

Criterion weighting scale		**Alternative rating scale**	
Linguistic expression	Triangular fuzzy number	Linguistic expression	Triangular fuzzy number
Very low (V.L.)	(0;0;0.1)	Very bad (V.B.)	(0;0;1)
Low (L.)	(0;0.1;0.3)	Bad (B.)	(0;1;3)
Moderately low (M.L.)	(0.1;0.3;0.5)	Moderately bad (M.B.)	(1;3;5)
Medium (M.)	(0.3;0.5;0.7)	Medium (M.)	(3;5;7)
Moderately high (M.H.)	(0.5;0.7;0.9)	Moderately good (M.G.)	(5;7;9)
High (H.)	(0.7;0.9;1)	Good (G.)	(7;9;10)
Very high (V.H.)	(0.9;1;1)	Very good (V.G.)	(9;10;10)

Step 2. *Creation of fuzzy decision matrix*. The fuzzy decision matrix ($\widetilde{\boldsymbol{D}}$) given in Equation 1 is composed of alternative ratings for each criterion (denoted as $\tilde{x}_{ij}$), where *m* alternatives and *n* selection criteria exist. In addition, the criterion weight matrices ($\widetilde{\boldsymbol{W}}$) given in Equation 2 comprise the weights of the criteria (denoted by $\widetilde{w}_j$). In these matrices, $\widetilde{w}_j$ and $\tilde{x}_{ij}$ are linguistic variables for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. These variables can be defined using triangular fuzzy numbers, i.e., $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\widetilde{w}_j = (w_{j1}; w_{j2}; w_{j3})$.

$$\widetilde{\boldsymbol{D}} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots. & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \ldots. & \tilde{x}_{2n} \\ . & . & \ldots. & . \\ . & . & \ldots. & . \\ . & . & \ldots. & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \ldots. & \tilde{x}_{mn} \end{bmatrix} \tag{1}$$

$$\widetilde{\boldsymbol{W}} = [\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_n] \tag{2}$$

Step 3. *Normalization of fuzzy decision matrix.* The decision matrix is normalized using Equations 3 and 4, where *Benefit* represents the set of benefit criteria, and *Cost* represents the set of cost criteria. Consequently, the normalized fuzzy decision matrix ($\tilde{R}$) shown in Equation 5 can be attained.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), j \in Benefit; c_j^+ = \max c_{ij}, if\ j \in B\text{enefit} \tag{3}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), j \in Cost;\ a_j^- = \min a_{ij}, if\ j \in Cost \tag{4}$$

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{mxn},\ \ i = 1, 2 \ldots, m;\ \ j = 1, 2 \ldots, n \tag{5}$$

Step 4. *Obtaining weighted normalized decision matrix*. This matrix (denoted by $\widetilde{\boldsymbol{V}}$) is obtained by multiplying the criteria weights ($\widetilde{w}_j$) and fuzzy decision matrix elements ($\tilde{r}_{ij}$) (Equation 6 and 7).

$$\widetilde{\boldsymbol{V}} = \left[\tilde{v}_{ij}\right]_{mxn}, i = 1, 2 \ldots, m; j = 1, 2 \ldots, n. \tag{6}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} (\cdot)\ \widetilde{w}_j \tag{7}$$

Step 5. *Determination of fuzzy ideal (A^+) and fuzzy anti-ideal (A^-) solutions.* A^+ and A^- are defined as in Equations 8 and 9, respectively. Here, $\tilde{v}_j^+ = (1, 1, 1)$ and $\tilde{v}_j^- = (0, 0, 0)$ for $j = 1, 2, \ldots, n$. There are as many $(1, 1, 1)$'s and $(0, 0, 0)$'s as the number of criteria in A^+ and A^- as indicated below.

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+) \tag{8}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-) \tag{9}$$

Step 6. *Determination of the distances of alternatives to A^+ and A^-*. The distances are determined using Equations 10 and 11.

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+)\ ;\ i = 1, 2, \ldots, m. \tag{10}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-)\ ;\ i = 1, 2, \ldots, m. \tag{11}$$

Here, d_i^+ and d_i^- represent the distances of the i^{th} alternative to the fuzzy ideal and fuzzy anti-ideal solutions, respectively. The vertex method, defined by Equation 12, is utilized to determine the distance between two triangular fuzzy numbers denoted by $\widetilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$.

$$d(\tilde{m},\tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \tag{12}$$

Step 7. *Determination of the closeness coefficients (CC_i) and alternative ranking.* CC_i's are calculated using Equation 13. Finally, the alternative ranking is obtained by sorting the CC_i's from the highest to the lowest value.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}; i = 1, 2 \ldots., m \tag{13}$$

3.2 Customized Fuzzy ORESTE Method

The customized interval type-2 fuzzy ORESTE (IT2F-ORESTE) method was used for alternative ranking to model the potential uncertainty that may be present in the structure of the determined rank values.

3.2.1 Interval type-2 fuzzy ORESTE (IT2F-ORESTE)

Trapezoidal intervals are constructed to model potential uncertainties. The trapezoidal interval type-2 fuzzy set is expressed by Equation 14, where $\widetilde{E_l^U}$ and $\widetilde{E_l^L}$ represent the upper and lower trapezoidal type-1 membership functions, respectively. The upper and lower membership functions of interval type-2 fuzzy numbers are demonstrated in Figure 3. Values $e_{l1}^U, e_{l2}^U, e_{l3}^U$, and e_{l4}^U are the definition points of the upper membership function and values $e_{l1}^L, e_{l2}^L, e_{l3}^L$, and e_{l4}^L are the definition points of the lower membership function. $H_1(E_l^U)$ and $H_2(E_l^U)$ represent the membership values corresponding to the e_{l2}^U and e_{l3}^U points of the upper membership function, respectively, and $H_1(E_l^L)$ and $H_2(E_l^L)$ represent the membership values corresponding to the e_{l2}^L and e_{l3}^L points of the lower membership function (Figure 3), respectively.

The flowchart of the algorithm for the IT2F-ORESTE method is shown in Figure 4.

The customized steps for the IT2F-ORESTE method are explained below.

Step 1. *Establishing the initial decision matrix by determining the alternatives and criteria.* First, the alternatives $(A_i, i = 1, 2, \ldots, m)$ and criteria $(K_j, j = 1, 2 \ldots, n)$ are determined, and an initial decision matrix is created.

Step 2. *Calculation of the rank values of the criteria and alternatives based on IT2F numbers.* In this step, the weak rankings of the criteria and alternatives based on each criterion are determined. The preference structure defined as a weak ranking helps determine the relative importance of alternatives and criteria. The criteria and alternatives are ranked by the decision-maker from the largest to the smallest. "P" (preference) indicates superiority between criteria, whereas "I" (indifference) indicates no superiority. The trapezoidal IT2F set in Equation 14 is defined for the classical order and uncertainties of criteria and alternatives. At this point, we use Equation 15, proposed by Lee and Chen (2008), to calculate the rank values of the criteria and alternatives built on the IT2F sets. We prefer this ranking because it is obtained from the mean and standard deviation of the consecutive points of the fuzzy number.

$$\widetilde{E}_l = \left(\widetilde{E_l^U}, \widetilde{E_l^L}\right) = \left(\begin{array}{c}\left(e_{l1}^U, e_{l2}^U, e_{l3}^U, e_{l4}^U;\ H_1\left(\widetilde{E_l^U}\right), H_2\left(\widetilde{E_l^U}\right)\right),\\ \left(e_{l1}^L, e_{l2}^L, e_{l3}^L, e_{l4}^L;\ H_1\left(\widetilde{E_l^L}\right), H_2\left(\widetilde{E_l^L}\right)\right)\end{array}\right) \tag{14}$$

$$\begin{aligned} r\left(\widetilde{E}_l\right) = {} & \textstyle\sum_{k\in(U,L)} M_1\left(\widetilde{E_l^k}\right) + \sum_{k\in(U,L)} M_2\left(E_l^k\right) + \sum_{k\in(U,L)} M_3\left(E_l^k\right) - \frac{1}{4}\left(\sum_{k\in(U,L)} S_1\left(\widetilde{E_l^k}\right) + \right. \\ & \textstyle\left. \sum_{k\in(U,L)} S_2\left(\widetilde{E_l^k}\right) + \sum_{k\in(U,L)} S_3\left(\widetilde{E_l^k}\right) + \sum_{k\in(U,L)} S_4\left(\widetilde{E_l^k}\right)\right) + \sum_{k\in(U,L)} H_1\left(\widetilde{E_l^k}\right) + \sum_{k\in(U,L)} H_2\left(\widetilde{E_l^k}\right) \end{aligned} \tag{15}$$

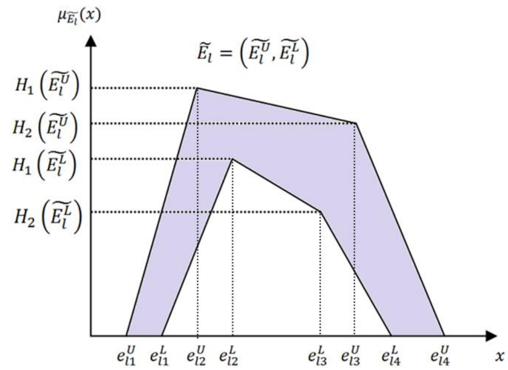

Figure 3. Upper and lower membership functions of the IT2F numbers

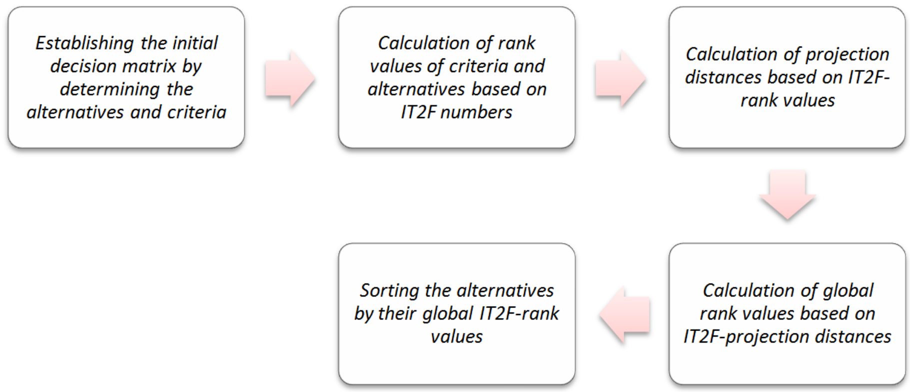

Figure 4. Algorithm flow of the IT2F-ORESTE method

Here, when $k \in \{U, L\}$, $M_p\left(\widetilde{E_l^k}\right)$, $S_q\left(\widetilde{E_l^k}\right)$, and $S_4\left(\widetilde{E_l^k}\right)$ are calculated as shown in Equation 16–18.

$$M_p\left(\widetilde{E_l^k}\right) = \frac{e_{lp}^k + e_{lp+1}^k}{2}, \text{ for p = 1, 2, and 3 (Average of the two consecutive elements)} \tag{16}$$

$$S_q\left(\widetilde{E_l^k}\right) = \sqrt{\frac{1}{2}\sum_{w=q}^{q+1}\left(e_{lw}^k - \frac{1}{2}\sum_{w=q}^{q+1} e_{lw}^k\right)^2} \text{ for q = 1, 2, and 3 (Standard deviation of the two consecutive elements)} \tag{17}$$

$$S_4\left(\widetilde{E_l^k}\right) = \sqrt{\frac{1}{4}\sum_{w=1}^{4}\left(e_{lw}^k - \frac{1}{4}\sum_{w=1}^{4} e_{lw}^k\right)^2} \text{ (Standard deviation of the four elements)} \tag{18}$$

Accordingly, the IT2F-Besson rank value of criterion j can be shown as $r_{Kj}(\widetilde{E}_l)$ for $j = 1, 2, \ldots, n$, whereas the IT2F-Besson rank value of the i^th^ alternative with respect to the j^th^ criterion, for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$, can be expressed as $r_{A_{i|Kj}}(\widetilde{E}_l)$.

Step 3. *Calculation of projection distances based on IT2F-rank values.* Using the IT2F-Besson rank values, the projection distances were calculated using Equation 19. In this study, R was set to one.

$$d_{ij}(\widetilde{E}_l) = \left[\frac{1}{2} r_{Kj}(\widetilde{E}_l)^R + \frac{1}{2} r_{A_{i|Kj}}(\widetilde{E}_l)^R\right]^{1/R} \tag{19}$$

Step 4. *Calculation of global rank values based on the IT2F-projection distances.* The $d_{ij}(\widetilde{E}_l)$'s, the IT2F projection distances obtained in Step 3 are sorted from the lowest to the highest value. Then, a global IT2F-Besson rank value, namely $r_{ij}(\widetilde{E}_l)$, is assigned to all sorted IT2F projection ranks. A smaller value of $r_{ij}(\widetilde{E}_l)$ indicates that the alternative is better positioned.

Step 5. *Sorting the alternatives by their global IT2F-rank values.* The average IT2F rank for each alternative is determined using Equation 20 with the sum of the global IT2F-Besson rank values overall criteria. The average IT2F-rank values are ordered from the smallest to the highest value to determine the global IT2F-rank values (final ranks) of the alternatives.

$$r_i(\tilde{E}_l) = \sum_{j=1}^{n} r_{ij}(\tilde{E}_l), i = 1, 2 \dots, m \tag{20}$$

A brief flowchart of the study is shown in Figure 5.

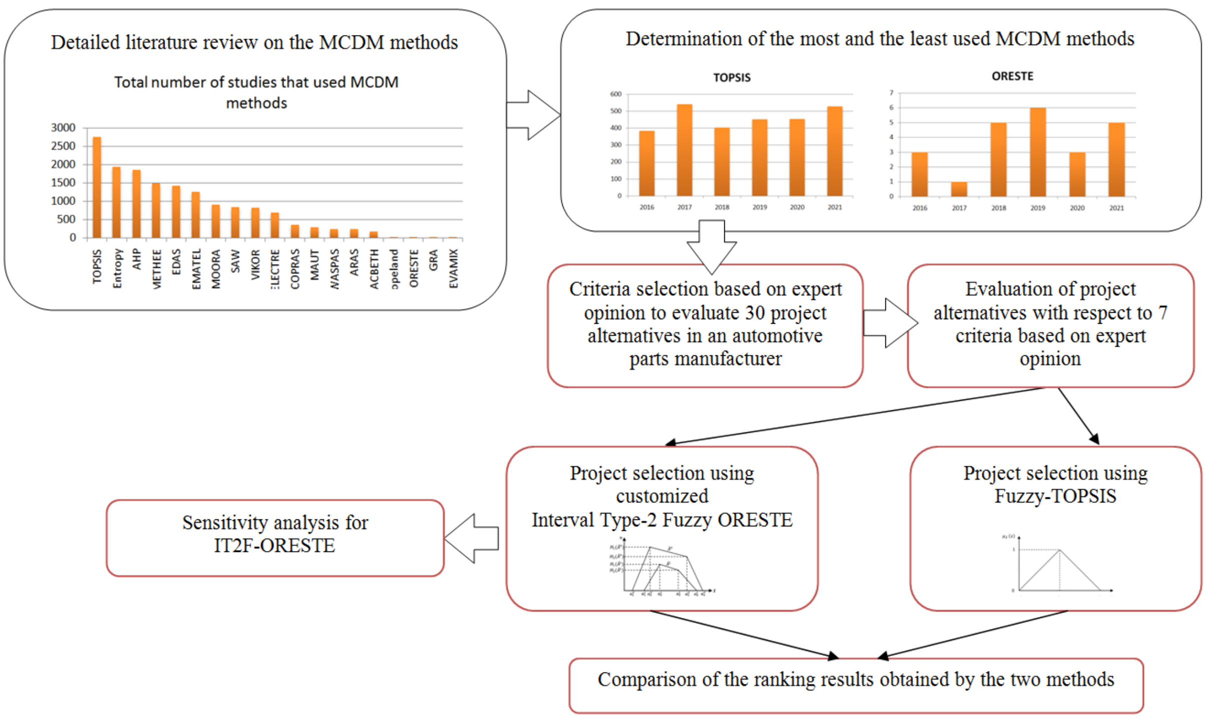

Figure 5. Flowchart of the study

4. CASE STUDY - ANALYSES

As the case study, 30 project alternatives, which include prospective automotive parts to be manufactured, were determined in an automotive-component manufacturing plant. Selecting the best project is critical for profitable manufacturing planning. Therefore, the evaluation criteria were determined by a company expert. A production and quality engineer with 10 years of experience in the field determined the following criteria: *model year*, *number of operations*, *part geometry*, *direction*, *mold cost*, *production capacity*, and *demand*. For the *model year*, newer models are better for ensuring the continuity of manufacturing, and fewer *number of manufacturing operations* are better. Considering *part geometry*, less complicated geometries are preferable for ease of manufacturing. For *direction*, two-sided components (left and right sides) have a double-order quantity advantage over one-sided components. In addition, higher *demand* and *production capacity* are better, as are lower *mold costs*. Accordingly, the benefit criteria are demand, model year, direction, and capacity, whereas the cost criteria are part geometry, number of operations, and mold cost.

The initial evaluation of the 30 project alternatives over seven criteria was conducted by a production and quality engineer using linguistic expressions. The raw qualitative dataset, i.e., the decision matrix established as a result of this evaluation, is provided in Appendix A. The criteria were also prioritized by the same expert engineer using linguistic expressions. The fuzzy TOPSIS and customized IT2F-ORESTE methods were implemented after prioritizing the criteria and evaluating the alternatives. Subsequently, the sensitivity analysis of IT2F-ORESTE was conducted. Finally, the results are discussed, and the methods are compared.

4.1 Implementation of Fuzzy TOPSIS and the Results

Step 1. First, the decision-maker determines the importance levels for the criteria based on the linguistic expressions provided in Table 3. These linguistic expressions are transformed into triangular fuzzy numbers, as listed in Table 3. The importance values of the criteria with linguistic variables and triangular fuzzy numbers are presented in Table 4.

Table 4. Defining importance values of criteria with linguistic variables and triangular fuzzy numbers

Criteria used in the study	**Importance (Linguistic variables)**	**Importance (Triangular fuzzy numbers)**
Demand	H.	(0.7;0.9;1)
Model year	M.L.	(0.1;0.3;0.5)
Direction	L.	(0;0.1;0.3)
Part geometry	L.	(0;0.1;0.3)
Number of operations	M.	(0.3;0.5;0.7)
Mold cost	M.	(0.3;0.5;0.7)
Production capacity	V.H.	(0.9;1;1)

V.L. = Very low; L. = Low; M.L. = Moderately low; M. = Medium; M.H. = Moderately high; H. = High; V.H. = Very high

Step 2. *Constructing fuzzy decision matrix.* Similar to Step 1, 30 project alternatives were evaluated through the linguistic expressions given in Table 3 by the decision-maker, as summarized in Table 5. Subsequently, these evaluations were converted into triangular fuzzy numbers, and a fuzzy decision matrix was obtained. The full decision matrix established and used in the study is presented in Appendix A.

Table 5. Decision matrix and fuzzy decision matrix

No	**Linguistic / Fuzzy**	**Demand**	**Model year**	**Direction**	**Part geometry**	**Number of operations**	**Mold cost**	**Production capacity**
1	Linguistic	V.G.	B.	V.G.	V.G.	M.	M.B.	M.G.
	Fuzzy	(9;10;10)	(0;1;3)	(9;10;10)	(9;10;10)	(3;5;7)	(1;3;5)	(5;7;9)
2	Linguistic	V.G.	V.G.	V.G.	G.	M.B.	B.	M.G.
	Fuzzy	(9;10;10)	(9;10;10)	(9;10;10)	(7;9;10)	(1;3;5)	(0;1;3)	(5;7;9)
3	Linguistic	M.	M.G.	V.G.	V.G.	G.	G.	M.G.
	Fuzzy	(3;5;7)	(5;7;9)	(9;10;10)	(9;10;10)	(7;9;10)	(7;9;10)	(5;7;9)
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
28	Linguistic	V.B.	M.	M.G.	M.G.	G.	G.	M.
	Fuzzy	(0;0;1)	(3;5;7)	(5;7;9)	(5;7;9)	(7;9;10)	(7;9;10)	(3;5;7)
29	Linguistic	M.B.	M.B.	M.G.	M.G.	G.	G.	M.G.
	Fuzzy	(1;3;5)	(1;3;5)	(5;7;9)	(5;7;9)	(7;9;10)	(7;9;10)	(5;7;9)
30	Linguistic	M.G.	V.G.	V.G.	G.	M.	M.B.	M.
	Fuzzy	(5;7;9)	(9;10;10)	(9;10;10)	(7;9;10)	(3;5;7)	(1;3;5)	(3;5;7)

V.B. = Very bad; B. = Bad; M.B. = Moderately bad; M. = Medium; M.G. = Moderately good; G. = Good; V.G. = Very good

Step 3. *Normalization of fuzzy decision matrix.* The normalized matrix ($\tilde{R}$) was obtained using Equation 4 and 5, and the results are presented in Table 6. The benefit criteria are *demand*, *model year*, *direction*, and *capacity*. The cost criteria are *part geometry*, *number of operations*, and *mold cost*.

Step 4. The weighted normalized decision matrix, i.e., $\tilde{\boldsymbol{V}}$, is obtained using Equation 7 (Table 6).

Step 5. Fuzzy ideal solution (A^+) and fuzzy anti-ideal solution (A^-) are defined as shown in Equations 8 and 9. As mentioned above, $\tilde{v}_j^+ = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$, where $j = 1,2,\dots,n$; further, there are as many (1, 1, 1)'s and (0, 0, 0)'s as the number of decision criteria. Considering that there are seven criteria in this study, A^+ and A^- are written as in Equations 21 and 22.

$$A^+ = ((1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1),(1,1,1)) \tag{21}$$

$$A^{-} = ((0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0),(0,0,0)) \tag{22}$$

Table 6. Normalized fuzzy decision matrix ($\tilde{R}$) and weighted normalized fuzzy decision matrix ($\tilde{V}$)

No	Norm. / W. Norm.	Demand	Model year	Direction	...	No. of operations	Mold cost	Production capacity
1	Normalized	(0.9;1;1)	(0;0.1;0.3)	(0.9;1;1)	...	(0;0;0)	(0;0;0)	(0.6;0.8;1)
	Weighted normalized	(0.6;0.9;1)	(0;0;0.1)	(0;0.1;0.3)	...	(0;0;0)	(0;0;0)	(0.5;0.7;1)
2	Normalized	(0.9;1;1)	(0.9;1;1)	(0.9;1;1)	...	(0;0;0)	(0;0;0)	(0.6;0.8;1)
	Weighted normalized	(0.6;0.9;1)	(0.1;0.3;0.5)	(0;0.1;0.3)	...	(0;0;0)	(0;0;0)	(0.5;0.7;1)
3	Normalized	(0.3;0.5;0.7)	(0.5;0.7;0.9)	(0.9;1;1)	...	(0;0;0)	(0;0;0)	(0.6;0.8;1)
	Weighted normalized	(0.2;0.4;0.7)	(0.1;0.2;0.4)	(0;0.1;0.3)	...	(0;0;0)	(0;0;0)	(0.5;0.7;1)
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
28	Normalized	(0;0;0.1)	(0.3;0.5;0.7)	(0.5;0.7;0.9)	...	(0;0;0)	(0;0;0)	(0.3;0.6;0.8)
	Weighted normalized	(0;0;0.1)	(0.1;0.1;0.3)	(0;0.1;0.2)	...	(0;0;0)	(0;0;0)	(0.3;0.5;0.7)
29	Normalized	(0.1;0.3;0.5)	(0.1;0.3;0.5)	(0.5;0.7;0.9)	...	(0;0;0)	(0;0;0)	(0.6;0.8;1)
	Weighted normalized	(0.1;0.2;0.5)	(0;0.1;0.2)	(0;0.1;0.2)	...	(0;0;0)	(0;0;0)	(0.5;0.7;1)
30	Normalized	(0.5;0.7;0.9)	(0.9;1;1)	(0.9;1;1)	...	(0;0;0)	(0;0;0)	(0.3;0.6;0.8)
	Weighted normalized	(0.3;0.6;0.9)	(0.1;0.3;0.5)	(0;0.1;0.3)	...	(0;0;0)	(0;0;0)	(0.3;0.5;0.7)

Step 6. d_i^+ and d_i^- show the distances of the ith alternative to the fuzzy ideal and fuzzy anti-ideal solutions, respectively. d_i^+ and d_i^- determined with the help of Equation 10–12 are shown in Table 7. As an example, the distance for the first alternative is calculated as in Equations 23 and 24.

$$d_1^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+)\ ;\ i = 1, 2, \dots, 7 \tag{23}$$

$$d_1^+ = \sqrt{\tfrac{1}{3}\left[(1-0.63)^2 + (1-0.9)^2 + (1-1)^2\right]} + \dots + \sqrt{\tfrac{1}{3}\left[(1-0.5)^2 + (1-0.78)^2 + (1-1)^2\right]} = 5.285 \tag{24}$$

Table 7. Distances from the ideal and anti-ideal solutions

No	di^-	d_i^+	CC_i
1	2.02	5.29	0.27
2	2.30	5.05	0.31
3	1.85	5.49	0.25
. . .	. . .	. . .	. . .
30	1.61	5.73	0.21

The closeness coefficient indices (CC_i) of the alternatives are determined using Equation 13, and the alternatives are ranked according to their CC_i values. As a result, *project 2* is determined to be the most suitable project using fuzzy TOPSIS. *Project 2* is followed by *projects 24* and *25*.

4.2 Implementation of Customized IT2F-ORESTE and the Results

The implementation steps of the customized IT2F-ORESTE for this case study are presented below.

Step 1. Initial decision matrix established by expert evaluation is provided in Appendix A.

Step 2. *Calculation of criteria ranks and alternative ranking based on each criterion based on IT2F sets.* First, the criteria (K_1: Capacity, K_2: Demand, K_3: Mold cost; K_4: Number of operations; K_5: Model (year); K_6: Part geometry; and K_7: Direction) were sorted from the largest to the smallest according to their importance levels as follows: K_1-P-K_2-P-K_3-I-K_4-P-K_5-P-K_6-I-K_7. Here, the letter "P" (preference) indicates that there is a superiority between two consecutive criteria, and "I" (indifference) indicates that there is no superiority between two consecutive criteria. Similarly, the weakness order of the alternatives based on each criterion was determined.

Considering the values used in the classical ranking of criteria and alternatives (i.e., smaller rank values represent superiority), the IT2F sets used for the values of $\widetilde{E_l} = \left(\widetilde{E_l^U}, \widetilde{E_l^L}\right)$ for $l = 1, 2, \dots, 7$ are written as (Lee and Chen, 2008)

Very good (V.G.) or very high (V.H.): $\widetilde{E_1} = \left(\widetilde{E_1^U}, \widetilde{E_1^L}\right) = (0; 0; 0; 0.1\colon 1; 1), (0; 0; 0; 0.05\colon 0.9; 0.9)$

Good (G.) or high (H.): $\widetilde{E_2} = \left(\widetilde{E_2^U}, \widetilde{E_2^L}\right) (0; 0.1; 0.1; 0.3\colon 1; 1), (0.05; 0.1; 0.1; 0.2\colon 0.9; 0.9)$

Medium good (M.G.) or medium-high (M.H.): $\widetilde{E_3} = \left(\widetilde{E_3^U}, \widetilde{E_3^L}\right) = (0.1; 0.3; 0.3; 0.5\colon 1; 1), (0.2; 0.3; 0.3; 0.4\colon 0.9; 0.9)$

Fair (F.) or medium (M.): $\widetilde{E_4} = \left(\widetilde{E_4^U}, \widetilde{E_4^L}\right) = (0.3; 0.5; 0.5; 0.7\colon 1; 1), (0.4; 0.5; 0.5; 0.6\colon 0.9; 0.9)$

Medium-bad (M.B.) or medium-low (M.L.): $\widetilde{E_5} = \left(\widetilde{E_5^U}, \widetilde{E_5^L}\right) = (0.5; 0.7; 0.7; 0.9\colon 1; 1), (0.6; 0.7; 0.7; 0.8\colon 0.9; 0.9)$

Bad (B.) or low (L.): $\widetilde{E_6} = \left(\widetilde{E_6^U}, \widetilde{E_6^L}\right) = (0.7; 0.9; 0.9; 1\colon 1; 1), (0.8; 0.9; 0.9; 0.95\colon 0.9; 0.9)$

Very bad (V.B.) or very low (V.L.): $\widetilde{E_7} = \left(\widetilde{E_7^U}, \widetilde{E_7^L}\right) = (0.9; 1; 1; 1\colon 1; 1), (0.95; 1; 1; 1\colon 0.9; 0.9)$

The aforementioned criteria are expressed by IT2F sets, as listed in Table 8. Then, Equation 15 is used to obtain the rank values of the criteria based on the IT2F sets.

Table 8. Definition of importance values of criteria with linguistic variables and IT2 fuzzy numbers

Criteria	**Linguistic variables**	**IT2F sets**
Demand	H.	$(0; 0.1; 0.1; 0.3\colon 1; 1), (0.05; 0.1; 0.1; 0.2\colon 0.9; 0.9)$
Model (year)	M.L.	$(0.5; 0.7; 0.7; 0.9\colon 1; 1), (0.6; 0.7; 0.7; 0.8\colon 0.9; 0.9)$
Direction	L.	$(0.7; 0.9; 0.9; 1\colon 1; 1), (0.8; 0.9; 0.9; 0.95\colon 0.9; 0.9)$
Part geometry	L.	$(0.7; 0.9; 0.9; 1\colon 1; 1), (0.8; 0.9; 0.9; 0.95\colon 0.9; 0.9)$
Number of operations	M.	$(0.3; 0.5; 0.5; 0.7\colon 1; 1), (0.4; 0.5; 0.5; 0.6\colon 0.9; 0.9)$
Mold cost	M.	$(0.3; 0.5; 0.5; 0.7\colon 1; 1), (0.4; 0.5; 0.5; 0.6\colon 0.9; 0.9)$
Capacity	V.H.	$(0; 0; 0; 0.1\colon 1; 1), (0; 0; 0; 0.05\colon 0.9; 0.9)$

V.L. = Very low; L. = Low; M.L. = Moderately low; M. = Medium; M.H. = Moderately high; H. = High; V.H. = Very high

For example, the importance level determined by the decision-maker for the "capacity" criterion is "very high" ($\widetilde{E_1} = \left(\widetilde{E_1^U}, \widetilde{E_1^L}\right) = (0; 0; 0; 0.1\colon 1; 1), (0; 0; 0; 0.05\colon 0.9; 0.9)$). Accordingly, to obtain the IT2F rank value (Besson rank value) using Equation 15, the corresponding $M_p\left(\widetilde{E_{l=1}^k}\right)$ and $S_q\left(\widetilde{E_{l=1}^k}\right)$ values are calculated as

$$\boldsymbol{M_1}\widetilde{\boldsymbol{E_1^U}} = 0; \boldsymbol{M_2}\widetilde{\boldsymbol{E_1^U}} = 0; \boldsymbol{M_3}\widetilde{\boldsymbol{E_1^U}} = 0.05; \boldsymbol{M_1}\widetilde{\boldsymbol{E_1^L}} = 0; \boldsymbol{M_2}\widetilde{\boldsymbol{E_1^L}} = 0; \boldsymbol{M_3}\widetilde{\boldsymbol{E_1^L}} = 0.25;$$

$$\boldsymbol{S_1}\widetilde{\boldsymbol{E_1^U}} = 0; \boldsymbol{S_2}\widetilde{\boldsymbol{E_1^U}} = 0; \boldsymbol{S_3}\widetilde{\boldsymbol{E_1^U}} = 0.05; \boldsymbol{S_4}\widetilde{\boldsymbol{E_1^U}} = 0.043; \boldsymbol{S_1}\widetilde{\boldsymbol{E_1^L}} = 0; \boldsymbol{S_2}\widetilde{\boldsymbol{E_1^L}} = 0; \boldsymbol{S_3}\widetilde{\boldsymbol{E_1^L}} = 0.25; \boldsymbol{S_4}\widetilde{\boldsymbol{E_1^L}} = 0.22$$

Thus, the IT2F rank value (Besson rank value) $r(E_1)$ obtained using Equation 15 for the "capacity" criterion was calculated as in Equation 25.

$$r_{KCapacity}(\widetilde{E_l}) = r(\widetilde{E_1}) = M_1\widetilde{E_1^U} + M_1\widetilde{E_1^L} + M_2\widetilde{E_1^U} + M_2\widetilde{E_1^L} + M_3\widetilde{E_1^U} + M_3\widetilde{E_1^L} - \frac{1}{4}\Big(S_1\widetilde{E_1^U} + S_1\widetilde{E_1^L} + S_2\widetilde{E_1^U} + S_2\widetilde{E_1^L} + S_3\widetilde{E_1^U} + S_3\widetilde{E_1^L} + S_4\widetilde{E_1^U} + S_4\widetilde{E_1^L}\Big) + H_1\Big(\widetilde{E_1^U}\Big) + H_1\big(\widetilde{E_1^L}\big) + H_2\Big(\widetilde{E_1^U}\Big) + H_2\big(\widetilde{E_1^L}\big) = 0 + 0 + 0 + 0 + 0.05 + 0.25 - \frac{1}{4}(0 + 0 + 0 + 0 + 0.05 + 0.25 + 0.043 + 0.22) + 1 + 0.9 + 1 + 0.9 = 3.96 \quad (25)$$

Similar procedures were applied to the rank values of other criteria. Accordingly, the IT2F-Besson rank values of the criteria were $r_{KCapacity}(\widetilde{E_l}) = 3.96$; $r_{KDemand}\big(\widetilde{E_l}\big) = 4.38$; $r_{KMoldCost}(\widetilde{E_l}) = 6.67$; $r_{KNumberofOperations}(\widetilde{E_l}) = 6.67$; $r_{KModelYear}(\widetilde{E_l}) = 7.87$; $r_{KPartGeometry}(\widetilde{E_l}) = 9.03$; and $r_{KDirection}(\widetilde{E_l}) = 9.03$. Similarly, for the alternatives, a fuzzy decision matrix consisting of IT2F numbers was obtained, where the alternatives were assessed according to each criterion (Table 9).

Table 9. IT2F decision matrix for the alternatives

Prj. no	Demand	Model (Year)		Mold cost	Capacity
1	((0;0;0;0.1:1;1), (0;0;0;0.05:0.9;0.9))	((0.7;0.9;0.9;1:1;1), (0.8;0.9;0.9;0.95:0.9;0.9))	...	((0.7;0.9;0.9;1:1;1), (0.8;0.9;0.9;0.95:0.9;0.9))	((0.1;0.3;0.3;0.5:1;1), (0.2;0.3;0.3;0.4:0.9;0.9))
2	((0;0;0;0.1:1;1), (0;0;0;0.05:0.9;0.9))	((0;0;0;0.1:1;1), (0;0;0;0.05:0.9;0.9))	...	((0.7;0.9;0.9;1:1;1), (0.8;0.9;0.9;0.95:0.9;0.9))	((0.1;0.3;0.3;0.5:1;1), (0.2;0.3;0.3;0.4:0.9;0.9))
3	((0.3;0.5;0.5;0.7:1;1), (0.4;0.5;0.5;0.6:0.9;0.9))	((0.1;0.3;0.3;0.5:1;1), (0.2;0.3;0.3;0.4:0.9;0.9))	...	((0;0.1;0.1;0.3:1;1), (0.05;0.1;0.1;0.2:0.9;0.9))	((0.1;0.3;0.3;0.5:1;1), (0.2;0.3;0.3;0.4:0.9;0.9))
. . .	. . .	. . .	...	. . .	. . .
28	((0.9;1;1;1:1;1), (0.95;1;1;1:0.9;0.9))	((0.3;0.5;0.5;0.7:1;1), (0.4;0.5;0.5;0.6:0.9;0.9))	...	((0;0.1;0.1;0.3:1;1), (0.05;0.1;0.1;0.2:0.9;0.9))	((0.3;0.5;0.5;0.7:1;1), (0.4;0.5;0.5;0.6:0.9;0.9))
29	((0.7;0.9;0.9:1;1;1), (0.8;0.9;0.9;0.95:0.9;0.9))	((0.7;0.9;0.9;1:1;1), (0.8;0.9;0.9;0.95:0.9;0.9))	...	((0;0.1;0.1;0.3:1;1), (0.05;0.1;0.1;0.2:0.9;0.9))	((0.1;0.3;0.3;0.5:1;1), (0.2;0.3;0.3;0.4:0.9;0.9))
30	((0.1;0.3;0.3;0.5:1;1), (0.2;0.3;0.3;0.4:0.9;0.9))	((0;0;0;0.1:1;1), (0;0;0;0.05:0.9;0.9))	...	((0.7;0.9;0.9;1:1;1), (0.8;0.9;0.9;0.95:0.9;0.9))	((0.3;0.5;0.5;0.7:1;1), (0.4;0.5;0.5;0.6:0.9;0.9))

The rank values of the alternatives based on the IT2F sets were calculated using Equation 15 and listed in Table 10.

Table 10. IT2F-Besson ranks for alternatives and projection distances by IT2B-rank values for alternatives

No	Rank/Distance	Demand	Model year	Direction	Part geometry	Number of operations	Mold cost	Production capacity
1	Besson rank	3.96	9.03	3.96	3.96	6.67	7.87	5.47
	Projection distance	4.17	8.45	6.50	6.50	6.67	7.27	4.72
2	Besson rank	3.96	3.96	3.96	4.38	7.87	9.03	5.47
	Projection distance	4.17	5.92	6.50	6.71	7.27	7.85	4.72
3	Besson rank	6.67	5.47	3.96	3.96	4.38	4.38	5.47
	Projection distance	5.53	6.67	6.50	6.50	5.53	5.53	4.72
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
28	Besson rank	9.69	6.67	5.47	5.47	4.38	4.38	6.67
	Projection distance	7.04	7.27	7.25	7.25	5.53	5.53	5.32
29	Besson rank	7.87	7.87	5.47	5.47	4.38	4.38	5.47
	Projection	6.13	7.87	7.25	7.25	5.53	5.53	4.72

No	Rank/Distance	Demand	Model year	Direction	Part geometry	Number of operations	Mold cost	Production capacity
	distance							
30	Besson rank	5.47	3.96	3.96	4.38	6.67	7.87	6.67
	Projection distance	4.93	5.92	6.50	6.71	6.67	7.27	5.32

Step 3. *Calculation of projection distances based on IT2F-rank values.* The projection distances were calculated using Equation 19 using the IT2F-Besson rank values for all criteria listed in Table 10. The value of R was set to one in this study.

As an example, the projection distance of *alternative-1* with respect to *demand* criteria is calculated via Equation19 into which the $r_{Kdemand}(\widetilde{E_l}) = 4.38$ (IT2F-Besson rank value of the *demand* criterion) and $r_{A_{1|Kdemand}}(\widetilde{E_l}) = 3.96$ (IT2F-Besson rank value of *1st alternative* with respect to the *demand* criterion) values are substituted. Accordingly, the projection distance is determined as

$$d_{1demand}(\widetilde{E_l}) = \left[\frac{1}{2}3.96 + \frac{1}{2}4.38\right]^{R=1} = \frac{1}{2}(3.96 + 4.38) = 4.17 \qquad (26)$$

Step 4. *Calculation of global rank values based on IT2F-projection distances.* The IT2F-projection distances obtained in the previous step were sorted from the lowest to the highest, and new global Besson rank values were attained for all 210 IT2F-projection distances ($30\, alternatives * 7\, criteria = 210$ values). A smaller $r_{ij}(\widetilde{E_l})$ value indicates that the corresponding alternative is in a better position.

For example, the minimum of all 210 projection distance values was 4.17, which occurred four times within the sequence. Therefore, when the values were sorted from the smallest to highest, the first four values were 4.17. Accordingly, the related global Besson rank is calculated using

$$Global\ IT2F - Besson\ rank = \frac{(1 + 2 + 3 + 4)}{4} = 2.5. \qquad (27)$$

All global Besson rank values were calculated in the same manner and are listed in Table 11.

Table 11. Besson rank values based on the projection distances and global IT2F-Besson rank values

Project number	Demand	Model year	Direction	Part geometry	Number of operations	Mold cost	Production capacity	Total
1	2.5	207.5	124.0	124.0	153.0	191.5	22.5	825.0
2	2.5	82.5	124.0	166.0	191.5	198.0	22.5	787.0
3	64.0	153.0	124.0	124.0	64.0	64.0	22.5	615.5
...	...	...	...	...	...	...	...	
28	170.0	191.5	178.5	178.5	64.0	64.0	44.5	891.0
29	100.0	201.5	178.5	178.5	64.0	64.0	22.5	809.0
30	36.5	82.5	124.0	166.0	153.0	191.5	44.5	798.0

Step 5. *Sorting the alternatives by their global IT2F-rank values.* The sums of the global IT2F-Besson rank values for all criteria for each project were obtained using Equation 20 and presented in the last column of Table 11. Finally, these values were sorted in ascending order, and the final rank values of the alternatives were determined, as shown in Table 12. Accordingly, the most suitable projects are found to be *projects 24* and *25*.

5. RESULTS AND DISCUSSION

In this study, a customized IT2F-ORESTE approach was proposed to prioritize 30 project alternatives (over seven criteria) in an organization operating in the automotive sector. Project alternatives were evaluated using fuzzy TOPSIS to confirm the effectiveness of the proposed method. The rankings obtained using these methods are presented in Table 12. Both cost and benefit criteria were considered for the ranking procedure. Table 12 shows that logical, consistent, and even superior rankings can be attained with the proposed IT2F-ORESTE implementation compared to fuzzy TOPSIS.

Table 12. Ranking results obtained by IT2F-ORESTE and fuzzy TOPSIS methods

Method		**Ranking**														
IT2F-ORESTE	*Rank*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
	Project no	24	25	16	13	26	3	14	22	20	21	27	12	17	5	6
	Rank	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*
	Project no	23	4	18	2	9	30	29	11	1	8	10	19	28	15	7
Fuzzy TOPSIS	*Rank*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
	Project no	2	24	25	26	14	16	27	22	1	17	13	30	1	2	3
	Rank	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*
	Project no	4	5	6	7	8	9	10	11	12	13	14	15	8	23	28

Examining the ranking attained through the customized IT2F-ORESTE method reveals that *projects 24* and *25* are in the first place. These projects have a higher demand and newer model year compared to that of others, and the parts to be manufactured are two-sided (so these parts have a double order quantity advantage). Further, they have low mold costs, a low number of operations, and high production capacity. Therefore, this result was among the best possible results. In addition, *project 16*, which comes third in the proposed method, has the minimum number of operations, minimum mold cost, high demand, high production capacity, and double-order advantage.

In contrast, *project 2* comes first in the fuzzy TOPSIS ranking. *Project 2* is a project with high demand and a newer model year; however, it has a double-order advantage, uncomplicated geometry, and high production capacity; further, the number of operations and mold costs are higher in this project compared to that for *projects 24* and *25*, which are selected as the best projects by the proposed method.

Comparable results were observed when the general rankings given in Table 12 were examined. There is some consistency in the rankings obtained through both the fuzzy TOPSIS and proposed IT2F-ORESTE implementations. For example, in both methods, the top 10 projects (*projects 24*, *25*, *16*, *26*, *14*, and *22*) and the last ones (*projects 15* and *28* in the last five) overlapped to some extent. Considering that the fuzzy TOPSIS method is frequently utilized in decision-making, the consistency in the rankings shows that the proposed IT2F-ORESTE method can safely replace this conventional method in selection problems with mixed data.

5.1 Sensitivity Analysis for IT2F-ORESTE

A sensitivity analysis evaluates the effect of reasonable changes in input parameters, such as criteria weights, on the outcomes of a decision-making model (Pamucar and Cirovic, 2015). Sensitivity analysis is important in determining the resilience of the MCDM model because the results obtained through MCDM models commonly depend on input data that can be influenced by various factors such as personal opinions, cognitive biases, and measurement errors (Demir *et al.*, 2024).

In MCDM models, sensitivity analysis depends on systematically changing the input parameters (e.g., criteria weights) within certain ranges to determine the sensitivity or responsiveness of the results to such changes (Pamucar and Cirovic, 2015). If the results do not change with changes in the input parameters, the model can be considered to be robust (Dürr *et al.*, 2023). Therefore, the sensitivity analysis examines the effect of changes in criteria weights on the final rankings. Accordingly, the final alternative ranking is tested to determine the robustness of the decision-making process (Pamucar and Cirovic, 2015).

In this study, the impact of changes in the prioritization of criteria on the final ranking was analyzed during the sensitivity analysis because the proposed IT2F-ORESTE method does not require weight calculation. Accordingly, we changed the prioritization of the seven criteria systematically by replacing two consecutive criteria in each trial to determine whether the ranking results changed significantly. These changes in prioritization are shown in *italics* in Table 13 and explained below.

- Trial-1, the first and second criteria are replaced,
- Trial-2, the second and third criteria are replaced,
- Trial-3, the third and fifth criteria are replaced,
- Trial-4, the fourth and fifth criteria are replaced,
- Trial-5, the fifth and sixth criteria are replaced,
- Trial-6, the fifth and seventh criteria are replaced.

Table 13. Importance levels of criteria for trials performed for sensitivity analysis

Importance (in descending order)	**Initial**	**Trial-1**	**Trial-2**	**Trial-3**	**Trial-4**	**Trial-5**	**Trial-6**
V.H.	Production capacity	*Demand*	Production capacity	Production capacity	Production capacity	Production capacity	Production capacity
H.	Demand	*Production capacity*	*Number of operations*	Demand	Demand	Demand	Demand
M.	Number of operations	Number of operations	*Demand*	*Model year*	Number of operations	Number of operations	Number of operations
M.	Mold cost	Mold cost	Mold cost	Mold cost	*Model year*	Mold cost	Mold cost
M.L.	Model year	Model year	Model year	*Number of operations*	*Mold cost*	*Direction*	*Part geometry*
L.	Direction	Direction	Direction	Direction	Direction	*Model year*	Direction
L.	Part geometry	Part geometry	Part geometry	Part geometry	Part geometry	Part geometry	*Model year*

V.L. = Very low; L. = Low; M.L. = Moderately low; M. = Medium; M.H. = Moderately high; H. = High; V.H. = Very high

The results of the sensitivity analysis are shown in Figure 6. As shown in Figure 6, the first four projects (*projects 24*, *25*, *16*, and *13*) had the same rank in all trials. Similarly, the last two projects, *projects 15 and 7*, did not change with the trials. In addition, the rankings of the remaining projects did not change significantly in the different trials. Consequently, because the ranking results for the first four projects and the final two projects are the same for all trials and the ranking of other projects does not change significantly with a change in criteria prioritization, the robustness of our proposed IT2F-ORESTE model is verified.

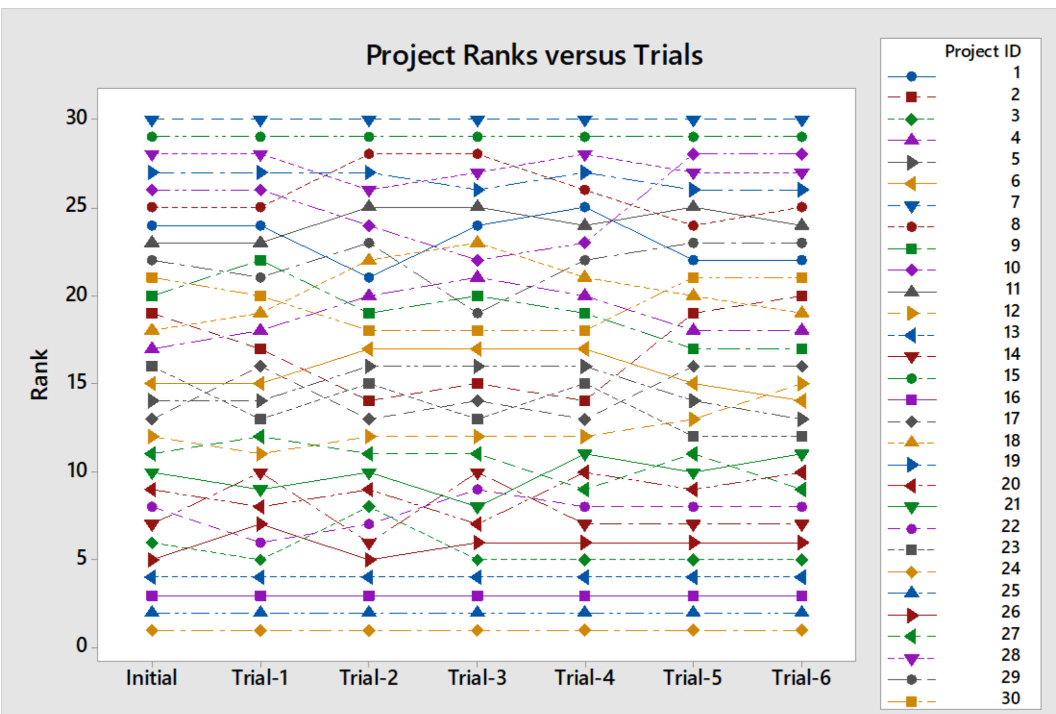

Figure 6. Final project rankings for different trials

5.2 Comparison and Practicability of the Methods

ORESTE calls for a preorder of criteria and alternatives in terms of ordinal data (Delhaye *et al.*, 1991; Chatterjee and Chakraborty, 2014.) In other words, it only requires criteria and alternative rankings for each criterion (Chatterjee and

Chakraborty, 2014; Adali and Işık, 2017). This method does not require definite information on the criteria weights or any type of preference function formulation (Chatterjee and Chakraborty, 2013), and therefore, it is especially appropriate for scenarios wherein the decision-maker cannot come up with crisp evaluation data and criteria weights (Adali and Işık, 2017). Moreover, in the TOPSIS method, weighting is difficult (Madanchian and Taherdoost, 2023), and therefore, the proposed IT2F-ORESTE method requires no determination of the criterion weights or objective thresholds.

The ORESTE method is based only on criterion ranking, and thus, it facilitates decision-making. Further, the decision-making process can be accelerated because the quantification of criteria weights and alternatives is not required during ORESTE implementation (Chatterjee and Chakraborty, 2014). In contrast, the TOPSIS implementation rests on the idea that the ideal alternative has the best level for all criteria, whereas the negative-ideal alternative has the worst values. Accordingly, the calculation of the distance between the ideal and negative-ideal solutions is exhausting in TOPSIS (Yong, 2006).

Moreover, the ORESTE method may be preferred in the absence of numerical evaluations (Adali and Işık, 2017). However, TOPSIS is appropriate when quantitative or objective data are available (Alsalem *et al.*, 2018). ORESTE considers alternatives and criteria ordering, and therefore, it seems more appropriate for selection problems using ordinal data. However, it can be utilized for problems with numerical or mixed data, indicating the quantity. In fact, this study shows that the proposed IT2F-ORESTE method is a good option for decision-making when mixed data are used. In addition, TOPSIS has several disadvantages, such as possible trade-offs between the criteria, effects of information overlap on the results, and simultaneous encounters of alternatives close to the positive and negative ideal points (Madanchian and Taherdoost, 2023).

Considering the aforementioned strengths and advantages, although the ORESTE and IT2F-ORESTE methods are less preferred in the literature, they can be used efficiently for project selection problems because they can obtain consistent, meaningful, and even superior results compared with the commonly used methods. Considering that project selection decisions are important strategic decisions that can affect the competitiveness of businesses in the markets in which they operate, the IT2F-ORESTE method proposed in this study can be used efficiently to facilitate decision-making.

6. CONCLUSIONS

Organizations face decision-making problems in almost every aspect of their businesses. Selecting and implementing viable projects play a critical role in achieving an organization's competitive goals. Therefore, with limited resources, many organizations seek to invest in viable projects to improve existing processes. Decision-making problems have become increasingly complicated because of the advances in technology and the rapid changes in customer expectations and price dynamics. In many cases, considerable human, time, and financial resources must be allocated for selecting viable projects. Organizations need to implement reliable methodologies to evaluate the viability of the proposed projects to reduce the consumption of such resources. Accordingly, a customized version of a less preferred methodology in decision-making processes, IT2F-ORESTE, was suggested in this study, and its effectiveness for selecting the most viable projects for an organization was demonstrated.

The proposed IT2F-ORESTE methodology was implemented to select the most beneficial project from among 30 alternatives in an automotive manufacturing plant. To the best of the authors' knowledge, this was the first study to apply IT2F-ORESTE for project selection in the automotive industry. The findings were evaluated against those of fuzzy TOPSIS to illustrate that the proposed IT2F-ORESTE method creates comparable and even superior results compared to those of traditional methods.

The cost and benefit criteria were included in the project ranking process employed in this study. The results revealed that the proposed IT2F-ORESTE method assigned the highest ranks to projects with high earnings potential, low cost, low number of operations, and high production capacity, whereas the traditional fuzzy TOPSIS method failed to select the best project alternative because it ranked a project with a high number of operations and costs as the best project. Thus, although IT2F-ORESTE was not previously preferred for project selection, it can attain similar and even superior rankings compared to those of the frequently used methods. This study demonstrated not only the effectiveness of the IT2F-ORESTE method for project selection but also its superiority compared to a frequently used project selection method.

Many organizations deal with the challenge of choosing viable projects that meet predetermined criteria. As this study was conducted only in the automotive industry setting, in future studies, the proposed IT2F-ORESTE method should be utilized for project selection decisions with different datasets in different industries. In addition, different fuzzy methods should be used for comparison in future studies because this study only compared the effectiveness of IT2F-ORESTE with fuzzy TOPSIS. In addition, the IT2F-ORESTE method should be further customized using different rank-value calculation methods, and the results should be compared.

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APPENDIX A - FULL DECISION MATRIX

Full decision matrix established in the study (Initial data)

Project no.	Demand	Model year	Direction	Part geometry	Number of operations	Mold cost	Production capacity
1	V.G.	B.	V.G.	V.G.	M.	M.B.	M.G.
2	V.G.	V.G.	V.G.	G.	M.B.	B.	M.G.
3	M.	M.G.	V.G.	V.G.	G.	G.	M.G.
4	M.G.	M.B.	V.G.	V.G.	M.G.	M.	M.
5	M.G.	B.	M.G.	M.G.	G.	G.	M.G.
6	M.G.	B.	M.G.	M.G.	G.	G.	M.G.
7	M.	B.	M.G.	M.G.	B.	V.B.	M.
8	M.	B.	V.G.	G.	M.G.	M.	M.
9	G.	M.B.	V.G.	G.	M.G.	M.	M.
10	M.B.	V.G.	V.G.	M.G.	M.	M.B.	M.G.
11	M.B.	M.B.	V.G.	V.G.	M.	M.	M.G.
12	M.B.	V.G.	V.G.	M.G.	M.G.	M.	M.G.
13	G.	M.G.	V.G.	V.G.	G.	G.	M.
14	G.	G.	V.G.	V.G.	M.G.	M.	M.G.
15	B.	M.G.	V.G.	G.	M.B.	B.	M.G.
16	G.	M.G.	V.G.	V.G.	V.G.	V.G.	M.G.
17	G.	V.G.	V.G.	V.G.	M.	M.B.	M.
18	M.	B.	V.G.	V.G.	M.G.	M.	M.G.
19	M.	M.	V.G.	V.G.	M.	M.B.	M.G.
20	M.B.	G.	V.G.	M.G.	G.	G.	M.G.
21	M.B.	G.	V.G.	M.G.	G.	G.	M.G.
22	M.G.	G.	M.G.	M.G.	G.	G.	M.G.
23	B.	M.	V.G.	V.G.	G.	G.	M.G.
24	V.G.	V.G.	V.G.	V.G.	G.	G.	M.G.
25	V.G.	V.G.	V.G.	V.G.	G.	G.	M.G.
26	G.	V.G.	V.G.	V.G.	M.G.	M.	M.G.
27	G.	M.G.	V.G.	V.G.	M.G.	M.	M.G.
28	V.B.	M.	M.G.	M.G.	G.	G.	M.
29	M.B.	M.B.	M.G.	M.G.	G.	G.	M.G.
30	M.G.	V.G.	V.G.	G.	M.	M.B.	M.

V.B. = Very bad; B. = Bad; M.B. = Moderately bad; M. = Medium;
M.G. = Moderately good; G. = Good; V.G. = Very good