Decision Making: Applications in Management and Engineering
Vol. 6, Issue 1, 2023, pp. 379-398.
ISSN: 2560-6018
eISSN: 2620-0104
DOI: https://doi.org/10.31181/dmame0306102022c

HYBRID MCDM METHOD ON PYTHAGOREAN FUZZY SET AND ITS APPLICATION

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Received: 8 May 2022;
Accepted: 14 July 2022;
Available online: 6 October 2022.

Original scientific paper

Abstract: *Here in this article a hybrid MCDM method on the Pythagorean fuzzy-environment is presented. This method is based on the Pythagorean Fuzzy Method based on Removal Effects of Criterion (PF-MEREC) and Stepwise Weight Assessment Ratio Analysis (SWARA) approaches. The objective and subjective weights are assessed by PF-MEREC, SWARA model and the preference order ranking of the various alternatives is done through Complex Proportional Assessment (COPRAS) framework on the PFS. The proposed method is the hybrid model of MEREC, SWARA and COPRAS methods. Further, the proposed model is used to identify the best banking management software (BMS) so that the bank can choose the robust bank management software tool to enhance its efficiency and excellence. Thereafter, sensitivity analysis and comparative discussion of the proposed model is done with the existing techniques to judge the reasonability and efficiency of the proposed model.*

Key words: *Pythagorean Fuzzy Set (PFS), Decision-Making, MEREC, SWARA, COPRAS, Banking Management Software*.

1. Introduction

There are many uncertain, fuzzy and incomplete problems in the real world. Hence, the fuzzy set theory, originated by Zadeh (1965) is a successful and vigorous tool for determining many same issues. To overcome its primary extension and shortcomings, intuitionistic fuzzy sets (IFS) has been established by Atanassov (1986), it satisfies the requirement of sum total of membership function (MF) and non-MF (N-MF) is less than or equal to one. Nevertheless, there may be difficulties in the policymaking procedure when both the FS and the IFS theories are not capable of addressing the uncertain and incompatible data. Viz., if a decision expert assigns 0.8 and 0.4 as his preference of belonging and non-belongingness of any object, then

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plainly, it can be easily seen that $0.8 + 0.4 > 1$. Hence, this situation is not handled by IFSs. To beat these shortcomings of IFSs, initially, Yager (2013) presented the fundamental of the PFSs. In a Pythagorean fuzzy set MF and N-MF satisfies the condition $(0.8)^2 + (0.4)^2 \leq 1$. In the PFS is a good device for expressing uncertain information ascending in practical, complicated MCDM problems. It has the same provision as IFSs, however has a lot of flexibility and more space to express fuzzy information than IFS. In this regard, PFS has attracted the eye of many scholars and has been studied extensively in management.

Some PF-aggregation operators are also presented such as PF-weighted averaging operators (Garg, 2019; Pamucar & Jankovic, 2020; Rong et al., 2020; Akram et al., 2021; Farid & Riaz, 2022) to help tackle MCDM problems. "Einstein geometric aggregation operators employing a new complex-IVPFS" (Ali et al., 2021). Some researchers presented the score functions on PFS (Zhang & Xu, 2014; Peng et al., 2017) can accurately rank general choices and also has a strong sense of partiality by taking hesitant information into account. Moreover, some researchers focused on Pythagorean fuzzy objective weighting methods (Biswas & Sarkar, 2019; Ozdemir & Gul, 2019) and subjective weight (Wei, 2019; Chen, 2019; Wang et al., 2019; Zavadskas et al., 2020). The subjective weights are submitted by DMs supported in their own knowledge, whereas they neglect the primary weight info explained by the valuation data. Some novel approaches to obtaining objective weight from assessment data don't take into account the DEs' preferences. So, a combined weighting approach is submitted, which may amalgamate each subjective and objective weight (OW).

Many multi-criteria decision-making (MCDM) approaches are dealing with a massive quantity of problems and estimating alternative and help the user in mapping the problem. Criterion weights has an important role in the decision-making (DM) procedure, as the suitable selection of criterion weights is best for ranking of alternatives. Thereafter, it's vital to discover a method to define the weights. Some approaches have been available in the literature. As a result, many scholars have studied the OW by criteria importance through intercriteria correlation (CRITIC) and entropy measure of PFSs. Xu et al. (2020) proposed an entropy measure on PFS to solve MCDM problems. Chaurasiya and Jain (2021) proposed MARCOS method on IFSs. The authors have applied the predictable MCDM method in various fields (Rani & Jain, 2019; Petrovic et al., 2019; Eiegwa, 2020; Mishra et al., 2021; Li et al., 2022; Yildirim & Yildirim, 2022).

In addition, criterion weight is very significant in solving MCDM difficulties. Therefore, the authors have moved their attention to methods related to criterion weight. Keshavarz-Ghorabaee et al. (2021) developed MEREC technique is one of the powerful approaches for defining the objective criterion weights (OCWs). Whereas, among the innovative technique to determining criteria weight (Zizovic & Pamucar, 2019). Hadi and Abdullah (2022) presented integrate MEREC-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method for IoT-based hospital place selection. Hezam et al. (2022) proposed an IF-MEREC-ranking sum-double normalization-based multi-aggregation method for evaluating alternative fuel vehicles concerning sustainability. Marinkovic et al. (2022) employed the MEREC-Combined Compromise Solution multi-criteria method to evaluate the application of waste and recycled materials to production. Integrated MEREC method on Fermatean fuzzy environment proposed Rani et al. (2022), MEREC-MULTIMOORA (Mishra et al., 2022), MEREC-MARCOS (Nguyen et al., 2022), Level based weight assessment-Z-MAIRCA method (Bozanic et al., 2020).

Kersuliene et al. (2010) has established the SWARA approach to be an effective device for calculating the SCWs. Alipour et al. (2021) employed a combined SWARA and COPRAS technique to assess the supplier selection of fuel cell and hydrogen constituents in the PFS domain. Saraji et al. (2021) proposed the hesitant fuzzy-SWARA-MULTIMURA method for online education. Some researchers have drawn attention to integrated methods to solve the MCDM problems, such as (Rani et al., 2020) developed a new integrate SWARA-ARAS method on PFS for healthcare waste treatment problem.

Since at present, many scholars have developed the following ranking methods to solve MCDM problems. For examples, Badi and Pamucar (2020) proposed integrate Grey-MARCOS methods for supplier selection. Durmic et al. (2020) proposed an integrated Full Consistency Method-Rough-Simple Additive Weighting (FUCOM-R-SAW) method has been employed to choose sustainable suppliers. Tesic et al. (2022) presented DIBR-fuzzy-MARCOS framework. Puska et al. (2020) suggested a way for measurement of alternatives and ranking according to compromise solution (MARCOS) method for project management software. Some researchers applied MCDM methods such as (Kaya, 2020; Pamucar, 2020; Keshavarz-Ghorabaee, 2021; Ashraf et al., 2022).

The COPRAS method, established by Zavadskas et al. (1994) is one of the practical well-orderly approaches to solve intricate MCDM difficulties. The main objective of the COPRAS approach, includes: (i) it is an appropriate and assess method to obtain the solution to the DM issue. (ii) It considers the ratio of the worst and the best outcome; (iii) it provides results in a short-time as compared to other MCDM methods. Several researchers have used the COPRAS technique for various applications (Mishra et al., 2020). These days, various academicians have expanded the traditional COPRAS technique under a range of vague environments. Zheng et al. (2018) studied a hesitant fuzzy (HF) COPRAS approach to solving the health decision-making problem. Thereafter, Mishra et al. (2019) proposed the integrated HF-COPRAS method to solve service quality problems. The PF-COPRAS approach has been used by (Rani et al., 2020*a*) to appraise pharmaceutical therapy for type-2 diabetic disease. Song and Chen (2021) proposed the COPRAS method on the probabilistic HFS, which is based on the new distance measures of probabilistic HF-elements. For waste-to-energy technology selection, (Mishra et al., 2022) suggested the COPRAS approach based on the IVPF-similarity measure. Currently, Chaurasiya and Jain (2022) have submitted the COPRAS technique on PFS in the MCDM problems which, competently launch the interrelation among criteria & permits decision experts (DE's) to catch the uncertainty elaborate in judgments of numerous incompatible criterions.

The main motivation for this study is, a new hybrid PF-MEREC-SWARA-COPRAS method is established that can efficiently deal with the implicit vagueness and uncertainty concerned with DE's judgment. Therefore, the summary of the article is as follows:

1) To develop a novel hybrid PF-MEREC-SWARA-COPRAS method under the PF-domain.
2) We calculate the decision experts' weights in PFS based on (Boran et al., 2009) formula.
3) To calculate objective criterion weights, by new MEREC and subjective criterion weight by SWARA method. Thereafter, we calculate combined criterion weights.

4) The proposed technique is employed to solve the problem of selecting banking management software. Subsequently, its method is compared with other existing methods and sensitively analysis by taking a set of criterion weights.

The paper is planned as follows: In section 2, we describe fundamental on PFSs. Section 3, presents a novel hybrid MCDM method on Pythagorean fuzzy set. Section 4, a case study of banking management software selection, which illustrates the efficiency and applicability of the advanced method. Along with it, sensitivity analysis and the results are compared with already existing methods to validate. Finally, in 5th section, conclusion and future outlook is considered.

2. Basic concept of PFS

This section delivers a brief-overview of the PFS.

Definition 2.1. (Yager, 2013) A PFS $A \subset U$ in a fixed set defined as:

$$A = \{\langle u_i, \mu_A(u_i), \nu_A(u_i)\rangle |\, u_i \in U\} \tag{1}$$

where $\mu_A(u_i): U \to [0,1]$ indicate the MF and $\nu_A(u_i): U \to [0,1]$ indicate the N-MF that mollify the state $0 \le \mu_A^2(u_i) + \nu_A^2(u_i) \le 1$. The hesitancy function $\pi_A(u_i)$ is denoted by $\pi_A(u_i) = \sqrt{1 - \mu_A^2(u_i) - \nu_A^2(u_i)}$, then it is Pythagorean fuzzy-index.

Definition 2.2. (Peng & Li, 2019) Let $\beta = (\mu_\beta, \nu_\beta)$ be a PFN. The modified normalized score and accuracy function of β is given as:

$$\mathcal{S}^*(\beta) = \frac{2(\mu_\beta)^2 + \left(1-(\nu_\beta)^2\right) + \left((\mu_\beta)^2\right)^2}{4} \text{ and } \hbar^\circ(\beta) = 1 - \hbar(\beta), \tag{2}$$

where $\mathcal{S}^*(\beta), \hbar^\circ(\beta) \in [0,1]$.

Definition 2.3. (Yager, 2013a, b) Assume $\beta = (\mu_\beta, \nu_\beta), \beta_1 = (\mu_{\beta_1}, \nu_{\beta_1})$ and $\beta_2 = (\mu_{\beta_2}, \nu_{\beta_2})$ be PFNs. Where the operations on the PFNs are depicted below as:

(i) $\beta^c = (\mu_\beta, \nu_\beta)$;

(ii) $\beta_1 \oplus \beta_2 = \left(\sqrt{\mu_{\beta_1}^2 + \mu_{\beta_2}^2 - \mu_{\beta_1}^2\mu_{\beta_2}^2},\ \nu_{\beta_1}\nu_{\beta_2}\right)$;

(iii) $\beta_1 \otimes \beta_2 = \left(\mu_{\beta_1}\mu_{\beta_2},\ \sqrt{\nu_{\beta_1}^2 + \nu_{\beta_2}^2 - \nu_{\beta_1}^2\nu_{\beta_2}^2}\right)$;

(iv) $\lambda\beta = \left(\sqrt{1 - \left(1 - \mu_\beta^2\right)^\lambda},\ (\nu_\beta)^\lambda\right), \lambda > 0$;

(v) $\beta^\lambda = \left((\mu_\beta)^\lambda, \sqrt{1 - \left(1 - \nu_\beta^2\right)^\lambda}\right), \lambda > 0$.

3. Pythagorean Fuzzy MEREC-SWARA-COPRAS Method

In this section, we have developed a new decision-making scheme, as hybrid PF-MEREC-SWARA-COPRAS method, to deal with the MCDM problems on PFS domain. The present method uses the MEREC method to evaluate the OCWs. This method uses the removal effect of each criterion on the performance of the alternatives to calculate the objective criterion weights. The SWARA method is an effective tool for evaluating SCWs. Thereafter, we have calculated criteria weights by combined formula. Whereas, the COPRAS technique uses the notion of relative degree to assess the importance of the ranking of the alternatives. During this method, the relative degree that describes the complex relative proficiency best selection is directly proportional to the comparative outcome and criterion weights pondered in the decision-making issue. So, we combine these three methods on PFSs to get additional precise and suitable judgments in an ambiguous reference. It is based on MEREC-SWARA and COPRAS method under the PFS. The working procedure of the hybrid framework is as given below (see Figure 1):

Step 1. For a MCDM problem under PF-domain, assume alternatives $T = \{T_1, T_2, \dots, T_m\}$ and the features/criteria $F = \{F_1, F_2, \dots, F_n\}$. A group of decision expert's (DE's) $E = \{DE_1, DE_2, \dots, DE_l\}$ represents their ideas on each alternative T_i with respect to each criterion F_j in terms of linguistic values (LVs). Let $X = \left(x_{ij}^{(k)}\right)$ be a linguistic decision matrix recommended by the DE's, where $x_{ij}^{(k)}$ present to the assessment of an alternative T_i regarding a criterion F_j in forms of LVs for k^{th} DE.

Step 2. Calculate a primary DE's weights (λ_k). For the judgements of the k^{th} DE's weight, let $E_k = (\mu_k, \nu_k, \pi_k)$ be a PFNs, then

$$\lambda_k = \frac{\left(\mu_k^2 + \pi_k^2 \times \left(\frac{\mu_k^2}{\mu_k^2 + \nu_k^2}\right)\right)}{\sum_{k=1}^{\ell}\left(\mu_k^2 + \pi_k^2 \times \left(\frac{\mu_k^2}{\mu_k^2 + \nu_k^2}\right)\right)} \tag{3}$$

Here $\lambda_k \geq 0$, $\sum_{k=1}^{\ell} \lambda_k = 1$.

Step 3. Define the aggregated pythagorean fuzzy decision matrix (APF-DM), corresponding to expert's weight. Let $\mathbb{N} = \left(\varepsilon_{ij}\right)_{m\times n}$ be the APF-DM, where

$$\varepsilon_{ij} = \left(\sqrt{1 - \prod_{k=1}^{\ell}(1 - \mu_k^2)^{\lambda_k}}\ ,\ \prod_{k=1}^{\ell}(\nu_k)^{\lambda_k}\right) \tag{4}$$

Step 4. Determination of criteria weights (CWs)

Step 4.1. Estimate objective criteria weights (OCWs) by MEREC technique using following steps:

Step 4.1a. Evaluate the score matrix $\mathcal{S}^*\left(\varepsilon_{kj}\right) = \left(\zeta_{ij}\right)_{m\times n}$ using equation (2) of each PFN ε_{ij}.

Step 4.1b. Normalize the APF-DM $(\mathbb{N}_1) = n_{ij}^x$. The decision-matrix components are scaled using a linear normalization. The elements of the normalized-DM are denoted by n_{ij}^x. Here F_b represents beneficial criteria and F_c represents cost criteria.

$$n_{ij}^x = \begin{cases} \dfrac{\min\limits_k x_{kj}}{x_{ij}}, if\ j \in F_b \\ \\ \dfrac{x_{ij}}{\max\limits_k x_{kj}}, \quad if\ \ j \in F_c \end{cases} \tag{5}$$

Step 4.1c. Compute the entire performance of the alternatives (Ω_i). A logarithmic function with identical CWs is employed to get alternative entire performance.

$$\Omega_i = \ln\left(1 + \left(\frac{1}{n}\sum_{j=1}^{n} |\ln(n_{ij}^x)|\right)\right) \tag{6}$$

Step 4.1d. Estimate the behavior of the alternatives by eliminating each criterion. The same logarithmic function as in step 4.1c is employed, the only difference is, the alternative appraisals are calculated on the basis of eliminating each criterion individually in this step. Hence, we have n sets of appraisals corresponding to n criteria. Assume Ω'_{ij} represent the entire evaluation of i^{th} alternative for eliminating the j^{th} criterion. The following process of appraisal using Eq. (7):

$$\Omega'_{ij} = \ln\left(1 + \left(\frac{1}{n}\sum_{k,k\neq j}|\ln(n^{x}_{ik})|\right)\right) \tag{7}$$

Step 4.1e. Calculate the summation of absolute deviations (D_j). We use the Eqs. (6), (7)

$$D_j = \sum_{i=1}^{m} |\Omega'_{ij} - \Omega_i| \tag{8}$$

Step 4.1f. Evaluate final OCWs. The D_j is employed to compute the objective weight of each criterion in this step. The process is applied to calculate ϖ_j.

$$\varpi_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{9}$$

Step 4.2. Determine the subjective criteria weights (SCWs) by SWARA technique. The procedures for assessment of the SCWs using the SWARA technique is given follow as:

Step 4.2a. Analyze the conventional values. Primary, score values $\mathcal{S}^*(\varepsilon_{kj})$ of PFNs by (2) are calculated using APF-DM.

Step 4.2b. Compute the rank of criteria by the expert's insight from the greatest significant to the smallest significant criteria.

Step 4.2c. Find the relative significance (s_j) of the mean value. Relative position is evaluated from the criteria that are placed at second location. The subsequent relative importance is obtained by comparing the criteria located at F_j to F_{j-1}.

Step 4.2d. Evaluate the relative coefficient (c_j) by Eq. (10)

$$c_j = \begin{cases} 1 & , \ j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{10}$$

where, s_j is relative significance.

Step 4.2e. Calculate the weights (p_j), as given by Eq. (11).

$$p_j = \begin{cases} 1 & , \ j = 1 \\ \frac{c_{j-1}}{c_j}, & j > 1 \end{cases} \tag{11}$$

Step 4.2f. Compute scaled weight. In common, the criterion weights are discussed by the expression.

$$\omega_j = \frac{p_j}{\sum_{j=1}^{n} p_j} \tag{12}$$

Step 4.3. Evaluate the combining CWs.

In the MCDM technique, all criteria have varying degrees of significance. Let $w = (w_1, w_2, \dots, w_n)^T$ be a set of CWs with $\sum_{j=1}^{n} w_j = 1$ and $w_j \in [0,1]$, given as:

$$w_j = \frac{\varpi_j * \omega_j}{\sum_{j=1}^{n} \varpi_j * \omega_j} \tag{13}$$

Step 5. Ranking of the alternative by COPRAS method.

The values of benefit-(σ_i) and cost-(φ_i) type criteria, $i = 1(1)m$ is given as:

$$\sigma_i = \bigoplus_{j=1}^{n} w_j \varepsilon_{ij}, \quad \text{(For benefit-type)} \tag{14}$$

$$\varphi_i = \bigoplus_{j=l+1}^{n} w_j \varepsilon_{ij}, \quad \text{(For cost-type)} \tag{15}$$

Step 6. Evaluate the relative degree (δ_i) of each alternative as follows:

$$\delta_i = \mathcal{S}^*(\sigma_i) + \frac{\sum_{i=1}^{m} \mathcal{S}^*(\varphi_i)}{\mathcal{S}^*(\varphi_i)\ \sum_{i=1}^{m} \mathcal{S}^*(\varphi_i)} \tag{16}$$

Where $\mathcal{S}^*(\sigma_i)$ and $\mathcal{S}^*(\varphi_i)$ represents the score values of σ_i and φ_i.

Step 7. Compute the utility degree (γ_i). Using Eq. (17)

$$\gamma_i = \frac{\delta_i}{\max\,(\delta_i)} \times 100\% \tag{17}$$

Step 8. Find the best ranking of alternatives.

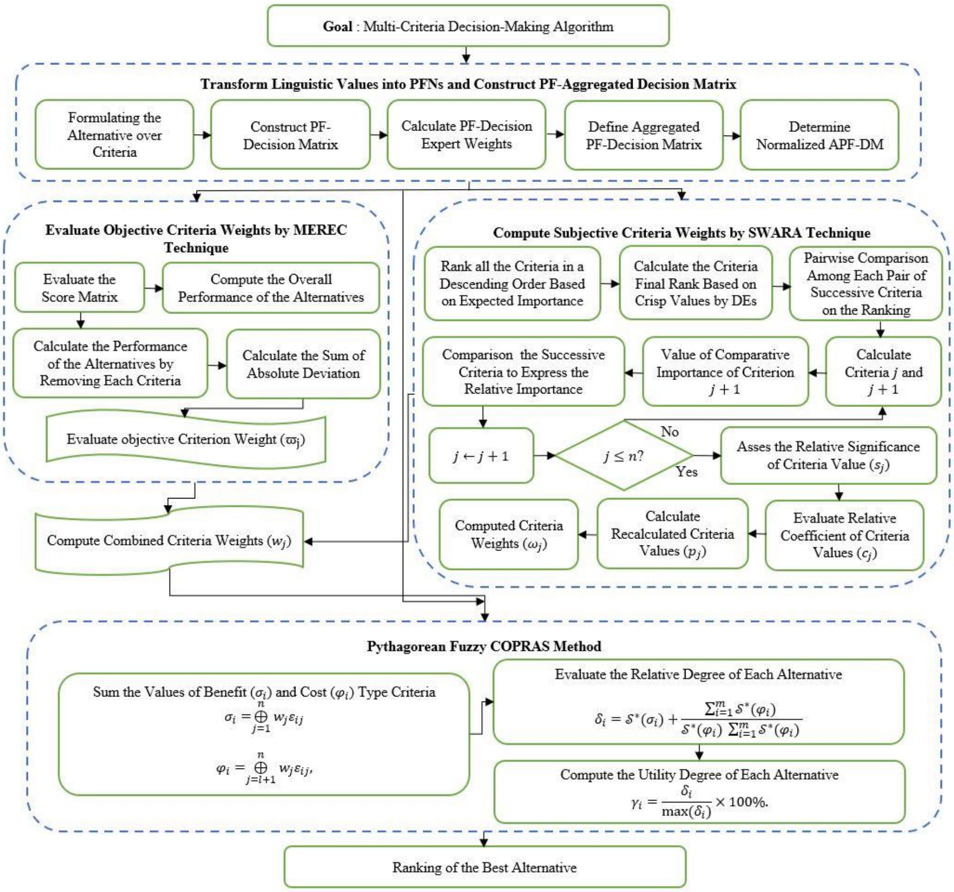

Figure 1. Representation of the PF-hybrid method for BMS selection

4. Application in Banking Management Software

All over the world, the banks are being digitized with the assistance of information technology tools. It provides extraordinary speed to banking operations. Thus, to be successful in banking services, one has to offer the best banking software choosing the best banking software requirements. The opinion of banking experts needs to become technologically more innovative to meet all the requirements and expectations of the clients. Banking software is a means of communication between the bank and the user. It serves to improve the workflow within the company and its branches, for easier investment policies, and to provide services that address the necessity of the users. Which is offers greater functionality, convenience, flexibility, reliability, security, instant transfers, mobile apps, the ability to remain adaptable and modern to meet the changing nature of market needs and competitiveness.

Innovations in information communication technology (ICT) and globalization are constantly changing business processes. These alterations range from easy structural changes to paradigm shifts Laudon and Laudon (2015). The bank's goal is to alleviate costs, increase efficiency and guarantee client holding with the use of technology. In the banking sector, the relationship among organizations and its clients is vital. Technological advancement enables closer and longer-terms affinities with clints. The CBS developed in the 1970s and has undergone important changes over time. The upgraded core banking system has capability of real-time processing and multichannel unification (Kreca & Barac, 2015). Due to the growing issues of electronic payments, some researchers and managers have turned their attention to banking software. For this MCDM methods are best suited that can based on numerous criteria.

Recently, due to digitization in the banking sector, it became very important to select the best banking management software. It provides extraordinary speed to banking operations. Thus, to be successful in banking services, one has to offer the best banking software choosing the best banking software requirements. Here, a case study of BMS for a banking area in India is measured to demonstrate the applicability and practicality of the evolved PF-MEREC-SWARA-COPRAS method. In the procedure of existing method, the bank shaped a team entailing of four decision experts who are responsible for BMS. Let the various banking tools available with us are: Mambu (T_1), Temenos (T_2), Oracle Flexcube (T_3), Finastra (T_4) and Finacle (T_5). We have to identify the best software tool for any banking management based on the following important features (criteria's) (Figure 2): Customizable interfaces (F_1), Data management and history tracking (F_2), Documentation (F_3), Live customer support (F_4), Online payments and bills (F_5), Mobile version (F_6), Self-service options for clients (F_7), Transaction processing (F_8).

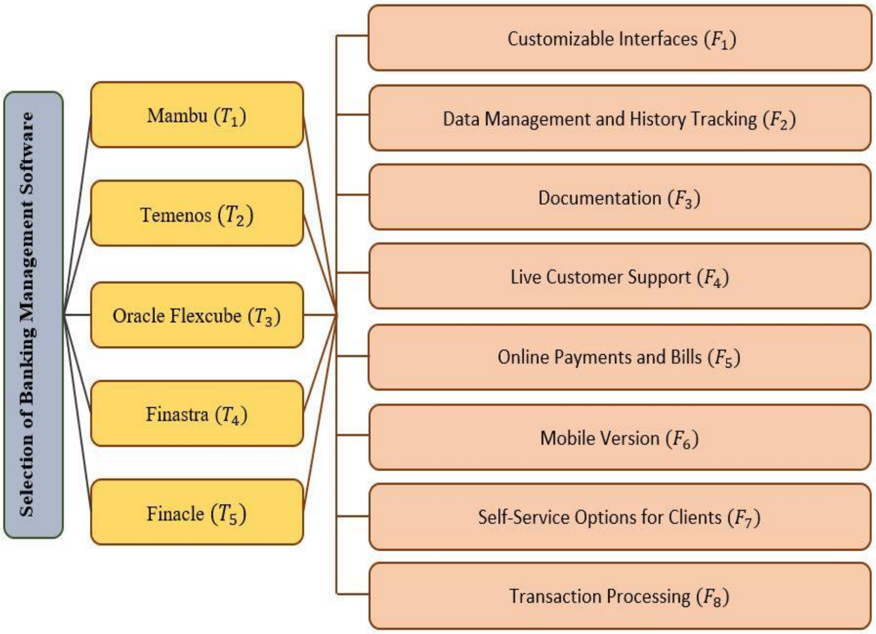

Figure 2. The selection of BMS

Table 1 presents the LVs given in PFNs for the relative behavioral rating of weights.

Table 1. Linguistic values (LVs) in terms of PFNs

LVs	PFNs
Thrillingly Significant (THS)	(0.90, 0.10)
Typically Significant (TS)	(0.80, 0.20)
Noteworthy (N)	(0.60, 0.40)
Reasonable (R)	(0.50, 0.50)
Inconsequential (IC)	(0.45, 0.55)
Trivial (TR)	(0.30, 0.75)
Pitty (P)	(0.10, 0.90)

Table 2 shows the weight of each DE's as calculated using Eq. (3).

Table 2. Decision expert weights

Decision Experts	LVs	PFNs	Weights (λ_k)
DE_1	N	(0.60,0.40)	0.2749
DE_2	R	(0.50,0.50)	0.2257
DE_3	TS	(0.80,0.20)	0.3058
DE_4	IC	(0.45,0.55)	0.1936

For assessing the alternatives linguistic values are transformed in terms of PFNs.

Table 3. LV for assessing the alternatives

LVs	PFNs
Extremely small (ES)	(0,1)
Very small (VS)	(0.10, 0.90)
small (S)	(0.20, 0.80)
Slightly small (SS)	(0.30, 0.70)
Below intermediate (BI)	(0.40, 0.60)
Intermediate (I)	(0.50, 0.50)
Above intermediate (AI)	(0.60, 0.40)
Slightly big (SB)	(0.70, 0.30)
Big (B)	(0.80, 0.20)
Very big (VB)	(0.90, 0.10)
Extremely big (EB)	(1, 0)

Here, Table 4 represents the ideas of DE's on each of the alternative T_i respect to each criterion F_j in terms of LVs defined in Table 3.

Table 4. The LV's calculation of alternatives given by DE's

Alternative	DEs	Criteria							
		F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
$\boldsymbol{T_1}$	DE_1	VB	VB	B	B	VB	B	VB	BI
	DE_2	B	SB	SB	I	B	VB	B	SS
	DE_3	B	VB	VB	SB	VB	B	VB	I
	DE_4	VB	VB	B	B	SS	B	B	AI
$\boldsymbol{T_2}$	DE_1	VB	B	SB	SB	VB	VB	VB	BI
	DE_2	B	B	I	SB	B	SB	B	AI
	DE_3	VB	VB	B	AI	B	I	B	I
	DE_4	B	B	VB	VB	AI	VB	SB	BI
$\boldsymbol{T_3}$	DE_1	VB	B	SB	SB	B	B	VB	I
	DE_2	VB	B	SB	AI	AI	SB	B	SS
	DE_3	B	VB	VB	I	VB	SB	B	BI
	DE_4	VB	AI	BI	VB	I	B	BI	AI
$\boldsymbol{T_4}$	DE_1	B	B	A I	SB	B	B	VB	I
	DE_2	B	B	SB	AI	SS	SB	I	AI
	DE_3	B	B	SB	SB	AI	AI	SB	BI
	DE_4	B	VB	VB	SS	SB	S	BI	I
$\boldsymbol{T_5}$	DE_1	VB	B	SB	SB	B	B	B	I
	DE_2	B	B	B	BI	SB	BI	AI	S
	DE_3	B	B	AI	SB	B	B	SB	I
	DE_4	VB	SB	VB	I	AI	AI	AI	SB

In Table 5, the LV's of alternatives given by DE's in Table 4 is converted to APF-DM using Eq. (4).

Table 5. Computed APF-DM

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
T_1	(0.8562, 0.1445)	(0.8733, 0.1281)	(0.8244, 0.1773)	(0.7262, 0.2784)	(0.8383, 0.1704)	(0.8297, 0.1710)	(0.8669, 0.1337)	(0.4649, 0.5432)
T_2	(0.8669, 0.1337)	(0.8389, 0.1618)	(0.7660, 0.2404)	(0.7406, 0.2648)	(0.8139, 0.1890)	(0.7992, 0.2096)	(0.8228, 0.1788)	(0.4867, 0.5178)
T_3	(0.8769, 0.1236)	(0.8179, 0.1850)	(0.7646, 0.2452)	(0.7078, 0.3025)	(0.7819, 0.2259)	(0.7529, 0.2481)	(0.8026, 0.2045)	(0.4619, 0.5463)
T_4	(0.8266, 0.1710)	(0.8258, 0.1749)	(0.7427, 0.2625)	(0.6321, 0.3772)	(0.6578, 0.3547)	(0.6622, 0.3543)	(0.7299, 0.2847)	(0.5009, 0.5027)
T_5	(0.8562, 0.1445)	(0.7841, 0.2163)	(0.7633, 0.2417)	(0.6204, 0.3873)	(0.7514, 0.2506)	(0.7161, 0.2931)	(0.7002, 0.3028)	(0.5139, 0.5036)

4.1. MEREC Technique

This measure reflects the difference between the performance of the composite option and its performance in removing the criterion. The following steps are used to calculate the OCWs by MEREC method: we compute the score matrix using Eq. (2). As $\{F_5, F_8\}$ a set of cost/non-benefit and others are benefit type of criteria, so, we normalized-APF-DM using Eq. (5) and shown in Table 6.

Table 6. Normalized APF-DM

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
T_1	0.9405	0.8286	0.8383	0.9689	0.6713	0.6888	0.6981	0.8804
T_2	0.9197	0.8903	0.9506	1.0000	0.7064	0.7358	0.7658	0.9384
T_3	0.9008	0.9308	0.9541	0.9286	0.7569	0.8119	0.7999	0.8729
T_4	1.0000	0.9150	1.0000	0.7804	1.0000	1.0000	0.9386	0.9759
T_5	0.9405	1.0000	0.9559	0.7594	0.8078	0.8823	1.0000	1.0000

To obtain the OCWs by MEREC method, we compute the overall performance of the

Table 7. Calculate the performance of the alternatives by removing each criterion.

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
T_1	0.1879	0.1747	0.1760	0.1910	0.1524	0.1551	0.1566	0.1811
T_2	0.1345	0.1309	0.1381	0.1436	0.1052	0.1098	0.1143	0.1367
T_3	0.1221	0.1257	0.1284	0.1255	0.1027	0.1105	0.1089	0.1186
T_4	0.0517	0.0411	0.0517	0.0218	0.0517	0.0517	0.0442	0.0488
T_5	0.0792	0.0862	0.0810	0.0541	0.0614	0.0718	0.0862	0.0862

alternative values from Eq. (6), given as (Ω_1 = 0.1943, Ω_2 = 0.1436, Ω_3 = 0.1336, Ω_4 = 0.0517, Ω_5 = 0.0862). Apply the Eq. (7), we appraise alternatives overall performances (Ω'_{ij}) in removing criterion and are given in Table 7.

Afterward, we compute the absolute deviation (D_j) values from Eq. (8). Finally, we compute OCWs $\left(\varpi_j\right)$ using Eq. (9) by MEREC method.

Absolute deviation (D_j) = (0.0340, 0.0508, 0.0342, 0.0734, 0.1360, 0.1105, 0.0992, 0.0380).

Objective weight (ϖ_j) = (0.0590, 0.0882, 0.0594, 0.1274, 0.2361, 0.1918, 0.1722, 0.0659).

4.2. Subjective Weights by SWARA Technique

The following steps are used to compute the SCWs by SWARA method (Tables 8-10).

Table 8. Evaluate of criteria weights by DE's

Criteria	DE_1	DE_2	DE_3	DE_4	Aggregated PFNs	Crisp values $\boldsymbol{S}^*(\boldsymbol{\varepsilon}_{kj})$
$\boldsymbol{F_1}$	VB	B	SB	VB	(0.8385, 0.1636)	0.7184
$\boldsymbol{F_2}$	VB	SB	I	B	(0.7688, 0.2397)	0.6185
$\boldsymbol{F_3}$	B	AI	I	SB	(0.6717, 0.3348)	0.4985
$\boldsymbol{F_4}$	SB	B	BI	AI	(0.6528, 0.3578)	0.4765
$\boldsymbol{F_5}$	VB	I	SB	SS	(0.7250, 0.2933)	0.5604
$\boldsymbol{F_6}$	B	SB	B	AI	(0.7514, 0.2506)	0.5963
$\boldsymbol{F_7}$	VB	AI	BI	I	(0.6974, 0.3230)	0.5262
$\boldsymbol{F_8}$	BI	B	I	SB	(0.6257, 0.3872)	0.4466

Table 9. Criteria weights evaluated by SWARA method

Criteria	Crisp values	Relative significance $(\boldsymbol{s_j})$	Relative coefficient $(\boldsymbol{c_j})$	Recalculate d weight $(\boldsymbol{p_j})$	Criteria weight $(\boldsymbol{\omega_j})$
$\boldsymbol{F_1}$	0.7184	-	1.0000	1.0000	0.1459
$\boldsymbol{F_2}$	0.6185	0.0999	1.0999	0.9092	0.1327
$\boldsymbol{F_6}$	0.5963	0.0222	1.0222	0.8895	0.1298
$\boldsymbol{F_5}$	0.5604	0.0359	1.0359	0.8587	0.1253
$\boldsymbol{F_7}$	0.5262	0.0342	1.0342	0.8303	0.1211
$\boldsymbol{F_3}$	0.4985	0.0277	1.0277	0.8079	0.1179
$\boldsymbol{F_4}$	0.4765	0.0220	1.0220	0.7905	0.1153
$\boldsymbol{F_8}$	0.4466	0.0299	1.0299	0.7676	0.1120

$(\omega_j) = (0.1459, 0.1327, 0.1179, 0.1153, 0.1253, 0.1298, 0.1211, 0.1120)$. There after we calculated the weights of the criteria by Eqs. (13). Combined weight (w_j) = (0.0690, 0.0938, 0.0562, 0.1178, 0.2372, 0.1996, 0.1672, 0.0592) ^{T}.

Table 10. Calculate the values from σ_i and φ_i

	$\boldsymbol{\sigma_i}$	$\boldsymbol{\varphi_i}$	$\boldsymbol{S^*(\sigma_i)}$	$\boldsymbol{S^*(\varphi_i)}$	$\boldsymbol{\delta_i}$	$\boldsymbol{\gamma_i}$
$\boldsymbol{T_1}$	(0.8048, 0.2161)	(0.3124, 0.8296)	0.6671	0.1291	0.7758	100.0
$\boldsymbol{T_2}$	(0.7729, 0.2504)	(0.3223, 0.8224)	0.6222	0.1356	0.7257	93.54
$\boldsymbol{T_3}$	(0.7475, 0.2786)	(0.3027, 0.8381)	0.5880	0.1223	0.7027	90.58
$\boldsymbol{T_4}$	(0.6753, 0.3593)	(0.2726, 0.8559)	0.4977	0.1054	0.6307	81.30
$\boldsymbol{T_5}$	(0.7036, 0.3231)	(0.2695, 0.8587)	0.5327	0.1033	0.6685	86.17

From equations (14)-(17), the values of $\sigma_i, \varphi_i, S^*(\sigma_i), S^*(\sigma_i), \delta_i \; and \; \gamma_i$ of T_i are assessed with respect to criteria F_j, shown in Table 10. Displayed in Table 10, the rank descending sequence of the banking management software choice is $T_1 \succ T_2 \succ T_3 \succ T_5 \succ T_4$. Thus, alternative T_1 is the best selection.

4.3. Sensitivity Analysis

Here sensitivity analysis is undertaken to calibrate the presented methods behavior. Eight different CW sets are taken and displayed in Table 11. The table shows for each set, one of the criteria has the highest weight, whereas the others have lesser weights. Using this procedure, a sufficient range of criterion weights has been built to examine the sensitivity of the evolved method to variants of CWs. The ranking outcomes of BMS amenity alternative and the relative degree δ_i of various criteria weight, according to the sensitivity analysis outcomes are displayed in Table 12 and figure 3. When the DE's provide weighting

Table 11. Diverse criteria weight sets for BMS alternative

	Set-I	Set-II	Set-III	Set-IV	Set-V	Set-VI	Set-VII	Set-VIII
$\boldsymbol{F_1}$	0.0690	0.0938	0.0562	0.1178	0.2372	0.1996	0.1672	0.0592
$\boldsymbol{F_2}$	0.0938	0.0562	0.1178	0.2372	0.1996	0.1672	0.0592	0.0690
$\boldsymbol{F_3}$	0.0562	0.1178	0.2372	0.1996	0.1672	0.0592	0.0690	0.0938
$\boldsymbol{F_4}$	0.1178	0.2372	0.1996	0.1672	0.0592	0.0690	0.0938	0.0562
$\boldsymbol{F_5}$	0.2372	0.1996	0.1672	0.0592	0.0690	0.0938	0.0562	0.1178
$\boldsymbol{F_6}$	0.1996	0.1672	0.0592	0.0690	0.0938	0.0562	0.1178	0.2372
$\boldsymbol{F_7}$	0.1672	0.0592	0.0690	0.0938	0.0562	0.1178	0.2372	0.1996
$\boldsymbol{F_8}$	0.0592	0.0690	0.0938	0.0562	0.1178	0.2372	0.1996	0.1672

Table 12. Relative degree for BMS alternatives for different criteria weight sets

	Set-I	Set-II	Set-III	Set-IV	Set-V	Set-VI	Set-VII	Set-VIII
T_1	0.7758	0.7838	0.7804	0.8156	0.7678	0.7481	0.7719	0.7592
T_2	0.7257	0.7311	0.7106	0.6862	0.7152	0.7143	0.7198	0.6987
T_3	0.7027	0.7261	0.7160	0.6996	0.7232	0.7263	0.7188	0.6812
T_4	0.6307	0.6789	0.6847	0.6717	0.6724	0.6639	0.6473	0.5987
T_5	0.6685	0.7277	0.7139	0.6966	0.6891	0.6767	0.6638	0.6239

sets I, VII, and VIII, the BMS ranks them in the same order, while for other sets its different (Table 13). According to the description above, the BMS selection is dependent on, and sentient to, these CW sets, As the proposed method is stable with a variety of weight sets.

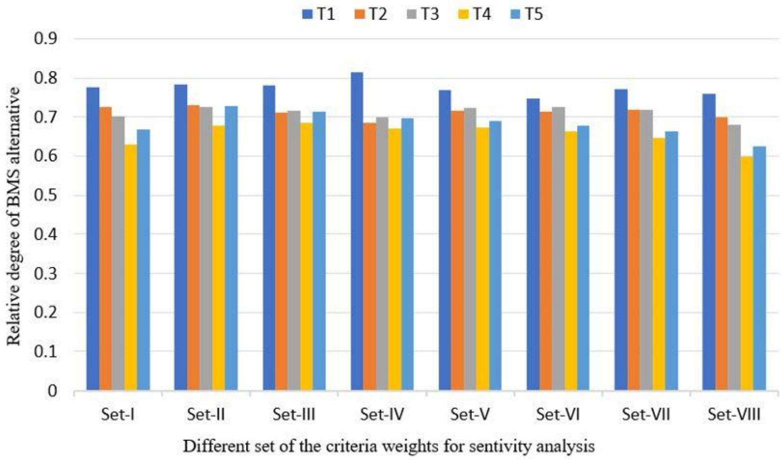

Figure 3. Outcome of δ_i for each alternative with various weight sets of criteria

Table 13 The comparative study with existing techniques

Methods	Standard	Expert's weight	Criteria weights	Ranking	BMS alternative
Zhang and Xu (2014)	PF-TOPSIS method	Not evaluate	Assumed	$T_1 \succ T_2 \succ T_3 \succ T_4 \succ T_5$	T_1
Kumari and Mishra (2020)	IF-COPRAS method	Evaluate	Completely unknown	$T_1 \succ T_3 \succ T_2 \succ T_5 \succ T_4$	T_1
Peng et al. (2020)	PF-COCOSO method	Not evaluate	Assumed	$T_1 \succ T_2 \succ T_3 \succ T_5 \succ T_4$	T_1
proposed method	PF-COPRAS	Evaluate	MEREC-SWARA combined method	$T_1 \succ T_2 \succ T_3 \succ T_5 \succ T_4$	T_1

4.5. Comparison and Discussion

In this section, now, we see that the framework submitted here has a lot of similarities with the existing methods. The PF-MEREC-SWARA-COPRAS method is found to be proficient for handling qualitative and quantitative MCDM issues, especially in cases where there are many conflicting criteria. The advantages or features of the presented framework can be discussed as follows:

- The method PF-TOPSIS (Zhang & Xu, 2014) and PF-COCOSO (Peng & Li, 2019) and the proposed PF-hybrid method are submitted in the context of PFS, whereas (Kumari & Mishra, 2020) have described IF-COPRAS method is used.
- In the developed PF-hybrid method, we have evaluated expert weights on the basis of expert opinion, leaving no space to treat vagueness, whereas PF-TOOPSIS (Zhang & Xu, 2014) and PF-COCOSO (Peng & Li, 2019) the procedure does not involve expert opinion.
- PF-COPRAS outperformed PF-TOPSIS and IF-COPRAS in terms of effectiveness and proficiency. In addition, the hybrid COPRAS method is more powerful and stable in terms of criterion weight disparity than PF-COCOSO (Peng & Li, 2019).
- The practical outcomes of the presented method provide some significant perceptions related to the evaluation criteria and the alternative for BMS in India. As may be displayed in Table 10, the most significant is the effectiveness of the BMS. We find the best alternative among the existing ones. The problem of banking management can be solved to a great extent by seeing the outcomes of this paper. We also analyzed the performance of BMS alternatives and compared the results for each criterion evaluated. According to the results, Mambu (T_1) first rank among all alternatives and (T_4) is the last in the ranking. Therefore, (T_1) can be chosen as the best alternative meeting all the valuation.

5. Conclusions

Currently, with the speedy growth of IT, it is a composite problem to select the best software for the diverse work of bank. MCDM is the best tool to deal with it. The key purpose of the present paper is to develop an MCDM method in a pythagorean fuzzy environment. To do this, we first submitted a new MEREC method and score function on PFS. The PFSs provide a precise and practical solution of the ambiguous real-life DM difficulties; consequently, a new hybrid PF-MEREC-SWARA-COPRAS method has been developed under PFS. Finally, the PF-COPRAS methodology is proposed for ranking the alternatives. In addition, the discussion of comparative study of the presented method with the existing methods. Based on a comparison with existing method, it is worth saying that the PF-COPRAS method provide an effortless calculation with accurate and effective outcomes for the development of MCDM difficulties. The application of the proposed hybrid method on selecting the optimal banking software tool helps in finding the best BMS.

- A new normalization score function for PFN is submitted, which minimizes intimation loss by taking uncertainty information into account. Compared to existing score functions, it has a more robust ability to differentiate when comparison two PFNs.
- The combined weight framework has been submitted on the basis of MEREC and SWARA weighted extensive methods, which consider both objective and subjective weight.
- MEREC presented a novel PF-decision-making technique basis on the COPRAS method, which can get the best alternative without any adverse events, get the outcome of the decision without segmentation, and has a robust ability and stability.

Some short comings of the projected structure are significant. A practical problem is that DM necessity skilled in the flexibility and ability to properly use the preferred style of PFS. The projected structure will help as a useful device for selecting the best BMS under multiple-criteria situations and ambiguous environments.

In the future, the evolved MCDM method may be further proceed to Fermatean-FSs, interval-valued PFS, and hesitant PFS. In addition, the researchers can extend our research via various MCDM platforms (for example, Mixed Aggregation by Comprehensive Normalization Technique (MACONT), Gained and Lost Dominance Score (GLDS), MAIRCA, and CoCoSo) to choose the most suitable BMS selection. The limitation of the current study is that only a small number of DE's were included, and it does not take into account the interrelationships among the criteria, which somehow limits the scope of the application of the proposed framework. Consequently, further research is still needed, which considers huge number of decision experts.

Author Contributions: Research Problem, R.K.C. and D.J.; Methodology, R.K.C.; Formal Analysis, R.K.C.; Writing-Original Draft Preparation, R.K.C; Modification, D.J.; Writing-Review & Editing, D.J

Acknowledgment: The authors would like to express their gratitude to the editors and anonymous referees for their informative, helpful remarks and suggestions to improve this paper as well as the important guiding significance to our researches.

Funding: This research received no external funding.

Data Availability Statement: Not Applicable.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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