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Double Decker Decision Framework with Fuzzy Data for Multi-Attribute Decision-Making

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ABSTRACT

This paper presents a new framework for decision-making with fuzzy data. Specifically, in a double-decker setup, the first deck contains methods that perform rank value calculation of alternatives. The second deck fuses the rank order to provide a holistic ordering of alternatives. The first deck is highly scalable, as it can accommodate multiple approaches for ranking, and the final ordering is obtained by sending the rank orders from the first deck to the second—where the simple rank procedure is utilized. Earlier frameworks cannot perform rank fusion or use techniques like averaging and the Borda count without considering the personal choice of alternatives. This framework circumvents this challenge, and its usefulness is demonstrated through numerical examples.

1. Introduction

Multi-attribute decision-making (MADM) is a subset of multi-criteria decision-making that considers a finite set of alternatives and a finite set of attributes rated by experts/agents to determine the relative importance of attributes and eventually the priority value of alternatives [1]. A fuzzy set [2] is a popular and simple model to represent uncertainty effectively. Combining these two fields led to the growth of decision-making under uncertainty, which is now gaining much attention from the research community. Diverse application spaces adopt MADM for solving crucial selection problems where multiple options exist, with performance in terms of attributes close and competing.

Scholars propose different integrated decision models for MADM with approaches for weight determination, data fusion or aggregation, and rank determination [3-5]. But an important aspect missing in these models is that any single rank procedure is insufficient to determine the alternatives' actual ranking, as different ranking methods adopt different normalization formulations, utility functions, and ordering style based on gain or distance from ideal and anti-ideal or loss factors. In

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such cases, there is an urge for rank fusion. Some trivial fusion concepts involve average and/or Borda count. Though the fusion is achieved, consideration of personal choices of alternatives is not possible.

In real-life applications, suppose a group of stakeholders plans to hire an employee for a project, she/he will be scored or rated based on different attributes. Ideally, these attributes are not equally important, so they have some biased importance. However, when a candidate presents herself/himself to the group, each stakeholder might form an opinion on each candidate. In certain specific cases, a stakeholder forms an interesting opinion on a candidate, which may not be included directly in the decision process. As an indirect involvement, this opinion might reflect on the different attributes. To alleviate this ambiguity and indirect influence effect, we encourage the articulation of the personal choice(s) of alternatives. These values in the unit interval describe the percentage of preference for a candidate or alternative.

Apart from this, the extant models adopt a single rank method for determining the ranks or priority of alternatives, which is not rational. Multiple rank methods must be used to circumvent the issue, and a final rank order must be determined to help stakeholders with their final decision. Since each rank method has its own merit and demerit, considering different methods is a promising idea. Some contributions of this study are as follows:

i. Present the double-decker framework for MADM with fuzzy data.
ii. Formulate a rank fusion procedure by including personal choices.
iii. Experiment with the framework for its usefulness in MADM problem solving.

The rest of the paper is organized in the following manner. In Section 2, the research design and the method are described. The numerical example is explained in Section 4. Sensitivity analysis is presented in Section 5. In Section 6, the conclusion and future directions are provided.

2. Research Methodology

2.1 Research design

Figure 1 provides the proposed research design, where we present two phases: Deck 1 and Deck 2. In Deck 1, the decision matrices are fed as input to different ranking methods for determining the rank values of alternatives and ordering alternatives. Suppose we consider *n* methods, we will have *n* rank orders – one rank order vector from each method. These vectors are given as input to Deck 2 along with the personal choice(s) for calculating the final ranking order of alternatives. From Deck 2, a combined ranking order is obtained. Specifically, *n* rank orders are combined into one rank order with the additional benefit of consideration of personal choices.

2.2 Review of decision methods – WASPAS and COPRAS

Chakraborty *et al.,* [6,7] presented the WASPAS method and clarified its usefulness in decision-making. Later, many researchers used and extended the method for different decision-making fields. Eghbali-Zarch *et al.,* [8] provided a framework with WASPAS and IDOCRIW construction and demolition management methods. Radomska-Zalas [9] utilized the WASPAS method for technology process evaluation. Helicopter selection for military activities is done by considering the WASPAS method [10]. Khan *et al.,* [11] extended WASPAS to a spherical fuzzy context for evaluating urban sustainable development strategies. Medical waste disposal methods are graded using fuzzy WASPAS within the healthcare unit [12]. Gorcun *et al.,* [13] selected tramcars using the Heronian operator and WASPAS method in a sustainable urban transport environment. Arslan and Cebi [14] proposed the WASPAS method under a decomposed fuzzy set for MADM.

Zavadskas *et al.,* [15] presented the COPRAS method assessing solutions to road design. Bathrinath et *al.,* [16] evaluated factors hindering sustainability in ship ports by extending COPRAS to a fuzzy context. The future of apitourism in Iran is evaluated by using DEMATEL and COPRAS methods under critical uncertainties. Krishna *et al.,* [17] used MOORA and COPRAS for decision-making in the dry turning process – Nimonic C263. Machine selection is supported by extending entropy and COPRAS to grey numbers. Mohata *et al.,* [18] selected vehicles with alternative fuels for passengers by combining the CRITIC and COPRAS methods. The government's role in mergers and acquisitions is understood via interval valued intutionistic fuzzy MULTIMOORA-COPRAS methods [19]. Raja *et al.,* [20] evaluated the performance of food order industries via the COPRAS method. Punetha and Jain [21] presented a model-based recommendation by combining entropy and COPRAS methods. Green supplier selection is achieved by extending the COPRAS method to p,q-Quasirung fuzzy context.

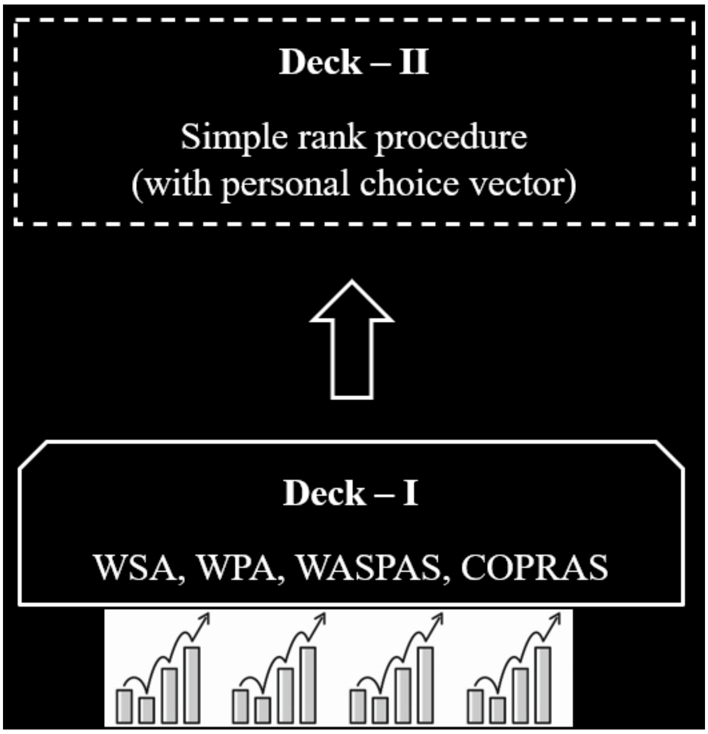

Fig. 1. Proposed Double Decker Decision Framework

2.3 Research method

This section presents the algorithm for the proposed research method. The algorithm, as stated earlier, has two phases/decks. The first deck considers the rank methods that process the rating data to obtain rank orders of alternatives. These rank orders are given as input to the second deck, and the simple rank procedure is put forward for rationally combining the rank orders. It must be noted that in the second deck, the personal choices are also given due consideration, while rank fusion, which in the previous forms, such as average and/or Borda count, is excluded.

The algorithmic steps are given below:

Step 1: Obtain the decision matrix of order $a \times c$ from each expert. Here, a alternatives are rated based on c attributes.

Step 2: Apply rank methods for determining the rank orders of alternatives. A vector of $1 \times a$ is obtained when a rank method is applied.

Weighted sum approach

Step 2.1: Consider the data from Step 1 and a weight vector of $1 \times c$ order.

Step 2.2: Apply Eq. (1) for determining the weighted sum vector of order $1 \times a$

$$ws_i = \sum_{j=1}^{c} w_j . x_{ij} \tag{1}$$

where w_j is the relative importance or weight of attribute j and x_{ij} is the fuzzy value.

Step 2.3: Arrange the values from Eq. (1) in descending order to determine the alternatives' rank order.

Weighted product approach

Step 2.4: Consider data from Step 2.1.

Step 2.5: Apply Eq. (2) to determine the weighted product vector of order $1 \times a$.

$$wp_i = \prod_{j=1}^{c} \left(x_{ij}\right)^{w_j} \tag{2}$$

where w_j is the relative importance or weight of attribute j and x_{ij} is the fuzzy value.

Step 2.6: Arrange the values from Eq. (2) in descending order to determine the alternatives' rank order.

WASPAS approach

Step 2.7: Consider weighted sum and weighted product vectors from Eq. (1)-(2) and apply Eq. (3) to determine the WASPAS rank order.

$$r1_i = 0.50. ws_i + 0.5. wp_i \tag{3}$$

where $r1_i$ is a rank value of alternative i from WASPAS.

Step 2.8: Arrange the values from Eq. (3) in descending order to determine the rank order of alternatives.

COPRAS approach

Step 2.9: Consider data from Step 2.1.

Step 2.10: Determine the benefit and cost sum vectors from Eq. (4)-(5), which yields vectors of order $1 \times a$.

$$B_i = \sum_{j=1}^{z} w_j . x_{ij} \tag{4}$$

$$C_i = \sum_{j=z+1}^{c} w_j . x_{ij} \tag{5}$$

where B_i is a vector sum benefit type, C_i is a vector sum cost type, z is the number of benefit type attributes.

Step 2.11: Determine the final rank value by applying Eq. (6).

$$r2_i = 0.50. B_i + 0.50. \left(\frac{\sum C_i}{C_i . \sum\left(\frac{1}{C_i}\right)} \right) \tag{6}$$

where $r2_i$ is the rank value of alternative i from COPRAS.

Step 2.12: Arrange the values from Eq. (6) in descending order to obtain the rank order of alternatives.

Step 3: By considering the rank orders from Step 2, apply the rank fusion procedure mentioned below. This yields a rank order of $1 \times a$ – combined rank order.

Step 3.1: Consider rank orders from Step 2.3, Step 2.6, Step 2.8, and Step 2.12 along with the personal choice vector of $1 \times a$.

Step 3.2: Apply Eq. (7) to obtain the weighted rank order, which is a matrix of $a \times r$ where a refers to the number of alternatives and r refers to the number of rank methods.

$$o_i = \sum_{j=1}^{r} p_i . y_{ij} \tag{7}$$

where p_i is the rank based on the personal choice value of alternative i and y_{ij} is the rank order of alternative i by rank method j.

Step 3.3: Determine the final combined rank order by applying Eq. (8). This is a vector of $1 \times a$ order.

$$F_i = a - o_i \quad (8)$$

where F_i is the final combined rank order of alternative i.

3. Numerical Example

This section describes the usefulness of the proposed double-decker framework via a numerical example. A company must select a project out of three candidate projects to achieve the annual target. Four factors or attributes are selected for rating these projects: total cost, duration, manpower requirement, and social impact. It must be noted that the first three factors are cost type, and the last factor is benefit type.

We denote the three projects as q1, q2, and q3 for simplicity. Four attributes are denoted as a1, a2, a3, and a4. Steps for determining the final ordering of projects are given below:
Step A: Collect rating data on three projects with respect to four attributes. This forms a decision matrix of 3×4 order.

Table 1
Data on projects rated over attributes

Choice	CW	0.2	0.3	0.15	0.35
	DM	a1	a2	a3	a4
0.5	q1	0.4	0.3	0.5	0.5
0.2	q2	0.5	0.6	0.6	0.5
0.3	q3	0.3	0.5	0.3	0.6

Table 1 shows the rating value as a fuzzy number – each project is rated over the specified attributes.

Step B: Consider the relative importance of the four attributes as 0.20, 0.30, 0.15, and 0.35, respectively. The personal choice of the officer-in-charge is 0.50, 0.20, and 0.30, respectively.

Step C: Apply the rank methods discussed in Section 2.2 to obtain the rank order of projects from WSA, WPA, WASPAS, and COPRAS (Tables 2 and 3).

Table 2
Results of rank methods – weighted sum, weighted product, WASPAS

RO	SUM	WSA	a1	a2	a3	a4
Rank 3	0.42	q1	0.08	0.09	0.075	0.175
Rank 1	0.545	q2	0.1	0.18	0.09	0.175
Rank 2	0.465	q3	0.06	0.15	0.045	0.21
RO	PROD	WPA	a1	a2	a3	a4
Rank 3	0.410236	q1	0.832553	0.696845	0.90125	0.784584
Rank 1	0.542752	q2	0.870551	0.857917	0.926238	0.784584
Rank 2	0.445694	q3	0.786003	0.812252	0.834773	0.836282
		WASPAS	WSA	WPA	AVG	RO
		q1	0.42	0.410236	0.415118	Rank 3
		q2	0.545	0.542752	0.543876	Rank 1
		q3	0.465	0.445694	0.455347	Rank 2

Table 3
Results of rank method - COPRAS

Choice	CW	0.2	0.3	0.15	0.35		
	DM	a1	a2	a3	a4		
0.5	q1	0.4	0.3	0.5	0.5		
0.2	q2	0.5	0.6	0.6	0.5		
0.3	q3	0.3	0.5	0.3	0.6		
Csum	Cost	a1	a2	a3			
0.245	q1	0.08	0.09	0.075			
0.37	q2	0.1	0.18	0.09			
0.255	q3	0.06	0.15	0.045			
Bsum	Benefit				a4		
0.175	q1				0.175		
0.175	q2				0.175		
0.21	q3				0.21		
	COPRAS	Bsum	Csum	1/Csum	Cval	AVG	RO
	q1	0.175	0.245	4.081633	0.331688	0.253344	Rank 2
	q2	0.175	0.37	2.702703	0.219631	0.197316	Rank 3
	q3	0.21	0.255	3.921569	0.318681	0.26434	Rank 1

Step D: The output of Step C and personal choice vector from Step B goes as input to the second deck of the proposed framework for determining the final combined rank order, which eventually is a vector of 1×3 order (Table 4).

Table 4
Results of rank fusion by SRP with personal choices

Choice	SRP	WSA	WPA	WASPAS	COPRAS
0.5	q1	3	3	3	2
0.2	q2	1	1	1	3
0.3	q3	2	2	2	1
SUM	WRO	WSA	WPA	WASPAS	COPRAS
11	q1	3	3	3	2
18	q2	3	3	3	9
14	q3	4	4	4	2
	Rank	SUM	a-SUM	RO	
	q1	11	-8	Rank 1	
	q2	18	-15	Rank 3	
	q3	14	-11	Rank 2	

4. Sensitivity Analysis

The role of personal choice is examined in this section by considering two cases, viz., with personal choices and without personal choices. In the former case, the weights of the personal choice vector and attributes are considered along with the dataset. In the latter case, the choice vectors are omitted. From Figure 2 and Table 5, it is clear that the personal choices influence rank order. Hence, appropriate consideration of these choices facilitates rational decision-making.

Table 5
Results of rank fusion with SRP and no choice vectors

SUM	SRP	WSA	WPA	WASPAS	COPRAS
2.75	q1	0.75	0.75	0.75	0.5
1.5	q2	0.25	0.25	0.25	0.75
1.75	q3	0.5	0.5	0.5	0.25
	Rank	SUM	a-SUM	RO	
	q1	2.75	0.25	Rank 3	
	q2	1.5	1.5	Rank 1	

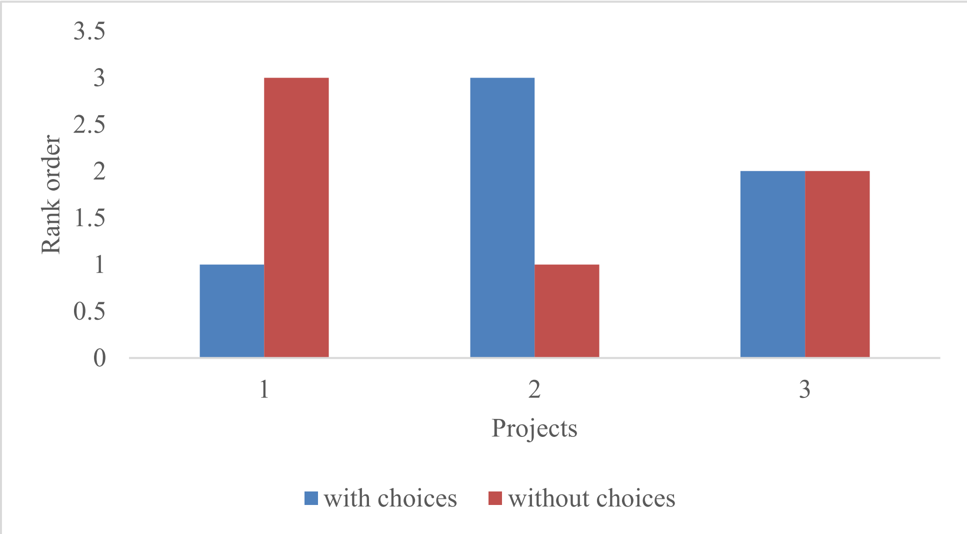

Fig. 2. Sensitivity analysis with/without choice vectors

5. Conclusion

This double-decker framework is a novel decision model for determining the ranks of alternatives. It adds value to the field of multi-attribute decision-making by providing an effective and simple rank fusion procedure that can flexibly scale by considering two decks. The SRP procedure in the second deck and the personal choice vector provide a simple yet rational rank fusion procedure. We consider four rank methods in the first deck, but it can be scaled further to different rank methods in a seamless manner.

Results show that personal choices significantly influence the final rank order, and the claims can be clarified from the sensitivity analysis. Since each rank method has its own pleasure and pain points, it is essential to consider the double-decker framework for determining the final combined rank order.

Some limitations of the study are: (i) partial information about the decision entity is not considered; (ii) attributes' weights are directly assigned; and (iii) the group decision approach is not considered. Some implications of the study are: (i) the framework is read-to-use and addresses the crucial problem of merit/limitation tradeoff in each method; (ii) some training is needed for the stakeholders to better utilize the framework; and (iii) deck – 1 maybe seamlessly scaled to accommodate different rank methods and final ordering can be obtained via deck – 2, thus enabling scale up and scale out features.

In the future, the study's limitations are planned to be addressed. Different fuzzy variants may be included in the framework. Also, different rank methods may be included from diverse categories such as utility, compromise, outranking, and the like. The application area can also be expanded to witness the merit of the double-decker framework in diverse decision-making applications in sustainability, health/medicine, engineering, and business.

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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