A Comparative Analysis of Multi-Criteria Decision-Making Methods

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ABSTRACT

Multi-Criteria Decision-Making (MCDM) techniques have found widespread application across diverse fields. The rapid evolution of MCDM algorithms has led to the development of hundreds of methods, each employing a distinct approach. Due to the inherent algorithmic differences, various MCDM methods often produce divergent results when applied to the same problem. This study presents a comparative analysis of 4 such methods: Root Assessment Method (RAM), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Faire Un Choix Adéquat (FUCA), and Collaborative Unbiased Rank List Integration (CURLI). The context of this evaluation is the ranking of 30 Vietnamese banks based on 6 criteria: capital adequacy, asset quality, management capability, earning ability, liquidity, and sensitivity to the market risk. Prior to this analysis, these banks had also been ranked by the CAMELS rating system. The CAMELS rankings serve as a benchmark to assess the performance of the RAM, MOORA, FUCA, and CURLI methods. This study's findings indicate that FUCA and CURLI are the most suitable methods for this application. On the contrary, RAM and MOORA proved unsuitable when compared to the CAMELS ranking.

Keywords-MCDM; bank ranking; CAMELS rating system

I. INTRODUCTION

In general, the MCDM techniques are employed for ranking alternative options when multiple, often conflicting, criteria need to be considered in order to make o decision regarding a specific problem [1-3]. These approaches have found extensive application across various domains, including economics, education, engineering, and energy [4-8]. However, the use of many distinct MCDM methods for a problem, each employing different algorithms, can lead to contrasting results when applied to the same specific problem [9, 10]. Consequently, the necessity of comparing the MCDM methods within a particular problem context has been emphasized. This comparative analysis is crucial for selecting the most appropriate method and ensuring the accuracy of the rankings obtained for the alternatives taken under consideration [11, 12]. MOORA stands out as one of the most prominent MCDM methods, having been widely across diverse fields [13]. RAM is a relatively novel MCDM method, which has a reduced number of computational steps and a simpler structure than others, along with the ability to balance both the benefit and cost criteria [14]. Furthermore, RAM can be integrated with various data normalization techniques [15]. While both MOORA and RAM possess unique algorithmic characteristics, they share a common requirement: the mandatory assignment of weights to criteria. Additionally, both methods necessitate data normalization even though the specific normalization techniques that are employed differ between them. On the contrary, FUCA and CURLI do not require data normalization. CURLI distinguishes itself from all other MCDM methods by eliminating the need for criteria weight calculation. Both FUCA and CURLI have been applied in various research studies across different domains.

The inherent differences among MOORA, RAM, FUCA, and CURLI raise a critical question regarding their comparative effectiveness. Until today, no research has comprehensively compared these four methods when applied to a specific problem. This is the primary motivation and main goal of this study. It should be emphasized that any comparative results among the MCDM methods are only valid within a specific case. The findings from the comparison of certain MCDM methods in one problem cannot be generalized or directly applied to another. For instance, AHP, PROMETHEE, and TOPSIS demonstrated similar performance when applied to house ranking in the construction sector [16]. Similarly, MABAC, COCOSO, MAIRCA, VIKOR, and ROV were found to have an equivalent performance in ranking the metal milling alternatives and assessing the indoor air quality in workplaces [17]. MODIPROM, TOPSIS, AHP, and VIKOR had similar performance in ranking elevator types [18]. In the context of ranking gold mining sites in Ghana, WSM, MULTIMOORA, and TOPSIS were equally effective [10]. SAW, TOPSIS, and PIV showed equivalent performance with a probability method when ranking battery-powered electric vehicles [19]. Furthermore, AHP, TOPSIS, VIKOR, WASPAS, GTMA, PROMETHEE 2, GRA, MULTIMOORA, ARAS, and COPRAS were reported to have similar performance in evaluating power system design alternatives [20]. When ranking plastic injection molding machines, PIV, FUCA, CURLI, and PSI presented comparable performance results [21]. PIV and FUCA also demonstrated similar effectiveness in ranking materials for connecting rods [22]. However, it has also been indicated that the MCDM methods can exhibit differing performance when applied in specific contexts. Among the methods used for ranking payment alternatives for sustainable housing development in Liverpool, UK and COPRAS demonstrated the best performance [23]. When the OCRA, COPRAS, ARA, TOPSIS, and SMART methods were employed to rank biomass energy types, only COPRAS and TOPSIS showed comparable performance. OCRA, ARA, and SMART exhibited similar performance among them but different from the first two [24]. BWM was verified to outperform AHP in ranking mobile phones [25].

For ranking energy development options in Serbia, among TOPSIS, VIKOR, PROMETHEE, MULTIMOORA, and COPRAS, the first three showed similar performance, while the last two differed from the initial three, but had similar characteristics among them [8]. TOPSIS and VIKOR were considered more effective than ELECTRE and MAUT for ranking earthquake-resistant solutions [26]. MARE had higher performance than AHP and ELECTRE III in ranking equipment for chemical production [27]. RAWEC demonstrated superiority over AROMAN in ranking cutting tool materials [28]. AHP and PROMETHEE performed better than TOPSIS in ranking main ship engines [29]. Finally, FUCA showed an advantage over the SPR method in ranking industrial tools and equipment [30]. It is evident that when comparing MCDM methods, the results vary depending on the application context. This study is a comparative analysis of four methods (MOORA, RAM, FUCA, and CURLI) in the context of ranking 30 Vietnamese banks.

II. MATERIALS AND METHODS

A. Bank Financial Indicators

Table I compiles the rankings of financial indicators for 30 Vietnamese banks, as reported in [31]. Six key indicators were utilized to evaluate each bank: capital adequacy (C1), asset quality (C2), management capability (C3), earnings ability (C4), liquidity (C5), and sensitivity to market risk (C6). C1 measures whether a bank has sufficient capital to absorb potential losses, indicating the bank's resilience to risk. C2 reflects the quality of a bank's loans and investments, particularly the non-performing loan ratio, showing the level of credit risk that the bank faces. C3 assesses the competence of the bank's management and risk governance system, thus demonstrating the effectiveness of the operations and control. C4 measures the efficiency of the bank's business operations and its profitability from various income sources. C5 indicates the bank's ability to meet short-term financial obligations, hence ensuring that it has enough cash to pay when needed. C6 measures the impact of the fluctuations in interest rates, exchange rates, and securities prices on the bank's financial condition. The values depicted in Table I, represent the ranks of these indicators and not their raw values. This means that each bank was independently ranked for each specific indicator and all these rankings are without units.

The data analysis presented in Table I, reveals considerable variations among the 30 reviewed banks. For instance, Bank #20 ranks 1st for C1, while Bank #18 ranks 30th for C1, C4, and C5. Bank #9 ranks 1st for C2 and 30th for C3, which is the same ranking with that of Bank #29 for C2. Moreover, Bank #25 ranks 1st for C3 similarly to Bank #29, which ranks 1st for C4; Bank #8, which ranks 1st for C5; and Bank #5, which ranks 1st for C6. These simple examples illustrate the significant divergence in the individual indicator ranks across the banks. Therefore, a comprehensive ranking of banks based on the aggregate of all indicators from C1 to C6 becomes essential. This necessity forms the rationale for employing the MOORA, RAM, FUCA, and CURLI methods in this study.

B. Employed MCDM Methods

1) MOORA

To rank the alternatives using MOORA, the following sequential steps are executed [13]:

Step 1: Construction of the decision matrix, which comprises of m rows and n columns, as defined in (1). In this case, m represents the number of alternatives to be ranked, and n denotes the number of criteria for each alternative. The value of the criterion j for alternative i is denoted as x_{ij}, where i = 1 to m and j = 1 to n:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: Computation of the normalized values:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (2)$$

Step 3: Calculation of the weighted normalized values, considering the weight w_j of criterion j:

$$V_{ij} = w_j \times n_{ij} \quad (3)$$

Step 4: Determining the values of Pi, Ri by using (4) and (5), where B and NB correspond to the number of "benefit" (larger is better) and "cost" (smaller is better) criteria, respectively:

$$P_i = \frac{1}{|B|} \sum_{j \in B} V_{ij} \quad (4)$$

$$R_i = \frac{1}{|NB|} \sum_{j \in NB} V_{ij} \quad (5)$$

Step 5: Calculation of the Q_i values:

$$Q_i = P_i - R_i \quad (6)$$

Step 6: Ranking the alternatives based on the principle that the alternative with the highest *Qi* value is considered the best.

2) RAM

The steps for ranking alternatives using RAM are [14, 15]:

Step 1: Similar to Step 1 of the MOORA method.

Step 2: Normalize the data:

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (7)$$

Step 3: Compute the weighted normalized values of the criteria:

$$y_{ij} = w_j \cdot n_{ij} \quad (8)$$

Step 4: Calculate the total weighted normalized scores of the criteria using:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad \text{if } j \in B \quad (9)$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad \text{if } j \in NB \quad (10)$$

Step 5: Determine the score for each alternative:

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \quad (11)$$

Step 6: Rank the alternatives in descending order of their scores.

3) FUCA

The steps for ranking the alternatives using FUCA are [32, 33]:

Step 1: Similar to Step 1 of the MOORA method.

Step 2: Rank the alternatives for each individual criterion.

Step 3: Calculate the score for each alternative using (12). Here, r_{ij} represents the rank of criterion *j* for alternative i, as determined in Step 2:

$$S_i = r_{ij} \cdot w_j \quad (12)$$

Step 4: Rank the alternatives in descending order based on their scores.

4) CURLI

The steps for ranking the alternatives deploying CURLI are [34, 35]:

Step 1: Similar to Step 1 of the MOORA method.

Step 2: Assign scores to the alternatives within each criterion using:

$$P_{ij} = \begin{cases} 1 & \text{if } x_i > x_k, i \neq k \\ -1 & \text{if } x_i < x_k, i \neq k \\ 0 & \text{if } x_i = x_k, i \neq k \end{cases} \quad (13)$$

Step 3: The score Ri for each alternative is calculated using:

$$R_i = \sum_{j=1}^{n} P_{ij} \quad (14)$$

Step 4: Rank the alternatives in ascending order based on their R_i scores.

C. Criteria for Method Comparison

The Spearman's rank correlation coefficient (S) reflects the stability of alternative rankings when derived using different MCDM methods [36]. This coefficient is calculated using (15), where Di represents the difference in rank for alternative i when ranked by various methods:

$$S = 1 - \frac{6 \sum_{i=1}^{m} D_i^2}{m(m^2 - 1)} \quad (15)$$

In this study, Spearman's rank correlation coefficient is computed for each MCDM method (MOORA, RAM, FUCA, and CURLI) and is compared with the CAMELS rating system. The latter is a comprehensive assessment tool used by bank supervisory authorities to evaluate the financial health and operational soundness of financial institutions. The acronym CAMELS stands for six key factors:

- Capital Adequacy (assesses the ability to absorb losses).
- Asset Quality (reflects the quality of loans and investments).
- Management (evaluates the competence of leadership and operational control).
- Earnings (measures profitability).
- Liquidity (indicates the ability to meet short-term financial obligations).
- Sensitivity to Market Risk (assesses the impact of market fluctuations).

Each of these elements is scored, thus offering an overall view of a bank's condition. This comparison provides the basis for evaluating the performance of the MCDM methods against each other. More specifically, the rankings of the banks that were previously established by the CAMELS system will serve as the benchmark for assessing the effectiveness of the selected MCDM methods.

III. RESULTS AND DISCUSSION

Following the procedural steps of MOORA, the Qi scores for each bank were calculated and their respective ranks were determined. Similarly, by applying the steps of RAM, the RIi scores and subsequent bank rankings were produced. For FUCA, the Si scores were derived to establish the bank ranks. Regarding CURLI, the Ri scores were also computed for ranking purposes. All these values are summarized in Table II, where the final column represents the bank ranks that were previously established by the CAMELS system.

TABLE I. FINANCIAL INDICATOR RANKINGS OF BANKS

Banks	C1	C2	C3	C4	C5	C6
Bank #1	13	14	15	11	16	22
Bank #2	18	10	11	6	26	8
Bank #3	27	28	6	14	28	2
Bank #4	16	4	7	16	19	21
Bank #5	29	29	3	10	17	1
Bank #6	24	26	10	21	12	3
Bank #7	6	20	21	24	22	14
Bank #8	14	4	23	7	1	12
Bank #9	8	1	30	17	17	28
Bank #10	22	13	18	13	11	13
Bank #11	7	17	11	2	8	7
Bank #12	5	24	29	15	12	18
Bank #13	25	10	13	11	9	23
Bank #14	28	4	28	28	23	24
Bank #15	9	15	13	3	3	20
Bank #16	3	27	5	22	23	29
Bank #17	17	9	27	29	27	15
Bank #18	30	10	24	30	30	5
Bank #19	21	19	16	25	4	15
Bank #20	1	21	22	23	20	30
Bank #21	26	25	9	19	12	9
Bank #22	19	22	25	20	29	6
Bank #23	2	16	4	3	9	11
Bank #24	11	2	20	9	2	19
Bank #25	23	23	1	8	12	4
Bank #26	12	17	7	5	5	17
Bank #27	20	3	2	27	6	25
Bank #28	15	4	18	26	20	27
Bank #29	4	30	25	1	6	9
Bank #30	10	8	17	17	23	26

TABLE II. RANKINGS OF BANKS USING DIFFERENT METHODS

Banks	MOORA		RAM		FUCA		CURLI		CAMELS
	Qi	rank	RIi	rank	Si	rank	Ri	rank	
Bank #1	0.0262	16	1.4258	16	15.1667	15	-3	14	14
Bank #2	0.0228	22	1.4243	22	13.1667	9	-25	9	9
Bank #3	0.0303	9	1.4277	9	17.5000	22	24	22	22
Bank #4	0.0239	20	1.4248	20	13.8333	10	-16	11	10
Bank #5	0.0256	19	1.4256	19	14.8333	12	-7	12	12
Bank #6	0.0276	15	1.4265	15	16.0000	16	9	16	16
Bank #7	0.0308	8	1.4279	8	17.8333	23	28	23	23
Bank #8	0.0175	28	1.4220	28	10.1667	3	-61	3	3
Bank #9	0.0291	12	1.4271	12	16.8333	19	18	18	19
Bank #10	0.0259	18	1.4257	18	15.0000	13	-5	13	13
Bank #11	0.0150	29	1.4209	29	8.6667	2	-80	2	2
Bank #12	0.0297	10	1.4274	10	17.1667	21	23	21	21
Bank #13	0.0261	17	1.4258	17	15.1667	14	1	15	14
Bank #14	0.0388	1	1.4314	1	22.5000	30	89	30	30
Bank #15	0.0181	26	1.4223	26	10.5000	4	-58	5	4
Bank #16	0.0314	7	1.4282	7	18.1667	24	34	24	24
Bank #17	0.0357	3	1.4300	3	20.6667	28	63	28	28
Bank #18	0.0372	2	1.4307	2	21.5000	29	74	29	29
Bank #19	0.0287	14	1.4269	14	16.6667	17	15	17	17
Bank #20	0.0337	5	1.4292	5	19.5000	26	49	26	26
Bank #21	0.0288	13	1.4270	13	16.6667	17	18	18	17
Bank #22	0.0349	4	1.4297	4	20.1667	27	57	27	27
Bank #23	0.0130	30	1.4200	30	7.5000	1	-94	1	1
Bank #24	0.0181	27	1.4222	27	10.5000	4	-60	4	4
Bank #25	0.0204	24	1.4233	24	11.8333	7	-41	7	7
Bank #26	0.0181	25	1.4223	25	10.5000	4	-58	5	4
Bank #27	0.0238	21	1.4248	21	13.8333	10	-19	10	10
Bank #28	0.0316	6	1.4282	6	18.3333	25	39	25	25
Bank #29	0.0216	23	1.4238	23	12.5000	8	-33	8	8
Bank #30	0.0291	11	1.4271	11	16.8333	20	19	20	19

A noteworthy observation from the data in Table II, is the consistent ranking of the banks when determined by MOORA and RAM. However, a significant divergence is apparent in the bank rankings produced by these two methods, compared to those from FUCA and CURLI, as well as the CAMELS system. This result can be attributed to the data normalization performed by MOORA and RAM. Specifically, MOORA applied normalization according to (2), while RAM utilized (7) for normalization. It should be noted that the data in Table I represent the ranks of the banks for each indicator and not their raw economic values. The application of data normalization methods, in this context, led to a loss of the data's original characteristics [39]. This could be the underlying reason for the substantial difference in bank rankings generated by the MOORA and RAM methods compared to those from FUCA, CURLI, and the CAMELS system. Conversely, FUCA and CURLI, since they do not perform data normalization, preserved the original nature of the data. Consequently, the bank rankings produced by these two methods exhibit high consistency with each other and a strong resemblance to the CAMELS system.

For the FUCA method, 29 out of 30 banks showed rankings that were consistent with those from the CAMELS system. Considering CURLI, 24 out of 30 banks displayed consistent rankings compared to the CAMELS results, excluding Bank #4, Bank #9, Bank #13, Bank #15, Bank #26, and Bank #30. However, even for these differing banks, the rank discrepancies when using CURLI were minimal compared to the CAMELS system. This strong consistency in bank rankings across FUCA, CURLI, and the CAMELS system is remarkable. Specifically, all three approaches consistently identified the top-performing banks, such as the 1st-ranked bank (Bank #23), the 2nd-ranked bank (Bank #11), and the 3rd-ranked bank (Bank #8). Similarly, they consistently identified the lowest-ranked banks, including the 30th-ranked bank (Bank #14), the 29th-ranked bank (Bank #18), and the 28th-ranked bank (Bank #17), among all others.

The above observations suggest that MOORA and RAM are not suitable for this specific case. On the contrary, FUCA and CURLI appear to be highly appropriate. To have an extra proof of our observations, Equation (15) was used to calculate the Spearman's rank correlation coefficient between the methods.

Table III summarizes the Spearman's rank correlation coefficientsbetween each MCDM method and the CAMELS system by treating the CAMELS system as a benchmark for evaluating the performance of the MCDM methods.

TABLE III. SPEARMAN'S RANK CORRELATION COEFFICIENTSBETWEEN MCDM METHODS AND THE CAMELS SYSTEM

	MOORA	RAM	FUCA	CURLI	CAMELS
MOORA	1	1	-1.030	-1.005	-1.026
RAM		1	-1.030	-1.005	-1.026
FUCA			1	0.998	0.999
CURLI				1	0.998
CAMELS					1

As demonstrated in Table III, the Spearman's rank correlation coefficients for both MOORA and RAM in comparison to the CAMELS system are extremely low (-1.026). This result confirms that the bank rankings generated by these two methods deviate significantly from those produced by the CAMELS system. It can be, therefore, stated that MOORA and RAM are unsuitable for this scenario. Conversely, the Spearman's rank correlation coefficients for FUCA and CURLI against the CAMELS system are remarkably high, at 0.999 and 0.998, respectively, demonstrating that these two methods are highly appropriate for this specific case.

IV. CONCLUSION

The comparison of different Multi-Criteria Decision-Making (MCDM) methods to rank the alternatives in a specific problem is essential. This process helps identify the most suitable method to use and ensures the most accurate ranking of the alternatives. This study compared four methods: Root Assessment Method (RAM), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Faire Un Choix Adéquat (FUCA), and Collaborative Unbiased Rank List Integration (CURLI) in the context of ranking 30 Vietnamese banks. The novel insights derived from this research are:

Data normalization should only be applied when the criteria used to evaluate the alternatives have different dimensions. If the criteria share the same dimension, normalizing the data can distort their original characteristics, hence impacting the ranking results significantly. When the criteria share a common dimension, FUCA and CURLI emerge as highly viable methods for ranking the alternatives.

The ranking results for Vietnamese banks show a high consistency between the FUCA, CURLI, and CAMELS system rating results. The Spearman's rank correlation coefficients (S) between the FUCA, CURLI, and CAMELS system are 0.999 and 0.998, respectively.

Among the 30 banks ranked, the top-performing banks were identified as Bank #23 (Rank 1), Bank #11 (Rank 2), and Bank #8 (Rank 3). Conversely, the lowest-ranked banks were Bank #14 (Rank 30), Bank #18 (Rank 29), and Bank #17 (Rank 28).

Evaluating the financial performance of banks would be more comprehensive if additional factors were considered, such as their ability to handle non-performing loans, their capacity for urgent financial resolutions, etc. Furthermore, incorporating expert opinions on the importance of various criteria would make the assessment of the banks' financial health more realistic. These limitations should be addressed in future research.

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